PACT Tropical Moist Forest Accreditation Methodology

Draft for comments

Version 1.0

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About this document

This PACT draft document describes the methodology developed by the Cambridge Center for Carbon Credits (4C) for estimating the number of credits to be issued to a project in the tropical moist forest (TMF) biome. It expands on the methodology outlined in (Swinfield and Balmford, 2023). We welcome comments and suggestions in the associated online document at https://tinyurl.com/cowgreport.

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1. Glossary of acronyms and terms

Term	
	Tracking carbon and landcover change
AGB	Above Ground Biomass
BACI	Before-after control-impact
BGB	Below Ground Biomass
GEDI	NASA Global Ecosystem Dynamics Investigation space-borne LiDAR
AFC	Annual Forest Change product from Vancutsem et al 2021
LUC	Land Use Class. These are undisturbed forest, degraded forest, deforested, regrowth forest, water and other (agriculture, urban etc.).
TMF	Tropical moist forest - these receive high rainfall which is not seasonal, supporting evergreen trees
	REDD+ Project terminology
REDD+	Reducing Emissions from Deforestation and Forest Degradation
PDD	Project design document, prepared in preparation of REDD+ project
	Economic terms
SCC	Social Cost of Carbon
RCP	IPCC Representative Concentration Pathway
	Technical terms
Carbon density	Amount of carbon storage in AGB, BGB and soil per unit land area (typically Mg C per hectare). A hectare is 100 x 100 m
LUC carbon density	The average carbon density of a LUC; setting this as a constant allows carbon stock changes to be calculated by simply tracking land use change.
Evaluation period	The time period for which carbon credits are being assessed.

2. Assumptions

	Assumption	Justification	Comments
	Carbon measurement		
A1	We consider the next 500 years when carbon accounting.	With a discount rate of 3%, the present value of damages 500 years in the future are 1 millionth of the damages today.	The lower the discount rate, the longer we need to model carbon releases.
A2	We can estimate project quality as being low or high. It is acceptable to use PDD estimates of leakage and AGB for projects that are assessed to be high quality.	Projects are routinely assessed as being high or low quality according to expert knowledge of the reputation of proponents, the quality of the data used by the project, how long the project has been running for, and qualitative appraisal of the resilience of the project.	There can be a significant difference in additionality and leakage depending on whether the project is assessed as low-quality or high-quality. We aim to remove elements of qualitative appraisal as algorithmic methods improve.
A3	LUC carbon density does not change appreciably over time.	A reasonable first-order assumption.	This may not be accurate, as carbon density increases each year after the last episode of deforestation or disturbance and carbon density of undisturbed forest is falling over time as a result of global warming (Hubau et al. 2020; Brienen et al. 2015). Our method will be upgraded to reflect this.
A4	AGB per LUC that is measured in a 30 km region around the project area (as opposed to the project area alone) is representative of the project.	Rare land use classes have only a few GEDI shots, so we needed to sample outside the project area. A 30 km buffer around the project was chosen as it ensured that a set of GEDI points were available to assess land use class carbon densities..	This may not be accurate as small patches of "undisturbed" forest outside project areas are likely to have lower AGB as they are affected by edge effects and historical disturbance. Preliminary sensitivity analyses have shown that median carbon density of the undisturbed class is fairly insensitive to including the 30 km buffer (vs. project only). This may be tested formally in future.
A5	The GEDI L4A product is an accurate measure of AGB for each LUC	This is the state of the art for tropical moist forests and can be replaced by better estimates as they become available (e.g. from improved GEDI allometries)	Nb, Estimates seem particularly bad for dry forests with open canopies but reasonable for TMF.
A6	GEDI L4A shots are correctly filtered using degrade_flag == 0, beam_type == 'full', l4_quality_flag == 1, leaf_off = 0	This is the best publicly-known setting right now according to the GEDI team (Personal communication)	Need to upgrade to better filtering as it becomes available

A7	Land use/forest change classification by Annual Forest Change map (AFC) (Vancutsem et al. 2021) is accurate for tropical moist forests	This is currently the best known source for tracking annual gains, losses and degradation of the tropical moist forests.	Building our technology on the AFC product makes us dependent on its continued existence - the long-term commitment of the JRC to resourcing its annual update needs to be checked . Mapbiomas is an appropriate source for Brazil and Indonesia and uses the same classes.
A8	Carbon density for each LUC is the same in the project and its counterfactual areas	A reasonable first-order assumption	Also see comments on A4. This could be refined if necessary
A9	Belowground biomass (BGB) and deadwood biomass are assumed to be 20% and 11% of AGB respectively.	(Cairns et al. 1997) (IPCC 2003)	When a forest loses x% of its AGB due to degradation, it also loses x% of its BGB and deadwood biomass. Soil carbon is assumed to remain unchanged.
A10	Total biomass values are converted to carbon densities by multiplying by the average carbon density of 0.47	(Martin and Thomas 2011)	This is known to vary somewhat between ecosystems. Martin and Thomas found a standard deviation of 0.025 across their Panamanian sample
A11	Matches can be found for all pixels that are sampled from the project area and its leakage buffer	Poor matches will be reflected in standardised mean differences greater than 0.2.	Matching the unique areas (especially inaccessible areas) within the project area may be impossible. A simple method for excluding inaccessible areas has been developed which assumes zero additionality in these areas. To avoid bias, the project area has to be reduced accordingly. A better approach would be to break up the evaluation of the project into standard units which can be automatically excluded if matching fails.
A12	Potential match pixels must be within a 2000 km buffer around the project as well as match on biome and country	Restricts matching to a similar vegetation type within the same geographic region	For projects under pressure from international threats it may be important to match globally, but this introduces further complications.

A13	Local leakage only occurs in a 5km buffer around the project	A 5-km buffer is grounded in the notion that forest protection has an effect on behaviour of people living close to its boundary. The choice of 5 km versus 10 or 15 km is somewhat arbitrary. A paper on deforestation leakage undermining the conservation value of tropical and subtropical protected areas (Ford et al. 2020) looked at leakage in a 10 km zone for 120 protected areas. Guizar-Coutiño (2022) evaluated the effectiveness of 40 REDD sites at reducing CO2 emissions using a 15 km buffer.	Quantifying local leakage and attributing causality to the project is challenging: first, actions beyond the control of the project can cause changes in leakage area carbon stock; second, for small projects, the leakage area can be many times larger than the project area and even small changes in stocks relative to the leakage counterfactual are amplified over the large area, so that the additionality signal is exceeded. Consequently, we take the view that the maximum amount of leakage that can occur is limited by the total quantity of additionality generated; in other words the food or fibre production attributable to leakage, can not exceed the amount displaced by the project. Local leakage can potentially be ignored but only through evidence that the actors, labour and finance involved were completely different from those involved in the project.
A14	Only REDD+ project areas (both Verra and non-Verra) should be excluded from counterfactual matches	Guizar-Countiño et al. 2022 found inclusion of other types of protected areas made little difference to additionality estimates	There may be arguments to match on specific land use management classes (e.g. community forest or industrial forest) or by ownership. This is not currently implemented. Need to expand this to include all REDD sites from VCS + Plan Vivo scrape
A15	CO_2 fluxes following a land cover class change are equal to the difference in stocks between those classes and this change is instantaneous	This assumption is satisfactory for estimates of fluxes arising from deforestation of undisturbed forest and provides estimates that are close to or as good as those used by most carbon projects which parameterise land cover class carbon density estimates from field plots.	The approach is naive for tracking land cover changes between other classes, particularly where complex degradation or regeneration dynamics are at play. In reality carbon stocks in different pools are drawn down or released at different rates (i.e. they are not instantaneous). Applying simple time lags to emissions is a straightforward improvement for future versions.
A16	Because each counterfactual point is forced to be the same land cover class as its paired project point at project start, additionality is assumed to be equal to the simple difference at the end of the evaluation period	This is for simplicity.	Selection bias could result in under-estimating the counterfactual loss trajectory in the pre-project period. This would materialise as a divergence of the counterfactual from the project line rather than vice versa as expected. This issue can be reduced by working with aggregated pixel blocks (as per Garcia and Heilmeyer, 2023).

	Permanence		
A17	The annual discount rate of the SCC is 3%.	This discount rate is compatible with an increase in the SCC of 2% per year as well as the implied Ramsey discount rate using the mean pure time preference rate and elasticity of marginal utility of the expert survey reported in Drupp et al. (2018).	Balmford et al. (2023) provide sensitivity analysis of eP to discount rate choice.
A18	Relative concentration pathway (RCP) 4.5 is used to project atmospheric carbon concentration.	RCP 4.5 is more conservative than RCP 2.6.	This assumes a moderately fast decarbonization, not as fast as RCP 2.6 but not as slow as RCP 8.5
A19	Subjective assessments of project quality are reflected in lower release rates during the project term and, importantly, that release schedules reflect credit value without exposing buyers to unanticipated reversal risk.	In the absence of better data this allows us to value impermanent storage of NBS credits, factoring a qualitative perception of risks.	There can be a significant difference in EP depending on whether the project is assessed as low-risk or high-risk. Low-frequency catastrophic events need to be included in the forecast of reversal risk, as well as more complex forecasts of drawdowns and release in both the project and counterfactual scenarios. We need to make this stochastic and to use informed parameters. Extensive ongoing work addresses these issues.
	Matching		
A20	A sampling density of 0.05-0.25 randomly generated spatial pixels per hectare over the project area is sufficient	This is currently set to generate a reasonably dense sample at the scale of most REDD+ projects. For larger projects we have reduced the sampling density due to the run time required on GEE. For smaller projects we want to establish a higher sample density to ensure precision in the treatment set.	Ideally, we should choose a target no of pixels based on statistical sampling theory
A21	The significant factors driving deforestation are covered by the following matching variables: jurisdiction (country), ecoregion, land use class, elevation, slope, accessibility [time to health care as a proxy for time to town], proportionate land cover in a 1km radius. We assume that matching using BACI + Mahalanobis distance sampling without replacement and without callipers gives reliable estimates of additionality.	These are well known proximal causes applied to "unplanned" deforestation (Geist and Lambin 2001). However, the ultimate causes may be "planned" deforestation for commodity production for international markets https://ourworldindata.org/drivers-of-deforestation	Population density is so coarse that it is currently not found to be a useful matching variable. Soil types are a categorical hierarchy but currently too fine to be used effectively for matching. A better layer should be sought. Including recent history of deforestation in 1 km radius around points improves matching but needs more thought to consider if this creates bias in outcomes. Additionality estimates are very sensitive to decisions about the choice of matching algorithm and its parameters (Guizar-Coutiño 2022)

A22	Counterfactual matches are only made within the same country	Political decisions are key to success of REDD+; matching by country is reasonable because reference areas are typically in the same region (VM0009) and subject to the same policies, legislation and regulation (VM0015).There is precedent for matching in country (Guizar-Countiño et al., 2022; West et al., 2023). Some projects may be exposed to threats which are international in nature, in which case a country-level counterfactual will underestimate additionality.	We have the ability to test the sensitivity of results to matching to similar ecoregions beyond the country, should this be necessary.
A23	To be matched, pixels must have the same land use at start of project and at 5 and 10 years before the start (t_0, t_{-5}, t_{-10})	This is a reasonable approximation to VCS which requires that REDD+ projects have remained forest for 10 years prior to project initiation (VM0007; VM0015).	It is possible to extend the demand that pixels be matched on the entire time series. However this can only ever go back as early as approximately 1990.
A24	Matching using BACI + Mahalanobis distance sampling without replacement and without callipers gives reliable estimates of additionality.	This is a widely used approach in assessment of conservation impacts (Schleicher et al., 2019)	Additionality estimates are very sensitive to decisions about the choice of matching algorithm and its parameters (Guizar-Coutiño 2022)
A25	The project area is the spatial polygon that defines the area in which the project is primarily operating to conserve forest. Consequences on carbon storage are only assessed within the project and surrounding leakage areas.		Verra trims project area boundaries to exclude any deforestation occuring within the project boundary in the run up to implementation. Under their standard there's no deforestation in the project area prior to project start, by definition. Thus, it is not necessary to apply BACI methodologies to the project area under these circumstances. Guizar-Coutiño et al. (2022) chose to work with CI methods not BACI for this reason. An alternative solution to this is to analyse project and buffer areas simultaneously, because the buffer areas include the deforested pixels that Verra has excluded from the project area.
A26	We assume that the evolution of the project and the counterfactual differ due only to human intervention.	This is the state of the art.	Project and counterfactual pixels that have the same parameters might still differ due to their inherent stochasticity. Moreover, project pixels are typically geographically contiguous, whereas counterfactual pixels may not be. In this case, even with perfect per-pixel matching, geographically contiguous disturbances may affect project pixels more than counterfactual pixels, and deforestation pressures on small parcel sizes may affect counterfactual pixels more than project pixels. We can test this through placebos.

3. Notation

Term	Meaning (units)	Default value
SCC(t)	Social cost of carbon at time interval t ($\$ \cdot GtCO_2^{-1}$)	
δ	Annual discount rate	3%/year
L	Lifetime of carbon in the atmosphere	500 years (**A1**)
R	Mean observed deforestation amount in the project in the prior 5 years from the time at which this computation is being carried out ($GtCO_2$)	
D	Social cost of damage from the release of sequestered carbon following the assumed release schedule	
t_0	Year of start of project implementation	
t_{now}	Year of evaluation	
t_{-5}	Five years before year of implementation	
t_{end}	Year when the project ends according to the project design document	
$t_{release}$	Year when all net sequestration in the evaluation period is released	
$P_{tot}(t)$	Total biomass in project in year *t*	
$C_{tot}(t)$	Total biomass in the matched counterfactual region in year *t*	

4. Inputs

1. Project design document (PDD) and any project monitoring reports which contain
   a. Years for which project ex-post additionality, leakage and other impacts need to be estimated
   b. A KML file with geodetic polygons that delineate the project zone(s).
2. GEDI Level 4a data providing aboveground biomass of a location (latitude, longitude) from the GEDI waveform from a shot at that location (Duncanson et al., 2022)
3. Land cover time series consisting of an image layer for each year. For any pixel, its land use class for a given year can be looked up as AFC[year][latitude][longitude. We use the Annual

Forest Change Collection (AFC) land use class at 30m resolution per pixel [Vancutsem et al, 2021]. The land use classes(LUC) are Undisturbed, Degraded, Deforested, Regrowth, Water, and Other.

4. Large Scale International Boundary (LSIB) Polygons (United States Department of State, Office of the Geographer. 2017)
5. RESOLVE Ecoregions 2017 (RESOLVE Biodiversity and Wildlife Solutions, Dinerstein *et at.* 2017)
6. NASA/CGIAR SRTM 90m Digital Elevation (NASA/CGIAR) to derive slope.
7. Accessibility to Healthcare in 2015 (Malaria Atlas Project; Weiss et al, 2018)
8. OpenLandMap USDA Soil Taxonomy Great Groups (EnvirometriX)
9. GPWv411: UN-Adjusted Population Density (NASA SEDAC)
10. Qualitative assessment whether the project is low or high quality. (**A2)**
11. Polygon database of all REDD+ projects + 5km buffer around each project in tropical moist forests (compiled from Verra registry and any other REDD+ projects we are aware of).
12. Social Cost of Carbon (SCC) Table from (Groom and Venmans. 2022). See also (Nordhaus 2014; Marshal and Kelly 2010)
13. Filters for country, ecoregion (Dinerstein et al. 2017), elevation range (Jarvis et al. 2008); GTOPO30), accessibility range 2015 (Weiss et al. 2018), soil type (Hengle and Nauman 2018) and above ground biomass range in 2010 (Spawn et al., 2020).
14. Population density for the nearest 5 year interval (Center for International Earth Science Information Network-CIESIN - Columbia University. NASA Socioeconomic Data and Applications Center (SEDAC) Palisades, NY 2018.
15. PDD estimate of AGB per LUC.
16. Leakage estimation from PDD.

5. Outputs

1. Additionality of the project for each year in the evaluation period which is the period from the official start year of the project until the most recent year of ex-post evaluation; if no alternative claims of additionality are available the evaluation is made up to the most recently available land cover data (GtCO_2)
2. Local leakage of the project for each year in the evaluation period (GtCO_2)
3. An estimate of equivalent permanence (eP) of the carbon sequestered in the evaluation period (0<= EP <= 1).
4. Paired pixels with the first element of the pair being from the match area and the second being in the region from which counterfactuals are drawn, used for visualisation.

6. Algorithm

Sketch

The project area is modelled as a population of 30m by 30m pixels, each of whose centroids lies within the given project polygons. Each pixel is associated with a land use class, such as ‘Undisturbed’ or ‘Deforested’ using the JRC Annual Forest Change map. We then use GEDI shots to estimate the carbon density of each land use class (LUC) (Section 6.1).

We match each project pixel to 100 counterfactual pixels which are from the same LUC and have similar environmental properties to the project pixel (e.g. similar accessibility), and compute the total biomass in the project area and the total biomass in all the counterfactual pixels, divided by 100.

(Section 6.2 and 6.3) Their difference is the additionality in the project. A similar computation is carried out for the leakage area. This leakage is subtracted from the additionality.

Finally the permanence of (additionality-leakage) in the evaluation period is estimated using the approach from (Balmford et al, 2023) (Section 6.4).

6.1 Data preparation for identifying candidate counterfactual pixels and tracking land use

1. Coarsened proportional land cover layers are produced for each land use class for each year at 1200 m resolution by first converting the 30 m land class pixels to a binary layer (i.e. is the pixel in the class or not for each of the 6 LUC) and then summing the binary layer and dividing by the total number of contributing pixels. This results in computing the proportion of each LUC in each 1200m x 1200m patch.

Comment: We now estimate the carbon density in Mg/ha for each LUC in the project area. AGB was predicted by the NASA team by modelling relative canopy height density values extracted from full waveform space-borne LiDAR measurement as a function of field measurements of AGB obtained from a global dataset, using ordinary least squares regression (Duncanson et al. 2022). **(A3)**

2. If the project is assessed as high quality, then the AGB per land class for both the project and control are determined using both the values reported in the PDD as well as the process detailed below. If the PDD does not report AGB values for certain land classes, the assumptions made in determining these values should be clearly stated. **(A2)**

3. Let *B* = a set of pixels, initially empty.

4. Find all GEDI level 4a shots falling within the project area as well as a 30 km buffer around it and add them to *B*. *Comment: Currently, this is done using the 'buffer' function in Google Earth Engine.* **(A4, A5)**

5. Let *S* be the set of shots in *B* after filtering using `degrade_flag == 0`, `beam_type == 'full'`, `l4_quality_flag == 1`, `flag != "leaf-off state"`. **(A6)**

6. For each shot *s* in *S*

    a. Set `s.LUC` from the Annual Forest Change land use class **(A7, A8)**

    b. Discard *s* if the LUC of any of the 8 immediately neighbouring pixels differs from the `s.LUC`. This corrects for the fact that GEDI shots have a 10 m geolocation error with respect to AFC (Dubayah et al. 2020).

    c. Save `s.land_use_class` and `s.agbd` in a table T.

7. Compute the median `s.agbd` value for each land use class from T.

8. Belowground biomass (BGB) and deadwood biomass is assumed to be 20% and 11% of AGB respectively (Cairns et al. 1997; IPCC 2003). **(A9)**

9. Total biomass (= AGB + BGB + deadwood biomass) is converted to carbon density in Mg/ha by multiplying by the average carbon density of 0.47 **(A10)**

6.2 Additionality

1. Let *T* be the set of pixels in the project area as defined by the project polygons at time t_0 (**A24, A25**). Let |*T*| be the number of pixels in *T.*
2. For each pixel in *T* find its land use class *V.*
3. For each year *t* of time series from t_0 to t_{now}, where t_0 = year of project start and t_{now} is the year of assessment.
    a. Let $N_{T,V}(t)$ be the number of pixels in each class *V* in *T* in year *t*
    b. The proportion of the project area in class *V* in year *t* is $N_{T,V}(t_{now})/|T|$.
    c. For each land use class *V*
        i. Find the total area in class *V* by multiplying $N_{T,V}(t)/|T|$ by the total project area, T *30*30 in square metres.
        ii. $S_{T,V}(t)$ = Carbon stock per ha in class *V* * total area of class *V* in the project.
    d. $P_{tot}(t)$ = total carbon stock for year *t* in the project area = $\Sigma_V S_{P,V}(t)$
    e. Do the following 100 times indexed by *i* (as a bootstrap and to match each pixel to 100 counterfactual pixels):
        i. Let *C* be the set of counterfactual matching pixels, which is the result of calling Procedure *Find Matches* with:
            1. Match source = all project polygons **(A11)**
            2. Match destination = the intersection of a 2000 km buffer around project(**A12**), the country boundary from LSIB countries for the project's country, and the ecoregion boundaries from RESOLVE Ecoregions for all the ecoregions that lie within the project
            3. Exclude region = other REDD+ project areas AND a 5 km leakage buffer around these REDD+ projects AND a 5km leakage buffer around the project polygon. **(A13, A14)**
        ii. Let |*C*| be the number of pixels in *C.*
        iii. For each pixel in *C* find its land use class *V.*
        iv. Let $N_{C,V}(t)$ be the number of pixels in class *V* in *C* in *T.*
        v. The proportion of the counterfactual area in class V in year *t* is $N_{C,V}(t)/|C|$.
        vi. For each land use class *V*
            1. Find the total area in class *V* in the counterfactual scenario by multiplying $N_{C,V}(t)/|C|$ by the total project area.
            2. $S_{C,V}(t)(i)$ = carbon stock per unit area in class *V* * total area of class *V* in the counterfactual scenario.
    f. $C_{tot}(t)$ = mean total carbon for year *t* in the counterfactual scenario = $\frac{1}{100}\Sigma_V \Sigma_i S_{C,V}(t)(i)$
    g. Calculate additionality within project area as **(A15, A16, A26)**:
       Additionality(t) = $P_{tot}(t) - C_{tot}(t)$

6.3 Leakage

Note: calculation of CO_2 stock changes in leakage zones follows the same logic as calculation of additionality CO_2 stock changes (above), with the only difference being the area where the calculations are made

1. If the project is assessed as high quality, then the leakage is determined as a fraction of the additionality as reported in the PDD as well as using the process detailed below. **(A2)**
2. The leakage area is a 5 km buffer around the project polygons. **(A14)**
3. Let *T* be the set of pixels in the leakage area at time t_0. Let |*T*| be the number of pixels in *T.*
4. For each pixel in *T* find its land use class *V.*

5. For each year t of time series from t_0 to t_{now}, where t_0 = year of project start and t_{now} is the year of assessment.
    a. Let $N_{T,V}(t)$ be the number of pixels in each class V in T in year t.
    b. The proportion of the project area in class V in year t is $N_{T,V}(t)/|T|$.
    c. For each land use class V
        i. Find the total area in class V by multiplying $N_{T,V}(t)/|T|$ by the total leakage area T *30*30 in square metres.
        ii. $S_{T,V}(t)$ = carbon stock per unit area in class V * total area of class V in the leakage area.
    d. $L_{tot}(t)$ = mean total carbon stock for year t in the leakage area = $\Sigma_V S_{P,V}(t)$
    e. Do the following 100 times indexed by i (as a bootstrap and to match each leakage pixel to 100 counterfactual pixels)
        i. Let C be the set of counterfactual matching pixels, which is the result of calling Procedure *Find Matches* with
            1. Match source = leakage area **(A11)**
            2. Match destination = 2000 km buffer around project **(A12**) + country boundary from LSIB countries for the project's country + ecoregion boundaries from RESOLVE Ecoregions for all the ecoregions that lie within the project
            3. Exclude region = other REDD+ project areas AND a 5 km leakage buffer around these REDD+ projects AND the project area.**(A13, A14**)
        ii. Let $|C|$ be the number of pixels in C.
        iii. For each pixel in C find its land use class V.
        iv. Let $N_{C,V}(t)$ be the number of pixels in class V in C in T.
        v. The proportion of the counterfactual area in class V in year t is $N_{C,V}(t)/|C|$.
        vi. For each land use class V
            1. Find the total area in class V in the counterfactual scenario by multiplying $N_{C,V}(t)/|C|$ by the total project area.
            2. $S_{C,V}(t)(i)$ = carbon stock per ha in class V * total area of class V in the counterfactual scenario.
    f. $L_{tot}(t)$ = mean total carbon stock for year t in the project area = $\frac{1}{100}\Sigma_V \Sigma_i S_{T,V}(t)(i)$
    g. $C_{tot}(t)$ = mean total carbon stock for year t in the counterfactual scenario = $\frac{1}{100}\Sigma_V \Sigma_i S_{C,V}(t)(i)$
    h. Calculate leakage as **(A15, A16)**:

        $Leakage(t) = L_{tot}(t) - C_{tot}(t)$

6.4 Permanence

This computation is carried out at the end of an evaluation period in year t_i. Let the end of the immediately previous time period where estimates of additionality and leakage are available be denoted by t_{i-1} (normally, this would be the end of the previous year, which may precede the year of project start).

1. Let $C(t_i)$ denote the net sequestration/release of (additionality -leakage) during the i^{th} evaluation period t_i, which is computed at the end of that period:

$$C(t_i) = (Additionality(t_i) - Leakage(t_i)) - ((Additionality(t_{i-1}) - Leakage(t_{i-1}))$$

1. Compute the average annual additionality, net of leakage, for the past 5 years in the project as:

$$R = \frac{1}{5}(C(t_i) - C(t_i\text{-}5)).$$

where t_i-5 denotes 5 years before t_i.

2. Adjust $C(t_i)$ for anticipated releases from prior evaluations that didn't happen:

    a. Let $r(t_1,t_i)$ denote the anticipated release in the evaluation period t_i estimated at any prior time t_1.

    b. Compute *Adjustment* = $\Sigma_{t1} r(t_1,t_i)$

    c. Let $C_{adj}(t_i)$ = $C(t_i)$ + *Adjustment.* If $C_{adj}(t_i)$ is negative, then the project will need to borrow credits from other projects or a credit buffer, requiring human intervention.

3. If $C_{adj}(t_i)$ is positive, the benefit of sequestration is $C_{adj}(t_i) * SCC(t_i)$, where $SCC(t_i)$ is the social cost of carbon in the time interval t_i (see Table in Appendix). Otherwise, the damage from carbon release is $-C_{adj}(t_i) * SCC(t_i)$. **(A17, A18)**

4. If a project is assessed to be high quality then the release during each evaluation period before the end of the project, t_{end}, is 0 and $r(t_i, t_{end} + j)$, j >0 is equal to R until $C_{adj}(t_i)$ drops to zero. **(A19, A2)**

5. If a project is assessed to be low quality then $r(t_i, t_i + j)$, j >0 is equal to R until $C_{adj}(t_i)$ drops to zero. **(A19, A2)**

6. Let $t_{release}$ denote the year when all net sequestration in the prior period is released. Under the release schedule assumed in the previous step, and with a discount factor δ, the damage from the carbon release (D) is calculated as:

$$D = \sum_{i=ti}^{ti + t_{release}} Release(i) \cdot SCC(i) \ /(1 + \delta)^{(i - ti)}$$

7. Equivalent permanence (eP) is calculated as $eP = (C_{adj}(t_i) - D)/C_{adj}(t_i)$

6.5 Find Matches (match source, match destination, exclude area) (This is called from Section 6.2 and 6.3)

Inputs:

1. Match source (polygon)
2. Match destination (polygon) = landscape within which project is located.
3. Exclude area (polygon) = areas where matches won't be sought. The match area is automatically excluded.

Algorithm

1. Let K be a sample of 30m-resolution pixels in the match source, sampled at a density of 0.25 points per hectare for smaller projects and 0.05 points per ha for large projects (>250k ha) (**A20**)
2. Let R be the potential set of pixels in the matching destination(s), i.e. the counterfactual area, but excluding pixels in the exclude area.
3. Let S be an empty set of pixels (the candidate matches). We later select the matches from this candidate set, so can be somewhat loose about the matching criteria in choosing pixels in S.

4. Because Google Earth engine cannot export more than 10,000 points at a time, we repeatedly sample points from the match destination R to incrementally build up S. Specifically, let P be a sample of 100 points from R alternating between randomly or stratified by land cover class
    a. For each pixel in K and for each potential pixel p in P add p to S if all of the following fields match **(A21)**:
        i. Country **(A22)**
        ii. Ecoregion
        iii. Land use class at t-10 and t-5 and t0
        iv. Elevation (±200m)
        v. Slope (±2.5°)
        vi. Accessibility in 2015 (±10 minutes)
5. Run step 4 until S has 10 times as many pixels as the project area K.

Comment: *Now we proceed to matching the match area pixels in K with candidate pixels in S for calculating additionality*

6. Let MP be the empty set of pixels (used to store the matched pairs)
7. For a 10% sample of pixels in K, pair one-to-one with the pixel in S that has exact match to:
    a. land use class (from input 2) at years t_{-10}, t_{-5} and t_0, where t = the project start date. **(A23)**
    b. Country
    c. Ecoregion

    and that has the minimum Mahalanobis distance across the following matching variables:

    d. Elevation
    e. Slope
    f. Accessibility
    g. Coarsened proportional cover of undisturbed and deforested land within a 1 km radius buffer around the points at t_{-10}, t_{-5} and t_0

    Comment: *We use the MatchIt package in R (version 4.4.0) in R (version 4.2.1), sampling without replacement and without callipers. [A24]*
8. Add all paired pixels to MP
9. Compute the standardised mean differences between each matching variable of the paired pixels in MP (specifically, between the treatment and control in treatment standard deviations).
10. Matching results are considered valid and can be used for additionality calculations if:
    a. All matching variables are balanced which is defined as the std mean diff <0.2
    b. A continuous matching variable in the range [0,1] with a value of close to 1 or 0 (>0.975 or <0.025) has standard mean difference > 0.2. This is because, when close to 0% or 100%, the standard mean difference can be misleading.
11. If results are not valid, then no credible claims can be made, so exit with failure to match.
12. Return MP

7. Known issues

1. The current method does not depend on empirical observations: landscape-level quantification of disturbance patterns estimated from remote sensing data products is needed to estimate area-specific release schedules.

2. The current method does not take into account spatial and temporal variability in disturbance and carbon release schedule: it will be preferable to take into account local environmental (temperature, dryness etc.) and socioeconomic (proximity to road, settlements, existing disturbed areas) factors, as well as past land use and disturbance history in order to account for this variability and to be able to make more accurate predictions in a shifting future.

3. The matching process is *ad hoc*, so we should test with placebos.
4. This methodology will not work well for plots/polygons that are smaller than 10ha or so because of the pixel size being 30m.

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9. Appendices

SCC spreadsheet.xlsx