Insuring against variability in the performance of Nature-Based Climate Solutions

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Abstract

Nature-Based Climate Solutions supply carbon benefits in exchange for much-needed funding, but their credibility is challenged by the inherent variability in net drawdown (i.e., *additionality*) from carbon sequestration or avoided emissions, and the risk of future releases (*impermanence*). We recently showed how project developers can gain credibility by conservatively anticipating that all net drawdown is eventually released following a *release schedule*, issuing additional credits if reality is less pessimistic than projections. This paper computes optimal release schedules using *ex post* observations of drawdowns, balancing the competing interests of generating credits evaluated as being more permanent with limiting the risk of negative additionality. We study this approach using Monte Carlo simulations of both theoretical and real-life projects and discuss how our

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approach incentivises project performance. By resolving the trade-off between a credit's permanence rating and risk reduction, our approach provides a pragmatic solution to a key challenge facing project effectiveness.

Keywords: Carbon credits, Temporary carbon storage, REDD+, Deforestation

1 Introduction

The international community has pledged to halt deforestation as a part of a package of measures designed to achieve net zero emission by 2050 [1–5]. In particular, REDD+ projects for tropical forest conservation aim to reduce carbon emissions and concurrently deliver biodiversity and social co-benefits [6]: it has been estimated that these nature-based solutions (NBS) could potentially deliver around a third of greenhouse gas emissions reduction needed to meet the 2°C target set by the Paris Agreement [7]. NBS project developers secure funding by issuing carbon credits, which can be sold on international carbon markets to entities seeking to offset unavoidable emissions from their activities. However, the scale of the voluntary carbon market has thus far lagged behind expectations and current investment in NBS projects is woefully insufficient to contribute meaningfully towards net zero targets [8–10].

Multiple factors limit investment in NBS carbon credits [11], including the uncertainties around the real benefits of NBS projects and reputational risks associated with project failure [9, 12]. It is challenging to quantify the net carbon drawdown of a project, also known as **additionality**, relative to a counterfactual scenario representing what would have happened without the project interventions. Developing quasi-experimental approaches to establish reliable counterfactual scenarios and measure drawdown more accurately remains an open area of active research [13–16].

Similarly, concerns over the **permanence** of carbon storage in NBS calls into question their value for climate change mitigation [17, 18]. Forest carbon storage is lost when forest is degraded due to disturbance [19, 20] or is converted to non-forest uses [21]. Higher carbon loss in a project relative to its counterfactual scenario causes release of net carbon drawdown (additionality) back into the atmosphere, during or especially after the end of the project: this means that NBS projects may only provide temporary carbon storage [12, 22]. It is currently common to account for this carbon release by setting aside a proportion of the credits generated into a buffer pool to compensate for later release events, but this approach neither adequately addresses releases occurring after the end of the project nor robustly couples the risk of carbon loss to the buffer pool size. As a result, the amount of buffer needed can be severely underestimated [23].

In contrast to debates about whether impermanent carbon storage contributes meaningfully to atmospheric carbon dioxide concentration and warming, we adopt a welfare-centred approach and focus on its social benefits in the context of the Cambridge Permanent Additional Carbon Tonne (PACT) framework. The PACT framework assesses additional carbon drawdown using a pixel-matching counterfactual analysis [24, 25] and addresses impermanence by conservatively viewing *all* carbon drawdown in NBS projects as impermanent: the drawdown is projected to be released back into the atmosphere over time following a **release schedule**. Both the economic benefit of drawdowns and damage of releases are calculated based on the Social Cost of Carbon (SCC) [26, 27], and future damages are discounted into present-day terms [28]. The net amount of carbon credits issued is the amount of drawdown multiplied by the **Equivalent Permanence** (EP), a value ranging between 0 and 1: EP = 0 and 1 indicate a drawdown that is immediately released (generating no benefit) and permanent drawdown, respectively (see SI **section A** for details). The calculation of EP enables comparison of diverse types of carbon credits on a common scale, notably between NBS and geological storage.

In the PACT framework, credits issued for a given crediting period are the sum of the actual carbon drawdown computed *ex post* (at the end of the crediting period) and the amount of release that was *predicted* to occur that period. This adjustment is necessary because when a project developer reduces the EP of credits issued in previous periods to account for impermanence, they anticipate the quantity of releases in each future period. If the actual release in some period is smaller than predicted, the amount of unrealised predicted release is accounted for in the form of bonus credits. This means that it is possible to issue credits even in a crediting period where the project has a negative drawdown.

2 Results

In an NBS project, where carbon drawdown can vary through time and is potentially reversible, the project developer needs to balance two competing interests: generating credits that are evaluated as being as permanent as possible (i.e., higher EP), and ensuring that there are as few failure events (defined in the paragraph below) as possible. This is the crux of the problem that we address with the new work presented in this study.

Since the amount of credits issued is the adjusted drawdown multiplied by its equivalent permanence, the project developer can increase the credits issued by estimating a higher equivalent permanence for the drawdown, deferring anticipated releases far into the future. However, by doing so, they anticipate fewer releases in the immediate future, so there is a higher chance that observed releases will exceed total predicted releases in those future periods, resulting in a negative adjusted drawdown (i.e., reversal of additionality). As there are no available credits to issue when this happens, we call them **failure** events. It is not realistic to expect NBS projects to be failure-free. Nevertheless, projects that frequently experience failure events are likely to be viewed as risky investments with low credibility by credit buyers, threatening the viability of the project. We posit that project developer's optimal behaviour is to limit probability of failure to a project-specific tolerable level, say 5%.

It is evident that both equivalent permanence and probability of failure are influenced by the release schedule: a front-loaded release schedule, where a developer anticipates more releases to occur in the near future, will lower equivalent permanence, but also reduce failure risk by increasing the amount of total predicted releases that can compensate for actual releases (see SI **section A** for a more formal statement of this dilemma). In this study, we resolve this trade-off between increasing permanence and reducing failure risk by finding an **optimal release schedule** that constructs the release schedules of carbon drawdown in each year in a risk-averse strategy, so as to prevent the probability of failure from exceeding a chosen level. We demonstrate with a simulation model how this approach is achieved, and how it ensures a balance between credit issuance and reduced failure risk.

2.1 Optimal release schedule

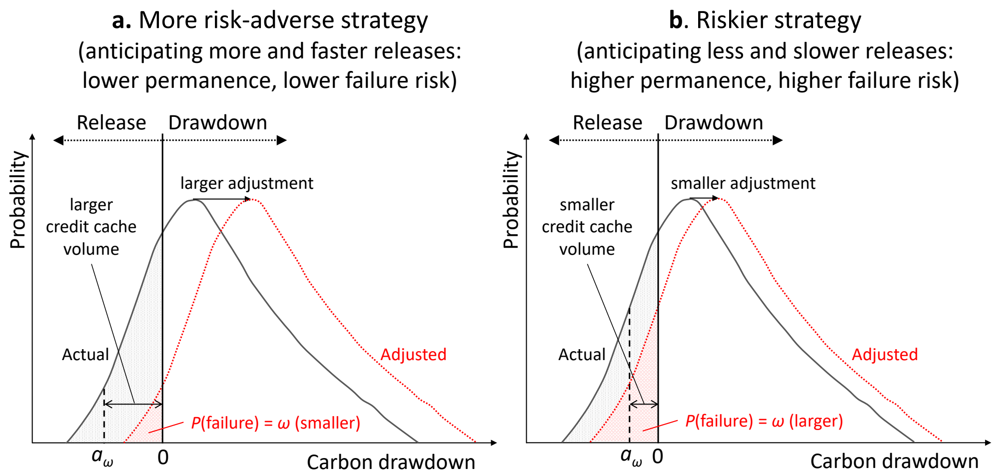

Fig. 1 The probability density function of the actual drawdowns (black curve) is derived from empirical data. The probability density function of the adjusted drawdowns (red dotted curve) is derived by adjusting the actual drawdown values with the total amount of anticipated releases. If the total amount of anticipated releases equals the absolute value of the ω-percentile of actual drawdowns ($|a_\omega|$, referred to as the **credit cache volume**), the probability of failure events (red dotted area) will be limited to ω (assuming $a_\omega < 0$). Panel (a) represents a more risk-averse strategy, where a developer anticipates a greater chance of future releases, resulting in a larger credit cache volume, lower permanence, and smaller probability of failure (ω); panel (b) represents a riskier strategy, where a developer anticipates lower releases, resulting in a smaller credit cache volume, higher permanence, and higher probability of failure.

We model the actual carbon drawdown in year t (Fig. 1, grey curve), computed at the end of year t, as a random variable, which may be positive in some years and negative in others, and has a distribution that reflects the uncertainty in project effectiveness. Carbon drawdown in year t is expected to be released in future years $t+j$ according to a release schedule, which can be conceptualised as deposits of drawdowns into future yearly "caches": the drawdown in year t that is anticipated to be released in a future year $t + j$ is viewed as credits taken from year t, and deposited into the cache of year $t + j$. The total adjusted drawdown available for credit issuance (Fig. 1, red curve) in each year t is calculated as the sum of the year's actual drawdown and the total amount of previously predicted releases in the credit cache (i.e., the sum of deposits taken from drawdown in all past years $t - i$).

A failure event occurs when the adjusted drawdown in a given year is negative: the probability of a failure event is therefore the area under the probability density function of the drawdown to the left of zero. We use the left-tail percentile of the curve, representing the "worst-performing" years, to track this probability. Suppose we aim to limit probability of failure to 5%, we can find the 5th-percentile of the actual drawdown curve("a_ω", Figure 1), such that the area under the curve to its left is equal to 0.05 (Fig. 1, shaded grey area): this means that the 5% "worst-performing" years will have an actual drawdown lower than the 5th-percentile value. When this 5th-percentile value is negative, the probability of failure will be larger than 5% unless it is adjusted by prior anticipated releases. By "depositing" anticipating releases, we shift the probability density function of the adjusted drawdown to the right compared to actual drawdown, reducing the probability of failure. When we shift the curve by the difference between the 5th-percentile and zero, the area under the adjusted drawdown curve to the left of zero will become 0.05, and the probability of failure will be successfully limited to 5%. In other words, the absolute value of the 5th-percentile value (henceforth called the **credit cache volume**) is the amount of total anticipated releases that should be deposited each year to bound the risk of failure to 5%. This can be achieved by depositing issued credits of each year as anticipated releases to fill up the credit cache volumes of subsequent years successively (see SI **section C** for illustration).

If the project developer is willing to tolerate a higher percentage ω of failure risk, the ω-percentile value will be less negative, and the credit cache volume will be smaller (Fig. 1b). This represents a more risky strategy where credits are deposited in the credit caches of each year in a more gradual manner, which results in higher equivalent permanence overall but also a higher failure risk (see SI **section B** for mathematical formulation and formal proof).

This approach requires the probability density function of annual net carbon drawdown to be known, which relies on a reasonably accurate estimation of carbon fluxes in a project, for example through remote sensing technologies. In the simplest cases, parametric distributions can be used to provide an analytical approximation for the value of the credit cache volume. In more complex cases, random sampling can be used to calculate the credit cache volume more accurately as the left-tail ω-percentile of the sampled drawdown distribution. This provides us with an easy-to-implement approach to construct optimal release schedules that limit risk of failure to a percentage of ω from empirical observations.

As new measurements and estimations of carbon drawdown or release are obtained every year, they can be included in the re-calculation of the carbon drawdown distribution and the credit cache volume. This approach thus allows for positive changes in project performance to be rewarded, creating incentives for project improvement: if positive carbon drawdown is observed over successive years, the drawdown distribution will shift to become more positive, meaning that the credit cache volume will become smaller with the same tolerance threshold of failure risk. This means that less anticipated release will be deposited in each future year, leading to an increase in equivalent permanence.

2.2 Simulations of theoretical projects

To illustrate how the optimal release schedule approach balances project performance, credit permanence and failure risk, we performed Monte Carlo simulations of theoretical projects with different carbon drawdown levels (see Methods section **Simulation of theoretical projects** for details).

Assuming a threshold of 5% failure risk, projects with higher carbon drawdown obtained more credits (Fig. 2a), as expected. Their credits also had higher equivalent permanence (Fig. 2b): this is because with an overall higher drawdown level, the estimated credit cache volume is smaller (fewer credits need to be deposited as anticipated releases in each year to cover the risk), leading to more gradual release schedules that increase the equivalent permanence. By following the optimal release schedule, we can achieve the desired 5% failure risk except when carbon drawdown is very close to zero (Fig. 2c).

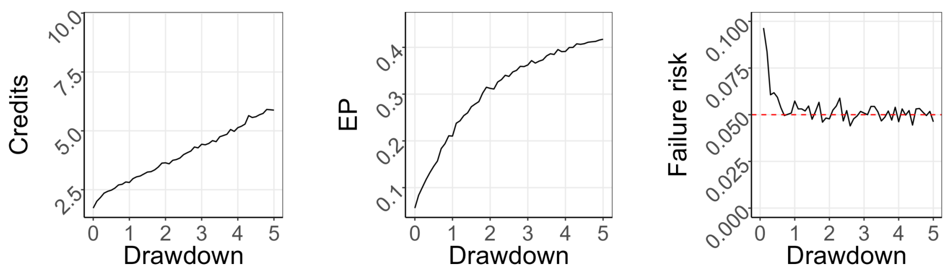

Fig. 2 The relationship between carbon drawdown level (unitless) and (a) credits issued; (b) equivalent permanence; (c) failure risk (proportion of years with non-positive credits throughout all years). The curves indicate mean values out of 100 repetitions of Monte Carlo simulation over 50 years. The horizontal red dashed line in the panel on the right indicates the 5% failure risk threshold.

2.3 Simulations of real-life projects

To exemplify how the optimal release schedule approach could be applied to real-life NBS projects, we made simulations for four ongoing REDD+ projects: Rio Pepe y ACABA (RPA), Gola, Alto Mayo, and Mai Ndombe. We derived their net carbon drawdown distributions from remotely sensed annual carbon loss values in the project area and in the counterfactual scenario, which are available from the year of the start of each real-life project (t_0) until 2021. We assumed a project duration of 50 years starting from t_0, with a five-year warm-up period where no credits are issued. We assumed post-project carbon release rate to be double the mean observed annual carbon loss rate in the counterfactual scenario. (see Methods and SI **section G** for details).

In three of the four projects simulated (RPA, Gola, and Alto Mayo), by following the optimal release schedule, failure risk could be limited to around the 5% threshold (Fig. 3, bottom row). Lower-risk projects consistently generated credits to be issued in all years in virtually all repetitions, whereas higher-risk projects has a non-negligible chance of not having credits to issue in certain years (Fig. 3, top row). Lower-risk projects (RPA, Gola) generated credits with high equivalent permanence in the beginning that decreases gradually over time as the project approaches its end: this can be explained by our assumption of higher carbon release rate after the project ends [22]. Higher-risk projects (Alto Mayo, Mai Ndombe) had credits with low equivalent permanence throughout the simulation (Fig. 3, middle row).

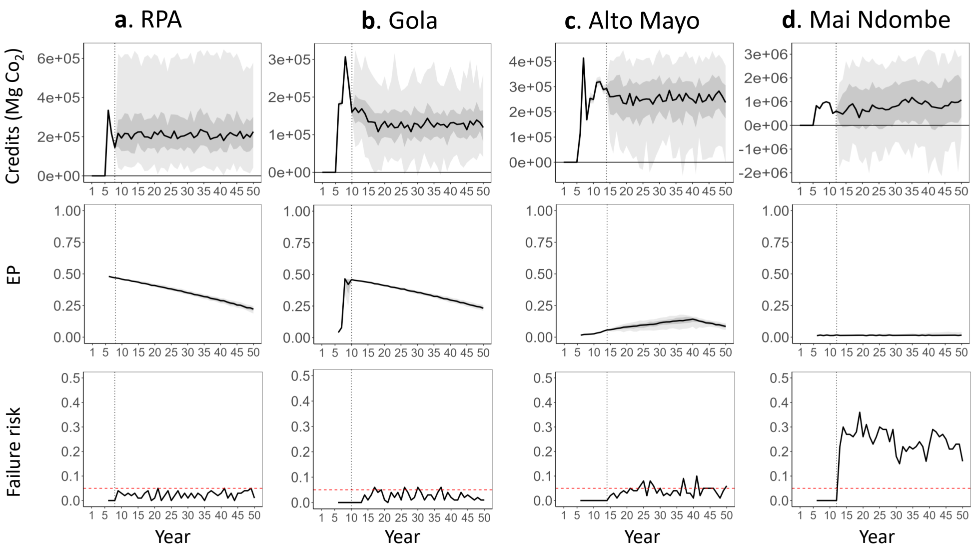

Fig. 3 Time series of credits (Mg CO_2), equivalent permanence (EP), and failure risk (proportion of years with non-positive credits) for the four NBS projects, simulated over 50 years with 100 repetitions, starting from t_0 (year of start of the project). Light and dark grey shaded areas show [5%, 95%] and [25%, 75%] percentile intervals of all repetitions, respectively, and red curves represent median values. Horizontal black solid lines indicate zero credits, and horizontal red dashed lines in the bottom row indicate the 5% failure risk threshold. Grey vertical dotted lines indicate year 2021 (the latest year with available remote sensing observations).

3 Discussion

Our approach computes an optimal release schedule that a NBS project developer should adopt to limit the risks arising from annual variability in net carbon drawdown (additionality), provided that they adopt the PACT framework of evaluating the social benefits of impermanent carbon credits. We demonstrate that this approach succeeds in limiting the risk of failure to a desirable level, except in projects with near-zero effectiveness at carbon drawdown (which, incidentally, allows us to identify ineffective projects).

Our approach dynamically adjusts the optimal release schedule based on observed carbon drawdown distributions updated with new observed data, allowing for credit permanence to be evaluated from an early stage, and for additional credits to be generated whenever the project performs better than predicted. This creates incentives for project developers and local communities to maintain long-term project custodianship, which has been identified as one of the key components needed for projects to be successful and effective [29–31]. It may also provide a form of inter-generational equity, as future custodians of a project receive credits from safeguarding the drawdown achieved in the past, as opposed to simply being expected to look after it without any reward.

We believe this approach to be a large improvement over the buffer pool approach, which does not base the size of the buffer pool on an empirical assessment of the expected probability of failure. In addition, in the buffer pool approach, the credits stored in the buffer pool are typically cancelled at the end of the project, which neither creates incentives for project improvement during the project nor after the project ends (although mechanisms such as a long-term monitoring system for reversals have been proposed to address this issue [32]). In contrast, by estimating anticipated releases past the end of the project, our approach provides incentives even *after* the project ends.

We also found a clear positive effect of longer project duration on credit permanence (SI **section F**). Given that project duration can be limited by uncertainty of the stakeholders about the durability of funding flows [30], we propose that rather than making overly optimistic claims about long project duration, continual and dynamic monitoring should be leveraged to demonstrate project improvement and update credit permanence, so that the more steady income flow itself can become an incentive for risk-averse local communities to maintain participation [33].

This approach is straightforward to implement as long as forest monitoring provides reasonably accurate estimates of carbon drawdown, which can be facilitated by advances in remote sensing technology and accumulation of monitoring data [34]. Moreover, models predicting disturbance risks and associated carbon losses [20] and data on drivers of forest carbon loss [35] could be incorporated to improve project-counterfactual matching in disturbance regime, detect temporal trends of carbon drawdown distributions, and infer the impact of rare but severe disturbance events, which can all help better evaluate credit permanence.

Our approach also easily allows for multiple projects to be aggregated and evaluated as a single project "portfolio", which leads to higher permanence and lower failure risk than could be achieved in each project individually (see SI **section H**). Aggregating projects (especially those that are diverse in geographic location and methodology) and assessing their ongoing risks with observed data allows credit buyers to manage risk sensibly in the volatile carbon market. It safeguards each individual project against rare but catastrophic disturbances (as the chance that multiple projects will be affected by the same kind of sporadic catastrophe at the same time is exceedingly low), especially for projects considered as "high-risk" either due to being at an early stage of implementation or having high deforestation pressure. Aggregating projects also increases the amount of observed data that can be utilised to inform drawdown distributions, especially where long-term data are still scarce [24, 36].

In this study, we optimised release schedules given the constraint of a maximum 5% failure risk, a simple threshold that represents no more than two failure events during a 40-year period. Future research directions include exploring the implications of jointly optimising the release schedule and the maximum failure risk threshold, for example by maximising the expected revenue from credit sales, assuming that failure events cause the credit price to fall.

Although our study focusses on avoided deforestation projects, the central principle of issuing impermanent credits with anticipated future releases can be applied to other types of NBS projects, provided that we can evaluate their benefits with counterfactual analysis and anticipate costs of future reversal of those benefits. For an example, for an afforestation project, we can model carbon releases as following an extreme value distribution, estimate the amount of releases expected to occur (return level) within a given time period [37], and allocate anticipated releases such that the long-term cumulative anticipated releases in a given period match the expected return level.

In conclusion, our study proposes a novel yet simple way to anticipate risks of carbon release and evaluate permanence of carbon credits generated by nature-based solutions, achieving a balance between sustainable income flows and project credibility and incentivising project improvement. Assuming that the social benefits of impermanent carbon credits are increasingly being valued, our findings offer a pragmatic solution to improve market confidence in NBS projects, paving the way for scaling up the implementation of this crucial climate mitigation strategy.

4 Methods

For all simulations in this study, we assumed annual crediting periods for simplicity. Although this differs from current common practice (e.g. five-year verification periods in the Verra methodology), our analysis can be trivially extended to permit longer crediting periods. A similar assumption has also been used in other modelling studies [38, 39]. We have released a detailed methodology for every step of the computation as well as a full implementation of our approach as open-source code [25, 40]. The simulation code used in this study was written and performed in R 4.3.2, and the *dplyr*, *magrittr*, and *ggplot2* packages were used for data processing and visualisation [41–43].

4.1 Simulation of theoretical projects

We simulated theoretical projects with exponential carbon loss distributions, whose parameter is denoted λ. Specifically, the project carbon loss distribution is parameterised with $1/\lambda_p = 1$, and the counterfactual carbon loss distribution is parameterised with $1/\lambda_c > 1$. As $1/\lambda$ is the mean of the exponential distribution, a higher $1/\lambda_c$ value indicates higher average annual carbon loss in the counterfactual scenario compared to the annual carbon loss in the project area, which leads to an overall higher net carbon drawdown rate ($1/\lambda_c - 1/\lambda_p = 1/\lambda_c - 1$).

At each year t in the simulation, we randomly drew values of carbon loss in the project (l_p) and counterfactual (l_c) from the respective exponential distributions. We calculated the drawdown as the difference between the two sampled values ($a_t = l_c - l_p$). We calculated the credit cache volume analytically, assuming it to be constant over the duration of the simulation (see SI **section D.1.1**).

To approximate real-life projects where observed data on carbon losses could be limited in the initial years, we defined the first five years of the simulation as the **warm-up period**, where observed drawdown and release values are used to inform the estimation of carbon loss distributions in later years. During the warm-up period, releases were ignored, and drawdowns were not issued as credits but stored in a project-level pool as an additional safeguard. In each year t after the warm-up period ($t > 5$), whenever there was a gap between the credit cache volume and total anticipated releases allocated to that year, the drawdown stored in this pool was allocated to fill in the gap as additional anticipated releases, until the pool was depleted.

We calculated total credits (c_t) as the sum of the drawdown (a_t) and total anticipated releases (σ_t) (Equation S1 in SI section A). These credits were then allocated as anticipated releases in future years, by filling up successively the credit cache volume in each year (for details, see SI **section C**). We assumed that carbon releases continue to occur past the end of the project occurs, at double the mean counterfactual carbon loss rate ($2/\lambda_c$), and allocated anticipated releases according to the same rule until all credits had been released. We calculated the equivalent permanence (EP) of the credits issued at each year (if any) following SI **section A**, assuming $t_0 = 2021$ for the determination of Social Cost of Carbon (SCC) values.

We simulated projects with net carbon drawdown rate varying from 0.1 to 9 ($1/\lambda_c$ from 1 to 10). For each drawdown rate value, we performed 100 repetitions of simulations lasting 50 years. For each repetition, we calculated the following three statistics: 1) mean annual credits across all years (excluding the warm-up period), 2) maximum equivalent permanence (EP) across all years, and 3) failure risk (proportion of years with non-positive credits throughout all years). For illustrative purposes, we also selected three of the simulation settings where drawdown rate is 0.1, 1, 4, respectively, and plotted the yearly time series of 1) credits issued, 2) equivalent permanence (EP), and 3) failure risk (proportion of years with non-positive credits over all 100 repetitions) (see SI **section E**).

4.2 Simulations of real-life projects

We selected four ongoing projects from three continents, varying in size from 20,000-45,000 ha. We used satellite-based datasets to track forest cover and aboveground biomass through time, and applied a pixel-matching approach to estimate net carbon drawdown in the project relatively to a counterfactual scenario (For more details, see SI **sections G1-G3**; also see PACT Tropical Moist Forest Accreditation Methodology [25]).

We calculated the credit cache volume with a sampling approach: as we expect the carbon loss distributions in the project area and in the counterfactual scenario to be variable through time, we also expect the credit cache volume not to be constant over time, and include new information of carbon loss to update the credit cache volume.

In each year t before 2021, we fitted statistical distributions to the carbon loss values in the project and counterfactual from the start of the project to year t; in each year t after 2021, we fitted statistical distributions to the carbon loss values in the project and counterfactual from the start of the project to 2021 (for details, see SI **section G4**). We then randomly sampled 1000 carbon loss values in the project and in the counterfactual, calculated their differences as the sampled drawdown distribution, and calculated the credit cache volume as the absolute value of its 5% percentile.

We defined the first five years of the simulation as the **warm-up period**, where observed drawdown and release values are used to inform the estimation of carbon loss distributions in later years. During the warm-up period, releases were ignored, and drawdowns were not issued as credits but stored in a project-level pool as an additional safeguard. In each year t after the warm-up period ($t > 5$), whenever there is a gap between the credit cache volume and total anticipated releases allocated to that year, the drawdown stored in this pool was allocated to fill in the gap as additional anticipated releases, until the pool is depleted.

We calculated total credits (c_t) as the sum of the drawdown (a_t) and total anticipated releases (σ_t) (Equation **A3**). These credits were then allocated as anticipated releases in future years, by filling up successively the credit cache volume in each year (for details, see SI **section C**). We assumed that carbon releases continue to occur past the end of the project occurs, at double the mean counterfactual carbon loss rate, and allocated anticipated releases according to the same rule until all credits had been released. We calculated the equivalent permanence (EP) of the credits issued at each year (if any) following SI **section A**.

For each project, we performed 100 repetitions of simulations lasting 50 years, starting from the year of the start of each real-life project (t_0). For each repetition, we calculated the following three statistics: 1) mean annual credits across all years (excluding the warm-up period), 2) maximum equivalent permanence (EP) across all years, and 3) failure risk (proportion of years with non-positive credits throughout all years).

Below is a step-by-step summary of the simulation procedure of real-life projects. At each yearly time step t:

1. Obtain project carbon loss (l_p) and counterfactual carbon loss (l_c) from t_0 to t (if $t \leq 2021$) or from t_0 to 2021 (if $t > 2021$).
2. Fit both carbon loss distributions, draw 1000 random values from each, calculate sampled drawdown as the difference between the two: $a_t = l_c - l_p$.
3. Calculate credit cache volume ($|a_\omega|$) by finding the left-tail 5% percentile of the sampled drawdown distribution, with a upper bound of zero.
4. Obtain drawdown values
   (a) If $t \leq 2021$: use observed values at year t
   (b) If $t > 2021$: draw random values from carbon loss distribution and calculate drawdown as the difference between the two
5. Calculate credits
   (a) Zero credits in the warm-up period, but positive drawdown is placed in a project-level drawdown pool (if $t \leq 5$).

(b) Calculate credits (c_t) as the sum of drawdown and total anticipated releases, which should be equal to the credit cache volume (extract drawdown from project-level pool to fill up gap if total anticipated releases is smaller than credit cache volume and if the pool hasn't been depleted) (if $t > 5$).

6. If $c_t > 0$, calculate anticipated releases (release schedule) based on the optimal release allocation rule: calculate the available space in the credit cache of each following year j (credit cache volume − anticipated releases already allocated), and fill them up successively from the smallest j to the largest, until all credits have been allocated to a future year.
   (a) For years after the end of the project ($j > 50$), the available space for release is set to be double the mean counterfactual carbon loss rate (i.e., $a_\omega = 2/\lambda_c$).
7. If $c_t > 0$, calculate the equivalent permanence (EP) of the credits following Equation **A3**.

Supplementary information. This article is accompanied with a supplementary information file.

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Declarations

Competing interests

A. B. is a trustee of the World Land Trust, a non-governmental organization that supports forest-based carbon projects. The Cambridge Centre for Carbon Credits (4C) has no commercial interest in carbon credits.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Data Availability

The data required for the simulations of real-life projects, namely the REDD+ project polygon, are available on Verra VCS Registry [44–47] and on the GitHub repository https://github.com/quantifyearth/tmf-implementation/

Materials Availability

Not applicable.

Code Availability

We have released a detailed methodology for every step of the computation as well as a full implementation of our approach as open-source code. The program pipeline for calculating annual carbon loss and additionality for a given REDD+ project can be accessed at the GitHub repository https://github.com/quantifyearth/tmf-implementation/ (Also see [25]), and the code required for running the simulation in this study can be accessed at the GitHub repository https://github.com/epingchris/carbon_release_pattern.

Author contribution

S. K. and D. A. C. supervised the project. E-P. R., S. K., J. G. and D. A. C. conceived the research plan. S. K. and J. G. constructed the mathematical and theoretical models. T. S. assembled input data. E-P. R. wrote code, ran model simulations, and analysed simulation outputs. E-P. R., S. K. and D. A. C. wrote the manuscript. All co-authors revised the manuscript.

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