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Do oversimplified durability metrics undervalue biochar carbon dioxide removal?

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Abstract

Soil amendment of biochar—the solid product of biomass pyrolysis—is one of few engineered strategies capable of delivering carbon dioxide removal (CDR) today. Quantifying CDR for biochar projects hinges critically on the durability of biochar materials once amended in soil. However, consensus on the definition of durability is still evolving, and as a result, standards developing organizations have generated a variety of different methodologies to assess the removal value of biochar projects. These methodologies primarily rely on single-parameter regression models to link the molar H/C ratio—an easily measurable bulk chemical metric—to the modeled durability of biochar materials. Specific deployment variables are not commonly considered. Thus, although H/C-based methodologies simplify project development and CDR assessment, questions remain as to how well they predict real project outcomes. Via a re-analysis of existing biochar incubation data and several case studies, we show that durability standards based on bulk compositional metrics are biased towards particular feedstocks and may not account for key environmental drivers. Without provisions for these factors, we find that existing assessment models appear to discount the removal value of biochar projects significantly. However, our conclusions rely on predictive models with important weaknesses and unknown uncertainty—pointing to a need to develop a use-aligned database. Limitations notwithstanding, our findings ultimately suggest the biochar 'durability problem' may be an artifact of the desire to simplistically define it. To reliably credit CDR, we propose a series of recommendations, including the creation of representative distributions for current feedstocks and environmental gradients to better align experimental data with real-world practices. Further, we suggest an approach to integrate in-field measurement protocols with existing strategies to evaluate CDR value, with potential to co-generate data to guide deployment, maximize agronomic co-benefits, and improve confidence in project integrity.

1. Introduction

To achieve net zero emissions targets and limit warming to 1.5 °C, it is essential to not only reduce anthropogenic emissions, but also to deploy carbon dioxide removal (CDR) [1]. In this framework, it is critical to ensure the permanence of the carbon removal, motivating a shift towards technologies that capture carbon over at least 1000-year time scales, or the mean residence time of carbon in the atmosphere [2, 3]. This need, in addition to rising concerns of quality and integrity in carbon markets [4], has led to an increasing emphasis on durable CDR [5–8].

Despite increasing emphasis on 1000-year permanence, many highly durable CDR technologies are currently transacted through futures contracts and offtakes, with delivery as far as 11 years in the future [4, 9]. In contrast, biochar (pyrolyzed biomass) is viewed as a medium-term durability option [5, 10–14] but constitutes 92% of delivered carbon removals due to its lower prices and spot purchase availability [15].

The permanence (i.e., the resistance to oxidative and microbial decomposition, also referred to as persistence, durability, and/or stability in previous contexts) of soil-amended biochar is the critical determinant of its utility for CDR [16–20]. A catch-all term for a wide variety of heterogeneous products on the combustion continuum [21–23], biochar is typically produced via slow pyrolysis of waste biomass residues and owes its CDR value to its long residence time in soil relative to fresh biomass [17]. Recent analyses indicate that biochar can deliver between 1.7 and 3.7 Gt of CDR annually [17], depending on feedstock constraints and assumptions regarding biochar permanence. However, the long-term performance of biochar in actual soil environments and its effects on soil health and crop productivity remain poorly understood.

Predictions for biochar permanence range from decades [24–27] and centuries [18, 28] to millennia [29–33] based on natural and anthropogenic analogues such as wildfires [34, 35] and charcoal-amended soils [36–41]. In support of millennial timescales are observations that wildfire-derived pyrogenic carbon is a major component of coals, carbonaceous rocks, soils, and marine sediments as early as the late Silurian (420 Ma) [42, 43]. Observations of anthropogenic black carbon in the *terra preta* soils of the central Amazon point to the persistence and agronomic benefits of biochar-type material over at least 2000 years [37–41]. Similarly, anthropogenic charcoals discovered in central European Chernozems and Chinese paddy soils are thought to have originated as early as the Neolithic period (10 000–2500 BCE) [36]. While these studies show that pyrogenic carbon can both benefit agricultural practices and persist over geologic time, because the initial charcoal content is unknown, these analogue studies cannot be used to calculate or rigorously define biochar durability for CDR.

To constrain initial carbon content, biochar durability estimates rely on short-term (≈1–2 years) incubation experiments with observed kinetics extrapolated using empirical models. These experiments combine biochar with a controlled medium (ranging from pure sand to soil) under defined temperatures and moisture levels, minimizing environmental variability and enabling precise mass balance [25, 26, 44–58]. However, discrepancies between laboratory and field studies—particularly concerning the kinetics of (bio)chemical reactions—are well-known and often attributed to soil disturbance and altered environmental variables [59–62]. Additionally, most durability experiments were conducted in research contexts and were not designed to reflect actual biochar deployments [63]. As a result, biochar durability in today's CDR ecosystem is defined by a suite of carefully controlled laboratory studies with unclear relevance to real-world biochar deployments.

Given the inherent difficulty and long duration of incubation studies, a large body of research has sought to develop proxies for biochar durability based on easily measurable metrics [18, 55, 58, 61, 64–67]. Generally, extrapolated kinetic data is assigned a permanence value and subsequently correlated to compositional metrics (e.g., elemental ratios, carbon content) or biochar processing conditions (e.g., pyrolysis temperature). Since Woolf *et al* published their greenhouse gas inventory model in 2021 [18], biochar durability standards have used bulk H/C content thresholds (i.e., H/C < 0.7) to assess projects. The underlying assumption is that lower H/C values indicate a greater fraction of aromatic structures and result in reduced *in situ* reactivity [17]. However, bulk chemical metrics are fundamentally non-unique and may not sufficiently describe the reactivity of biochars in soil [30, 32]. A previous analysis of durability observations found that single-parameter models fail to explain variance in durability outcomes [61]—the most common model achieves a correlation coefficient (R^2) of only 0.32 [18].

In summary, biochar durability assessments currently rely on limited, short-term datasets (<20 scientific articles [61], ≈1–2 years) and a non-unique compositional proxy. The potential impacts of environmental variables (e.g., clay content, organic matter, soil pH, water content, crops, and microbial communities) are not accounted for. This creates the potential for an ecological fallacy, wherein the characteristics inferred from limited datasets do not reflect outcomes at specific deployment sites.

Here, we re-analyze data from the largest existing biochar kinetic database [61, 68] to pose the question: are we accurately predicting the CDR value of biochar projects? Specifically, we examine existing durability metrics and develop three case studies of *eucalyptus saligna* biochar to identify (1) sources of variation in durability outcomes and (2) their practical implications for biochar CDR quantification. We find that extrapolated data often supports higher CDR value than standard methodologies would assess, indicating that concerns about biochar durability stem not from material limitations, but from practices that overlook project-specific differences and rely on limited data—a positive manifestation of an ecological fallacy. To address this, we suggest a series of actions, beginning with a forward-looking map of representative conditions surrounding biochar deployments, including feedstocks, conversion technologies, and environmental variables, to guide laboratory and field experiments. These experiments are essential to systematically develop and deploy in-field biochar performance measurement. In-field measurement is crucial for advancing biochar as a CDR technology by unlocking additional project value, supplying data for durability and deployment modeling, ensuring project integrity, and improving the accuracy of regional carbon budgets.

2. Methods

2.1. Dataset and processing

Prior work [61] compiled data from observations of biochar decay in the laboratory ($n = 128$) and the field ($n = 8$). The dataset was digitized or collected via author correspondence by the previous investigators and is available in the supporting information (SI).

The dataset consists of biochar pyrolyzed from one of seven biomass feedstock classes, including 'wood' ($n = 80$), 'crop' ($n = 34$), 'grass' ($n = 22$), 'leaf' ($n = 2$), 'biosolids' ($n = 1$), 'manure' ($n = 4$), or 'other' ($n = 38$). Experiments range in duration from 90–3102 d, with a mean and median of 666 and 368 d, respectively. Consistent with recommendations from Azzi *et al* [61], we omitted 49 singular observations of biochar decay due to issues described in the SI. Four additional datasets were dropped in regression analyses due to missing data.

2.2. Curve fitting

Biochar decay kinetics are typically modeled with multi-pool exponential or power functions. Multi-pool models assume discrete carbon pools with varying decay rates [18, 32, 66, 69], though the number of pools is arbitrary without direct characterization [32, 70, 71]. Power models [58, 72], which assume a time-dependent decay rate that slows as biochar becomes less reactive [61, 73], provide a better fit for existing data (Bayesian Information Criteria) [61]. However, power models assume that declines in decay rate will persist and may not asymptotically approach zero [61]. Despite these limitations, we use a clipped power model for the following analyses according to recommendations from previous work [61] (equations available in the SI).

2.2.1. Proxies for biochar durability

The perceived insensitivity of biochar durability to feedstock characteristics and deployment factors has led to the creation of 'universal' regression models, which link permanence factors (usually at the 100-year time horizon [74]) to a single-parameter proxy. To assess this strategy, we develop our own model via the following protocol:

(i) We fit 83 biochar decay series from 17 publications [25, 26, 44–58] to a power model.
(ii) We extrapolate the model to obtain the relative amount of biochar remaining after 100 years (i.e., the 100-year permanence factor, BC_{100}). BC_{100} values, except where indicated otherwise, were temperature-adjusted to 20 °C (see the SI for soil temperature methods).
(iii) We correlate the molar H/C ratio (H/C_{org} where available, H/C_{tot} otherwise) to BC_{100} via a linear regression model (see figure S1 in the SI). Linear regression models remain the most conservative choice for biochar durability [61].

Per this model, we determined

$$BC_{100} = 1.22 - 0.60 \times H/C \qquad (1)$$

and predict that 80% (95% confidence interval: [0.76, 0.85]) of biochar will be retained after 100 years for materials with H/C of 0.7.

2.2.2. Statistical analysis

Nonlinear curve fitting results are non-unique and thus highly susceptible to initial parameter values and other user-defined algorithmic decisions. Although we adopt similar strategies to those developed by Azzi *et al* [61], we use different modelling tool chains and obtain slightly different BC_{100} outcomes. Our fitting strategies are available as an analysis notebook included in the SI. This work adapted parts of code published previously [68].

3. Results and discussion

3.1. Feedstock-specific durability outcomes and metrics

We re-analyzed the largest existing biochar decay database [61] to compare outcomes predicted for single feedstock classes (i.e., crops, grass, manure, and wood) with a global dataset regression ($n = 83$, equation (1), figure 1). The collective dataset reveals that woody feedstocks comprise ≈60% of the data, underrepresenting feedstocks such as manure and grass ($n = 7$ and 4, respectively). Of the woody biochars, 25/49 are derived from *eucalyptus saligna*, with 22 pyrolyzed at 450 °C or 550 °C—low to moderate temperatures relative to typical production conditions [74]. In contrast, the UC Davis Biochar Database [75], with over 1000 entries, shows that half of biochars (with tabulated data) are produced above 500 °C, and only 28% are labeled as wood-derived, suggesting the decay database may not represent current biochar deployments.

Comparison among models built at the level of a feedstock class (i.e., crop-, grass-, manure-, and wood-based biochars) and the global regression reveals meaningful differences associated with individual observations. Non-woody feedstocks deviate most clearly from the global regression (equation (1), see figure S1 in the SI) and have large uncertainty at both the level of the individual observation (i.e., the extrapolation), and the level of the secondary linear regression model (figures 1(a)–(c)). In contrast, woody feedstocks show strong overlap with the global H/C distribution and regression (figure 1(d)). Uncertainty at high H/C is larger for all precursor types, possibly due to data limitations or the effects of environmental factors in less-carbonized biochars [66].

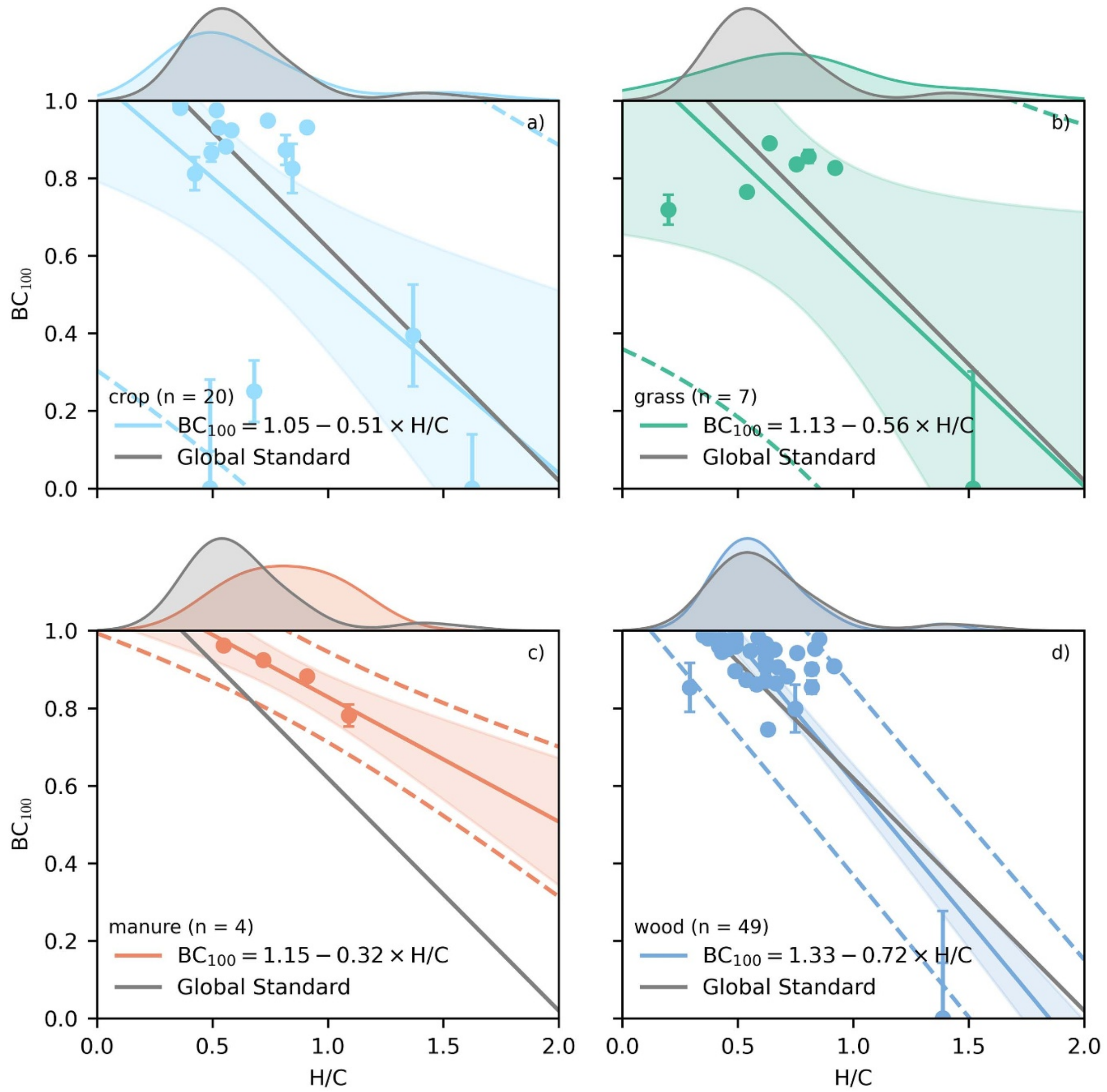


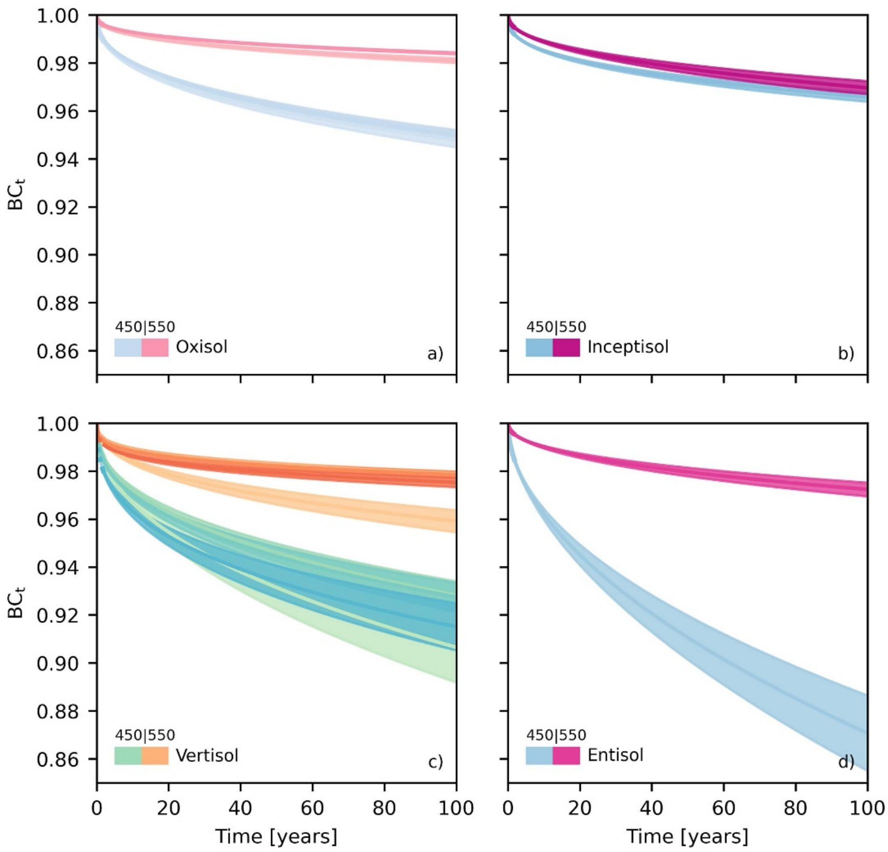
Figure 1. The fraction of biochar remaining after extrapolation of incubation data to 100 years (BC_{100}) for observations of crop residues (a), grasses (b), manure (c), and wood (d) collected from Azzi *et al* [61]. Lines show the linear regression for the feedstock relative to the regression results for the full dataset ($n = 83$). Shaded regions indicate $2-\sigma$ confidence intervals, with dashed regions indicating the $2-\sigma$ prediction interval over the same range. Error bars indicate the uncertainty of the BC_{100} prediction ($1-\sigma$). The secondary x-axis in (a)–(d) depicts the kernel density estimation of the distribution of H/C values for the corresponding feedstock relative to the entire dataset shown in gray. H/C_{org} values were used wherever organic C content was available. H/C_{tot} was used otherwise.

While the kernel density estimations of H/C values for the individual feedstock classes generally align with the overall distribution, the extrapolated 100-year permanence values (BC_{100}) show inconsistencies (figure 1). These discrepancies may result from data limitations (e.g., manure), appreciable variability (e.g., crop and grass), and differences in material reactivity that H/C alone fails to capture. To further assess these factors, we analyze the influence of pyrolysis temperature and soil composition relative to the H/C metric using a subset of experiments.

3.2. Pyrolysis temperature and soil type relative to H/C metrics

Another potential limitation of H/C-based calculations of biochar CDR is the exclusion of additional environmental factors, such as soil type, pH, soil organic matter content (SOM), and soil clay content (SCC). Fang *et al* studied *eucalyptus saligna* biochar produced at 450 °C and 550 °C, with H/C of 0.62 and 0.49, respectively, in two-year incubation experiments across various soil types at 20 °C [46, 47]. All biochar samples were produced at the same facility and from equivalent biomass precursors. Using a power model, we calculate the fraction of biochar remaining over time (BC_t) for each of the 16 reported observations (figure 2).

Per the Woolf model [18], we should anticipate equal durability within a temperature group (i.e., materials with equivalent H/C) and roughly 15% greater permanence for the chars produced at 550 °C, regardless of project-specific deployment variables.



Soil type	Oxisol	Inceptisol	Vertisol	Entisol
n (per temperature)	2	1	4	1
pH	5.65	5.7	8.1	8.77
Background SOM (%)*	7.6	1.6	0.8	4.0
SCC (%)	44.0	1.0	53.0	21.0
ΔBC_{100} (%)	3.54+/-0.21	0.40+/-0.35	5.8+/-0.6	11.7+/-2.0

Figure 2. Power model extrapolations of laboratory incubation data for *Eucalpytus saligna* pyrolyzed at 450 °C (blue/green tones) and 550 °C (red/orange tones) incubated for ≈750 d in a oxisol (a), inceptisol (b), vertisol (c), and entisol (d). The table indicates the soil type, soil pH, soil organic matter (SOM) content, soil clay content (SCC), and percent difference in BC_{100} for biochars pyrolyzed at 450 °C and 550 °C (ΔBC_{100}), averaged across replicates where possible (for observations with $n > 1$). N.B. while background SOM* is equivalent for the observations in the vertisol, labile organic matter (LOM) was added at 0%, 1%, 2% and 4%, with increased LOM addition leading to more extensive biochar decomposition [46].

Contrary to these expectations, we see weaker-than-predicted temperature effects (figure 2). Although the 550 °C chars universally achieve better durability outcomes, there is clear variation across soil types. Only in the entisol (figure 2(d)) do we observe variation across temperature groups ($\Delta BC_{100} \approx 12\%$) that approaches what might be expected based on previous models. Durability is noticeably higher in the inceptisol (figure 2(b)) for the 450 °C char. Understanding the mechanisms driving this outcome is essential, given that raising the pyrolysis temperature by 100 °C is expected to increase energy requirements for biochar production by 20% [66, 76].

Pyrolysis temperature, although generally thought to be a key driver of biochar structure and reactivity [65], appears to only weakly influence durability outcomes here; in contrast, the variation in durability across SCC, SOM, and pH gradients explicitly shows that soil variables can exert important effects on biochar deployment outcomes (figure 2). The lowest durability outcomes on average appear to occur in the entisol and vertisol, which are both characterized by higher soil pH and SCC (figures 2(c) and (d)). Soil pH, SOM, and SCC (among other factors) are known to influence biochar decomposition [55, 77–79]. Although these variables are not well understood, [47, 72, 80–83] prior work suggests that acidic conditions [77, 84], high SOM content, [46, 78], and low SCC [79, 85] may contribute to faster biochar decay. However, these effects all fail to provide a consistent explanation for observed decomposition, with contradictory trends emerging across and within temperature groups (see section S2, figures S3, S5 in the SI). Clearly, analyzing individual drivers of

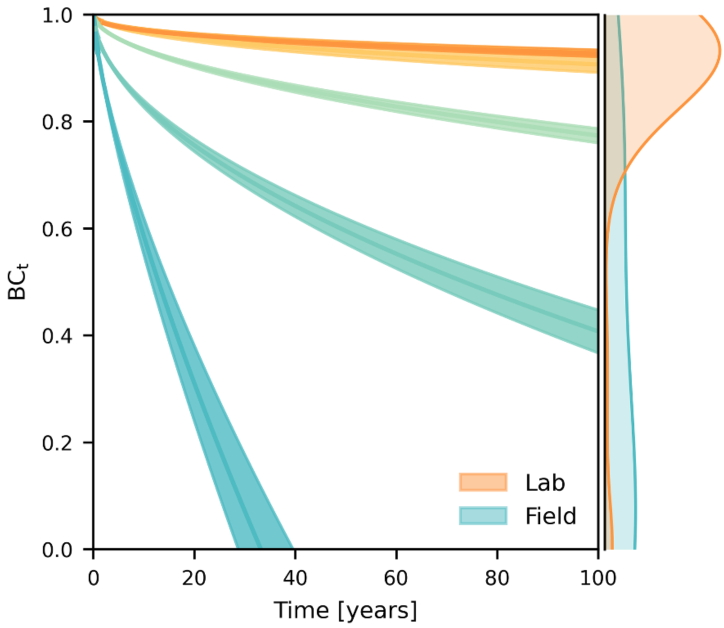


Figure 3. (BC_{100}) for observations of *eucalyptus saligna* biochar in laboratory incubations (orange tone series, $n = 3$) and field trials (blue tone series, $n = 3$). Shaded regions indicate the $1 - \sigma$ prediction interval. The marginal plot along the ride side shows the kernel density estimation (KDE) of the distribution of BC_{100} values for laboratory incubations ($n = 79$) and field incubations ($n = 6$) across the entire dataset. Here, we have included two additional datasets previously omitted from the Azzi *et al* reanalysis [61] due to oscillatory behavior. N.B. the BC_{100} values in the KDE were set to zero for observations yielding negative 100-year permanence factors.

biochar decay in isolation is overly simplistic, given the complexity and interaction of multiple factors.

3.3. Experimental scale: laboratory- and field-scale intercomparison

With only a handful of experiments conducted in the field and significant soil variability indicated above, the extent to which lab incubations replicate field-relevant decomposition drivers remains uncertain. Upscaling laboratory-derived results to the field is challenging [49, 59, 60] as field campaigns face effects of factors like roots, microbes, freeze-thaw cycles, precipitation, and material migration absent in lab studies [25, 74, 86]. To our knowledge, no study has systematically compared laboratory and field durability outcomes, indicating that additional, unconstrained uncertainty exists with respect to on-field durability.

Via another case study of six observations [46, 55] of nearly identical *eucalyptus saligna* biochars (HTT 450 °C, RT 40 min, H/C 0.62), we find that field-amended biochars decay faster than their lab-incubated counterparts (figure 3, N.B. we included two additional observations previously omitted in [61] and did not temperature adjust to 20 °C). While laboratory tests suggest minimal decomposition over 100 years, two of three field trials show over 50% biochar loss. Unlike the laboratory trials with predictable decay patterns, the field data is more variable, possibly due to meteorological conditions [61] (data fits and residuals in the SI). Overall, laboratory tests tend to estimate higher biochar permanence than field trials (figure 3 marginal plots), though field data remains limited.

Three additional caveats are worth discussion: experiment duration, soil temperature adjustment, and soil properties. Two-year laboratory studies contrast with one-year field trials, potentially biasing the field data towards faster-decomposing biochar components and limiting inter-comparison [25, 72, 74, 87]. The field trials were conducted in cooler environments (12.3 °C–17.3 °C on average, ranging from 4.3 °C–30.2 °C at 5 cm depth relative to 20 °C in the laboratory). Lower temperatures are expected to slow decay [47], however, so it is unlikely that temperature effects explain differences in durability. Differences within laboratory and field groups suggest deployment-specific factors, such as soil properties (SCC, SOM, pH), which may influence biochar durability. Again, these variations underscore the importance of environmental factors in determining biochar decay outcomes.

3.4. Implications for CDR assessment

The biochar 'durability problem' is further complicated by the challenge of translating the observations above to a methodology for CDR certification. Unsurprisingly, varying approaches and priorities yield different quantification metrics. To understand variability across methodologies, we computed the gross CDR value of 1 tonne of field-amended biochar (*eucalyptus saligna*) as predicted by the incubation data relative to four peer-reviewed [18, 61, 65, 88] durability standards (figure 4, equations available in

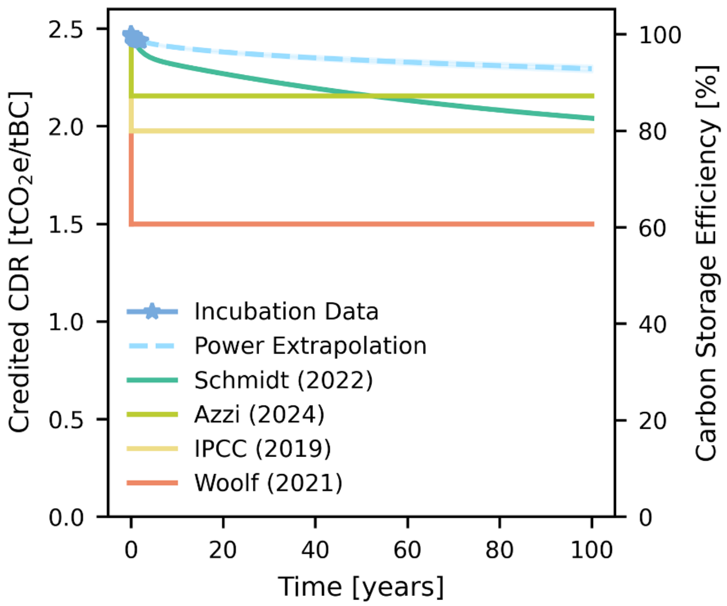


Figure 4. Storage of carbon dioxide (tCO_2e/tBC) over time for a singular observation of *eucalyptus saligna* pyrolyzed at 450 °C as predicted by the incubation data relative to four biochar durability methodologies (see the SI) [18, 61, 65, 88]. N.B. this does not embed any information related to project life cycle analysis or emissions incurred by biochar production, processing, or transport. The Azzi *et al* [61], IPCC [65], and Woolf *et al* [18] methods for computing CDR are time-independent, and thus the carbon storage potential for a given material decays stepwise to its calculated value. Tonnes of CO_2 equivalent (tCO_2e) are computed according the dry mass of biochar, organic carbon content, and a molecular weight conversion factor (equation available in the SI).

the SI). Net CDR calculation, which embeds life-cycle emissions accounting and ultimately determines the climate change benefit of a given deployment [89], is not considered here.

The data supports higher permanence than is suggested by all standards interrogated here. Importantly, this outcome is not unique to selected observations. Out of 83 observations where fitting was possible, our nominal BC_{100} prediction exceeded the corresponding Woolf (2021) [18], Azzi (2024) [61], IPCC (2019) [65], and Schmidt (2022) [88] method value 76, 47, 71, and 67 times, respectively. Confronted with the high uncertainty of H/C-based methodologies for biochar CDR, it is highly appropriate that SDOs adopt conservative valuation strategies. However, these tools also appear to undervalue biochar projects at a time when biochar is virtually the only deliverable CDR option [15].

4. Roadmap to precision biochar deployment at scale

4.1. The case for field measurement

Our analysis shows that durability standards undervalue biochar CDR relative to what is supported by existing data. Figure 5 illustrates the limitations of the prevailing approach: relying on short-term kinetic experiments, extrapolation, and secondary regression models introduces an ecological fallacy, where models calibrated to aggregate data fail to predict specific deployment outcomes. This appears to result in conservative CDR assignments and substantial 'uncredited mass'—biochar mass that is ineligible for CDR crediting, despite providing CDR benefits (figure 5). If true, existing methods fail to fully account for the biochar mass eligible for CDR and its time-dependence, highlighting the need for time-aware strategies. Although these methods are pragmatically conservative, recognizing the additional, time-dependent pool of uncredited biochar—and confronting weaknesses inherent to the current kinetic database—could create opportunities to enhance project value and integrity.

We propose addressing CDR uncertainty and potential conservatism with a two-step method: estimate removal value provisionally (*ex ante*) and adjust it later (*ex post*) with field measurements (via loss on ignition [90] techniques, spectroscopic tools [91], molecular marker tests [28], or litter bag trials [92]). We foresee two end-member scenarios: (1) *ex post* measurement indicates higher-than-anticipated carbon storage, i.e., undercrediting, or (2) *ex post* measurement indicates lower-than-anticipated carbon storage, i.e., overcrediting. In the first scenario, *ex post* measurement reveals additional credits available up to some continuously adjusted maximum value. This value could be determined via a reassessment of the 100-year permanence computed according to a field data-informed measurement history. In the second scenario, we propose that credits should be

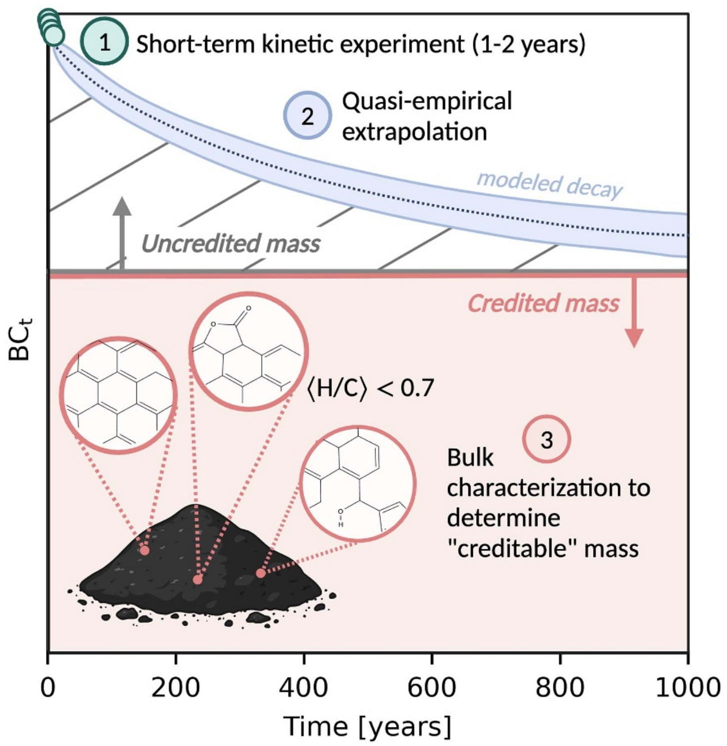


Figure 5. Conceptual model of current challenges in biochar crediting strategies: short-term experiments (1) provide the basis for quasi-empirical modeling of biochar carbon remaining (BC_t) as a function of time (2). Extrapolated data, in conjunction with bulk chemical characterizations of biochar, forms the basis for determining the CDR-creditable mass of biochar (3). The inset figure shows three potential carbon structures in biochar that contribute to a bulk (i.e., average) H/C ratio of 0.7.

re-purchased or released from a buffer pool. Given the evidence presented in figure 4, however, we believe the latter scenario is unlikely.

In view of these different scenarios, and although field measurements are considered both expensive and challenging [74, 90, 93], we argue that field measurement is both scientifically necessary and financially salient, presenting the opportunity to (i) capture additional project value, (ii) generate data for predictive modeling, and (iii) enhance project integrity:

(i) In-field measurement of durability may reveal additional biochar mass eligible for crediting. Even at the low-cost end of \$100/t biochar of CDR [15], the most conservative (and common) model [18] underestimates the dollar value of biochar CDR by over \$90/t (figure 4). Downstream field measurements that improve the accuracy of biochar durability projects could thus be offset in cost by increased revenue from deployment. Field measurement is also likely to co-generate incentives for better management practices; if project developers can gain more value from their deployments, they may be more inclined to protect them.

(ii) Unlike most CDR technologies, biochar provides two revenue streams: one for the physical biochar product and one for the CDR credit. However, because CDR credits are tied to field-deployed biochar (with a few exceptions), lack of demand for the physical product currently limits credit sales [94]. Uncertainty around biochar's agronomic benefits, such as improved crop yield and soil quality, hampers demand [19, 95, 96]. More data is needed to prove these co-benefits, and combining *in situ* durability measurements with real-time agronomic data could be used for modeling efforts to not only predict biochar durability, but also to guide its optimal use.

(iii) In-field biochar measurement presents opportunities to improve the spatiotemporal accuracy of carbon budgets at multiple scales. At the project scale, developers seeking to co-deploy biochar with other CDR activities promoting soil organic carbon storage (e.g., reduced/no-till, rotational grazing, cover crops), will need accurate in-field measurement of biochar to prevent double counting (i.e., separate biochar carbon inputs from accruals associated with other activities) [93]. At regional scales and beyond, better soil carbon accounting is needed to understand long-term climate dynamics and guide climate policy [97, 98].

4.2. Bridges to field MRV

While our analysis points to the importance and potential system-wide benefits of in-field biochar measurement, there are a series of short-term research needs that will both bridge towards this goal and improve the accuracy of existing systems. We present the following priorities:

(i) *Establish representative biochar experiments.* The alignment of feedstocks, processing conditions, and soils from credited biochar with those in the experimental database remains unclear, with minimal overlap expected. Closing this gap will require collecting descriptive data from current projects and mapping the underlying distributions. This will guide the design of targeted incubation and field experiments to ensure durability assessments accurately reflect real biochar project characteristics.

(ii) *Deploy coordinated global field trials.* Developing a robust experimental design to monitor biochar deployment across key feedstocks, conversion technologies, crops, and critical environmental gradients (e.g., drylands to flooded soils) is crucial for creating reliable field measurement tools and predictive models that include agronomic benefits. Field trials could be integrated as research plots within larger deployments, using previous field-based work [25, 26, 51, 55, 93] as a blueprint. Careful selection of environmental and land-use gradients, synchronization of measurement schemes, and establishment of benchmarked sites will be vital for intercomparison and testing of technologies that may reduce field measurement costs over time.

(iii) *Systematically link characterization methods with experiments and field trials.* Harmonizing experiments and field trials should enable a cost-effective balance between prediction and measurement. A key component in achieving this balance will be developing robust characterization methods. Structure-driven reactivity paradigms (e.g., aromaticity controlling degradability) have become the industry standard and assume that biochar's chemical structure can be described by bulk compositional metrics. However, modern understanding of biochar implies a range of chemical structures with varying reactivity, [30, 32] necessitating characterization with high spatial resolution. Advanced methods such as thermal and chemical oxidation tests, [50, 99, 100] high-pressure hydrogen pyrolysis [101], and microscopy-driven reflectance techniques [29, 30, 102] show promise in addressing biochar reactivity and heterogeneity but remain unlinked to decay kinetics. Furthermore, chemical theories of biochar reactivity conflict with 'soil carbon continuum' theories, which suggest organic carbon decay is governed by decomposer activity, redox conditions, soil minerals, and environmental factors, rather than specific material chemistry alone [103–105]. Thus, even with better chemical descriptors, linking characterization to experimental and field outcomes will be essential—and unlikely to yield a simple proxy like those used today.

Aligning experimental durability quantification with current and anticipated biochar project distributions is essential but will take time. In the interim, adapting existing durability standards to support measurement-driven *ex post* carbon stock adjustments can reduce reliance on unrepresentative datasets, enhance project credibility, and incentivize proactive biochar asset management, while enabling assessment of deployment co-benefits (soil health) and risks (particularly for crops). Eventually, this shift may require reconsideration of existing crediting strategies—a structural change in markets that warrants further discussion. In the meantime, we propose a focused effort to select research plots for a global network, accelerating predictive model development. These steps will improve market efficacy and facilitate more accurate carbon stock accounting at regional and national scales.

5. Conclusions

An examination of the largest existing database of biochar decomposition data reveals that highly relevant deployment variables, including biomass precursor type, environmental variables and field-measured decomposition rates, are not sufficiently represented in current durability standards. Thus, the collective characteristics, especially as encapsulated by correlations between single-parameter H/C proxies and lab-based incubations, are unlikely to apply uniformly to outcomes for a given deployment. While this exemplifies an ecological fallacy in the marketplace for biochar, it also results in pervasive undercrediting given the current assumptions and models used to calculate CDR. This undercrediting is problematic from economic and policy perspectives. It also points to the need to develop a system for quantifying the time-dependence of biochar stocks under actual deployment conditions.

To address these linked problems, we identify several important components. The deployment characteristics of biochar need to be assembled and evaluated with statistical rigor. In turn, this information should guide the design of carefully coordinated field-trials that support development and deployment of in-field measurement techniques. We further suggest an approach to in-field measurement that would integrate with existing strategies to facilitate a transition. Adoption of in-field measurement practices would provide several important benefits, including recovery of uncapitalized CDR value, increased confidence in project integrity, and critical data needed to support predictive models of both agronomic benefits and real-world durability. As biochar deployment advances in scale, field measurement will likely be integral to ensuring a high-integrity, high-efficiency market for biochar CDR.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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Conflict of interest

The authors declare no competing financial interests.

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