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A global meta-analysis of forest bioenergy greenhouse gas emission accounting studies

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Abstract

The potential greenhouse gas benefits of displacing fossil energy with biofuels are driving policy development in the absence of complete information. The potential carbon neutrality of forest biomass is a source of considerable scientific debate because of the complexity of dynamic forest ecosystems, varied feedstock types, and multiple energy production pathways. The lack of scientific consensus leaves decision makers struggling with contradicting technical advice. Analyzing previously published studies, our goal was to identify and prioritize those attributes of bioenergy greenhouse gas (GHG) emissions analysis that are most influential on length of carbon payback period. We investigated outcomes of 59 previously published forest biomass greenhouse gas emissions research studies published between 1991 and 2014. We identified attributes for each study and classified study cases by attributes. Using classification and regression tree analysis, we identified those attributes that are strong predictors of carbon payback period (e.g. the time required by the forest to recover through sequestration the carbon dioxide from biomass combusted for energy). The inclusion of wildfire dynamics proved to be the most influential in determining carbon payback period length compared to other factors such as feedstock type, baseline choice, and the incorporation of leakage calculations. Additionally, we demonstrate that evaluation criteria consistency is required to facilitate equitable comparison between projects. For carbon payback period calculations to provide operational insights to decision makers, future research should focus on creating common accounting principles for the most influential factors including temporal scale, natural disturbances, system boundaries, GHG emission metrics, and baselines.

Keywords: biomass, carbon accounting, carbon payback period, classification and regression tree analysis, climate change, life cycle assessment, meta-analysis, wildfire

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Introduction

The greenhouse gas (GHG) benefits of displacing fossil energy with biofuels are driving policy development in the absence of complete information. Getting the accounting correct is particularly important given the recent heavy emphasis on use of biomass energy to meet national and regional emissions reduction goals. For example, by 2020, between 8% and 11% of the UK's primary energy supply should be from biomass (United Kingdom, 2012; see Beurskens & Hekkenberg, 2011 for renewable energy projections of other EU states). The initial assumption regarding biomass energy was that of 'carbon neutrality', whereby a biologically based energy feedstock does not contribute to a net increase in atmospheric CO_2 relative to a defined fossil-fuel energy baseline (Searchinger *et al.*, 2009). The carbon neutrality of forest biomass is a source of considerable debate because of the complexity of dynamic forest ecosystems, varied feedstock types, and multiple energy production pathways. The evaluation of forest biomass carbon neutrality requires a defined set of criteria that capture initial forest conditions, *in situ* carbon dynamics (e.g. fluxes), energy conversion efficiency, and a well-defined fossil energy source for comparison, among others (Walker *et al.*, 2013; Mika & Keeton, 2014). Much of the research to date has focused on the appropriate choice of baseline (Gunn *et al.*, 2012; Lamers & Junginger, 2013; Walker *et al.*, 2013) or leakage (Gan & McCarl, 2007).

Defining a baseline for carbon stocks in a forest ecosystem has been the focus of considerable research and policy debate, because it is the carbon benchmark against which the effect of biomass energy development is evaluated and therefore influences the carbon neutrality of a project (Zanchi *et al.*, 2012). A 'reference point'

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baseline uses the carbon stock on a given land area at a given point in time as the benchmark (EPA, 2014, Fig. 1). A 'dynamic' (or 'anticipated future') baseline requires defining a business-as-usual (BAU) condition that is projected without any new use of biogenic feedstocks for energy. Carbon stock changes under bioenergy scenarios are then compared to a fossil-fuel energy scenario to quantify the overall emissions effect from fuel switching (Fig. 2). In this case, the choice of baseline directly influences the determination of carbon neutrality.

Leakage, defined as activity shifting in the presence of a biomass project (Henders & Ostwald, 2012), has the potential to drive forest harvest outside the project area to continue meeting *a priori* economic demand for biomass (e.g. wood products). Although the leakage concept has been well defined, it is challenging to quantify because of the varying size and global nature of markets for different forest products (Gan & McCarl, 2007; Chen, 2009; Fankhauser & Hepburn, 2010).

There are many other attributes that can influence the length of the carbon payback period or point at which the biomass energy produced becomes carbon neutral from an atmospheric perspective (Lamers & Junginger, 2013; Vanhala *et al.*, 2013). These attributes are often project specific and can include biomass feedstock source or type, forest type, fossil-fuel source replaced, and life cycle analysis boundaries, among others (Lamers & Junginger, 2013; Walker *et al.*, 2013). Given the range of attributes influencing biomass projects, the carbon benefits of any given project can be influenced by site-specific aspects and decisions made by researchers in establishing the parameters for comparison.

Previous efforts to synthesize the literature on this topic have generally focused on part of the system (Mann, 2011; Muench & Guenther, 2013), had a small sample size ((Holtsmark, 2013; Sedjo, 2013), or the methods chosen relied on a descriptive analytical framework restricting the authors' deductions to very general conclusions (Helin *et al.*, 2013; Lamers & Junginger, 2013;

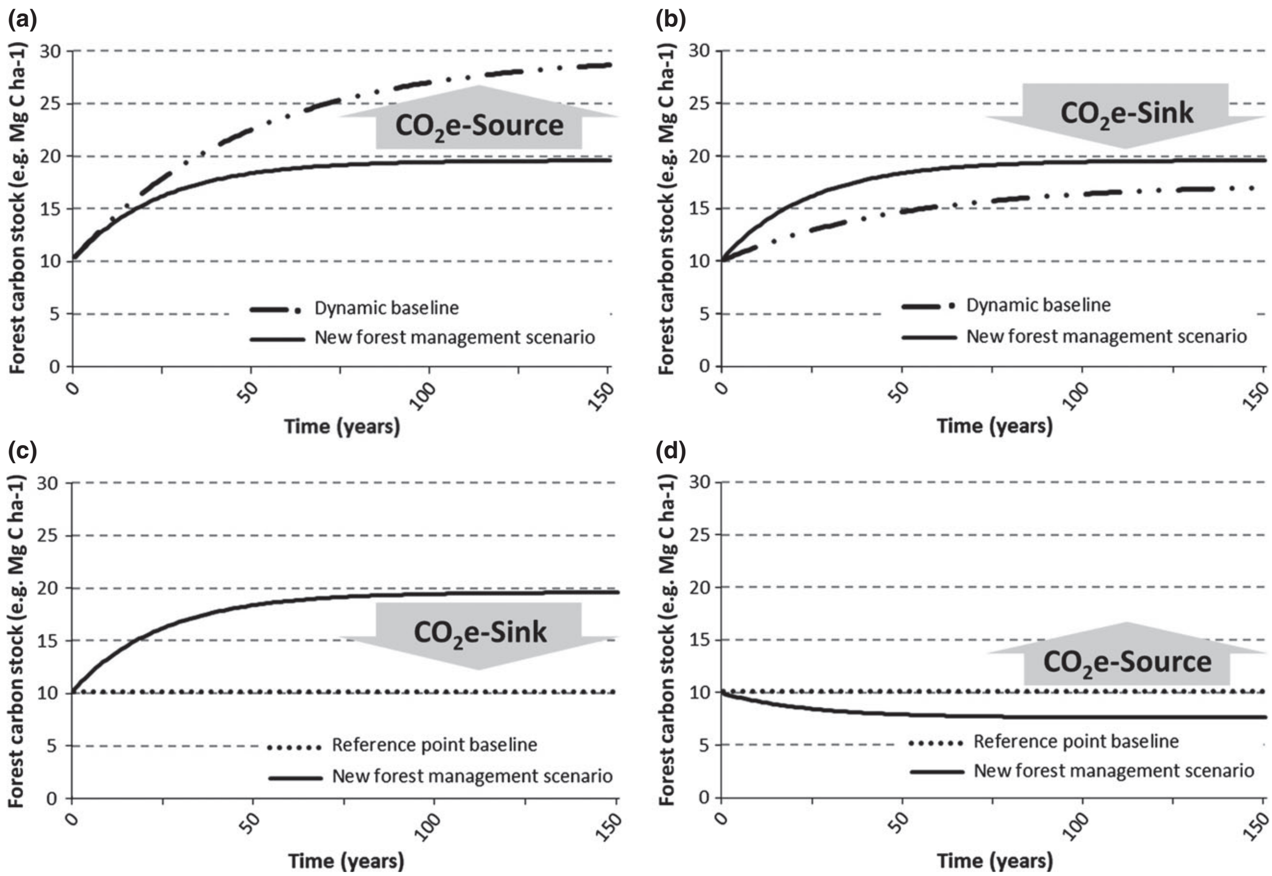

Fig. 1 With a dynamic or anticipated future baseline, future emissions are compared to a modeled baseline that assumes a given trend in forest carbon pools in the absence of the bioenergy activity (a, b). A reference point baseline is defined by the forest carbon stock in a given area at a given point in time. With a reference point baseline, future emissions are compared to this static point in time (c, d). The carbon balance of a particular bioenergy can change as a function of baseline type.

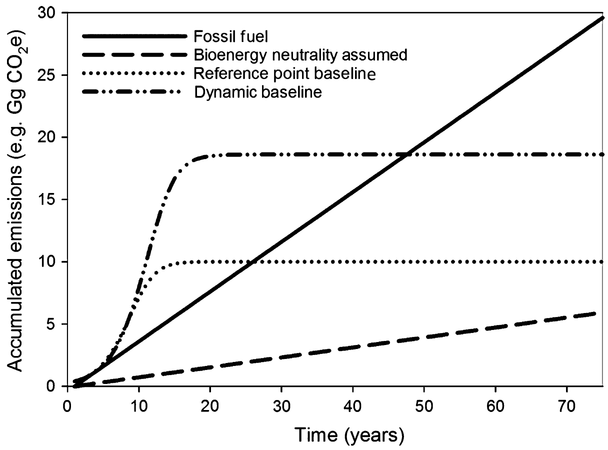

Fig. 2 Baseline choices influence carbon payback when comparing bioenergy alternatives with fossil-fuel emissions. In this hypothetical case, the reference point baseline assumes a scenario where forest carbon stocks briefly decrease followed by a recovery compared to a reference point in time. The dynamic baseline assumes a project scenario where forest stocks decrease compared to business as usual and require a longer time span to recover.

Miner *et al*., 2014), which all limit the ability to identify system-wide influential factors. Our objective was to identify the attributes of bioenergy GHG emissions analysis that exert the strongest influence over the length of the carbon payback period using an exhaustive review of the literature on this topic paired with a quantitative analytical approach.

Materials and methods

We conducted a literature review using Scopus, searching for the keywords *carbon accounting, forest biomass, greenhouse gas emissions,* and *bioenergy* in studies published between 1991 and 2014. We identified 59 peer-reviewed studies that investigated the carbon neutrality of forest-based bioenergy systems on a temporal scale, as well as seven influential studies in the gray literature (see supporting information). When a particular study included multiple scenarios such as a range of forest ecosystems, benchmark fossil energy sources (e.g. coal, mix, natural gas, oil), or energy conversion efficiency (e.g. electricity, liquid transportation fuel, combined heat and power, heat), we divided the study into separate cases. If the overall results of a single, multi-case study were not directly attributable to specific cases, we associated each case with the overall result. The 59 studies utilized in this analysis included a total of 149 cases.

We identified twenty attributes to classify the publications (Table 1). The baseline assumption referred to authors' choice of assuming carbon neutrality or applying a dynamic or reference point baseline for the forest ecosystem carbon stocks (see Fig. 1). Author clusters described a set of authors that published frequently together or were located at the same institution and using a common set of assumptions or models. Wildfire refers to the inclusion or exclusion of wildfire dynamics in the study's methodology. The stochastic nature of wildfire dynamics (e.g. frequency, size, etc.) can alter source-sink dynamics, adding additional uncertainty to ecosystem model results. The GHG impact of biomass removal from forests to reduce wildfire severity or risk is currently not settled in the scientific community and might rely largely on model assumptions, site conditions, and analytical system boundaries (Camp-

Table 1 Attributes included in the classification and regression tree analysis used to identify the most influential factors for carbon payback period

Attribute	Definition
Author clusters	Authors are from same institution or publish together
Publication year	
Carbon payback period	Study result in upper and lower bounds of carbon payback period in years
Geographic Region	Africa, Australia, Canada, Europe, South America, US, Global
Climatic zone	Tropical dry, temperate, cold; based on Köppen classification
Geographic Scale	County, forest, state, national, regional, global
Spatial unit	Stand, forest, landscape
Temporal scale	Total years considered in analysis
Data source	Hypothetical, regional, field data
Baseline assumption	Reference point, dynamic or neutrality assumed for forest ecosystem carbon stock (see Fig. 1)
Forest type	Natural forest, plantation, or both
Biomass source	Additional harvests or current logging residue only
Wildfire	Inclusion of wildfire dynamics
LCA pools	Number of LCA carbon pools included
LCA boundaries	Comparable system boundaries for fossil-fuel and bioenergy systems or imbalanced (e.g. more detailed bioenergy analysis)
Energy types compared	Electricity, transportation fuel, heating fuel, combined heat and power
Fossil fuel replaced	Coal, energy mix, natural gas, oil product
Wood products	Inclusion of wood product LCA (upstream emissions associated with processing and disposal)
Product substitution	Substitution of wood products for alternative fossil-fuel emission intensive products
Leakage	Accounted for leakage with project implementation

bell *et al.*, 2011; Hurteau *et al.*, 2012). While some authors argue that the carbon stock reduction associated with biomass removal is compensated for by reduced fire severity and risk (Hurteau *et al.*, 2008, 2014a), other studies suggest the opposite (Mitchell *et al.*, 2012). Despite a considerable wildfire risk in large areas of the world's forests, the inclusion of wildfire dynamics when calculating carbon payback period is not commonplace in fire-prone regions (e.g. Jonker *et al.*, 2014). We also screened each case to determine which forest and nonforest carbon pools were considered within each analysis (attribute 'LCA pools'). Seven carbon pools were restricted to the forest ecosystem (Above ground live biomass, Aboveground standing dead biomass, Belowground live biomass, Belowground dead biomass, Forest floor, Merchantable timber, Harvest residue), four carbon pools described the processing of material (Forest treatment operations, Recovery of biomass in the forest, Transport, Mill residue), while two carbon pools described product fate (Wood products in use, Wood products in landfill), and two described indirect effects (Leakage, Product substitution). The studies evaluated were characterized by a very inconsistent inclusion of carbon pools, ranging from the inclusion of 1–16 carbon pools, with an average of nine pools. Leakage was considered in only eight cases, and product substitution was only considered in 21 cases of the 149 total cases.

We analyzed the cases using classification and regression tree analysis. Classification and regression tree (CART) analysis is a nonparametric test where algorithms for constructing decision trees usually work top-down, by choosing a numeric or categorical variable at each step that best splits the set of items (De'Ath & Fabricius, 2000), making it a useful tool for meta-analyses (Dusseldorp *et al.*, 2013). The goal is to create a model that predicts the value of a target variable based on several input variables. Variables used for the first splits are considered the most predictive ones, explaining the highest amount of variance in the dependent variable. Using the JMP PRO 10.0.0 software (SAS, Cary, NC, USA), we validated the model with a randomized binary variable to assess the optimum number of splits based on R^2 values. As not all of the 59 studies analyzed used carbon payback period as a carbon emissions metric, only those 38 studies that incorporated a calculation of a carbon payback period and covering 123 cases were included in the CART analysis.

Results

The CART model validation resulted in a minimum number of eight splits (R^2 = 0.87). We validated the stability of the CART model by including and excluding studies represented by disproportionally high cases or long payback periods. We concluded that the outliers did not change the number of splits required nor the attribute ranking based on their predictive power. The hierarchical ranking of these attributes based on their effect on carbon payback period for forest biomass projects indicated that the single largest determinant of carbon payback period length was the inclusion of wildfire dynamics (Fig. 3). Studies that included wildfire dynamics had a mean carbon payback period of 856 years (SD = 1299), while those that did not had a mean carbon payback period of 51 years (SD = 75). This initial level of classification had a significant influence on the importance of subsequent factors, such that there was no overlap between influential attributes following this highest level classification (Fig. 3). Studies having the shortest carbon payback period (μ = 5 years, SD = 15) did not account for wildfire dynamics or leakage, were from an author group other than authors who were at some point associated with the Joanneum Research Forschungsgesellschaft mbH (Graz, Austria), included a fossil energy source other than natural gas, and did not use a dynamic baseline. Studies having the longest carbon payback period (μ = 2945 years, SD = 1082) were a subgroup of studies that included wildfire dynamics but also considered a wood products LCA, utilized electricity generation as the dominant technology, and were conducted in natural forests (Fig. 3). The total range of payback periods covered a span from 0 to 4500 years, with the largest ranges occurring in studies that included wildfire dynamics or wood products LCA (Fig. 4). The three attributes commonly identified as important for evaluating the carbon neutrality of biomass projects (baseline, leakage, and product substitution) were less influential overall. In studies where wildfire dynamics were considered, leakage and baseline were not influential in the first four levels of classification (Fig. 3). In studies where wildfire dynamics were not considered, leakage was the second level and baseline the fifth level of classification (Fig. 3). In these cases, including leakage increased the carbon payback period such that the interquartile range exceeded that of cases that did not include leakage (Fig. 4b) and the type of baseline had little influence over the carbon payback period.

Discussion

CART analysis

Project baseline and leakage are two attributes consistently used in the quantification of forest carbon projects and in quantifying the atmospheric greenhouse gas effects of a forest bioenergy project (Guest *et al.*, 2013). While these attributes are important for forest carbon offset projects (Hurteau *et al.*, 2012), our results suggest they are less informative for evaluating the carbon benefits of forest biomass projects. Interestingly, the choice of baseline type (dynamic or reference point) was only influential in 33% of cases, and only after studies had been segregated based on four other attributes (Fig. 3).

The inclusion of wildfire dynamics was the attribute with the greatest influence over carbon payback period

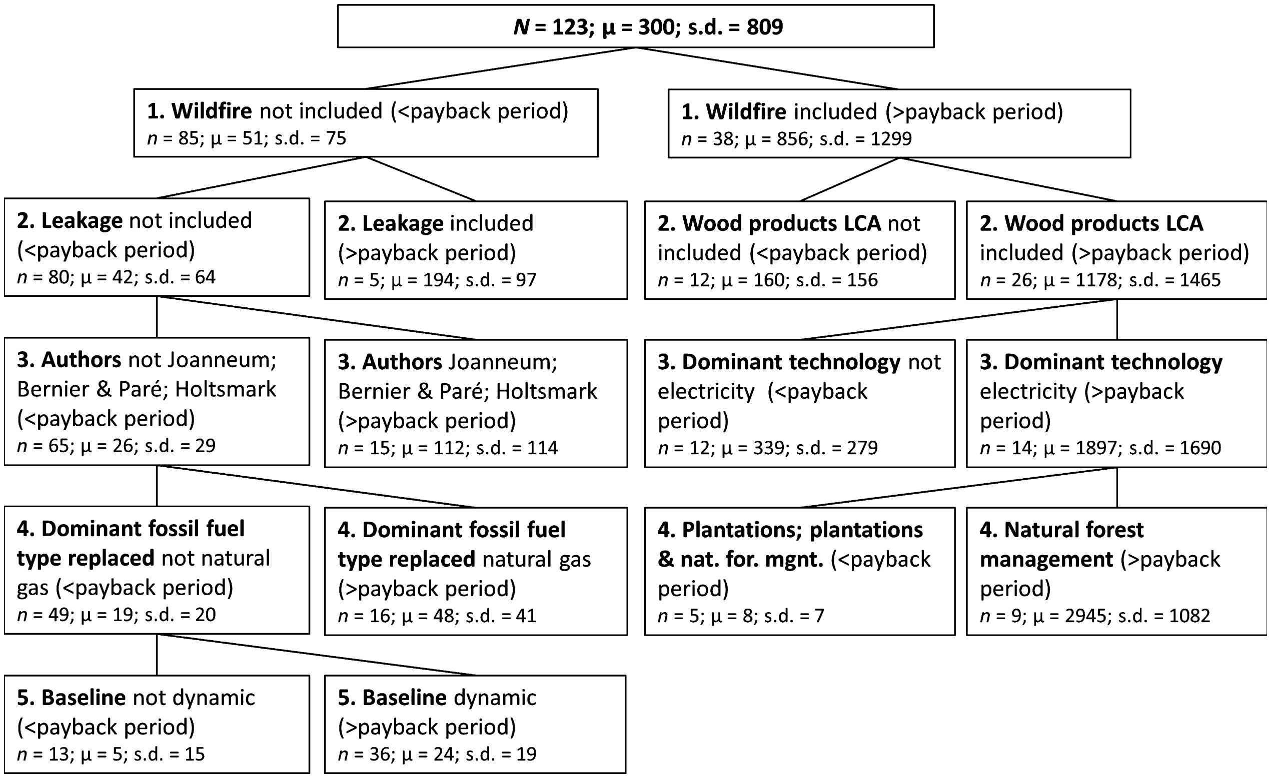

Fig. 3 Classification and regression tree (CART) analysis on the influence of different variables on carbon payback period in years for forest bioenergy. CART ranks independent variables based on predictive power with the variable that explains the highest amount of variance in the dependent variable on top. A total of eight splits resulted in a R^2 of 0.87, additional splits did not produce meaningful increases in R^2.

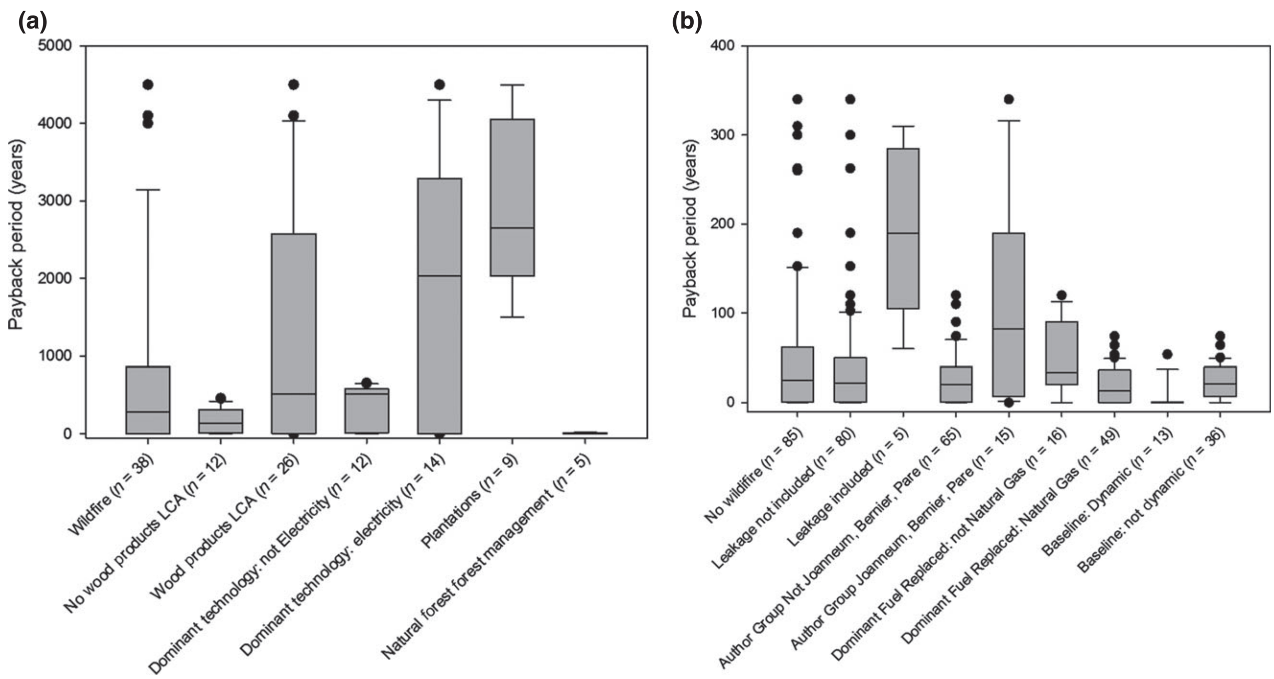

Fig. 4 Carbon payback periods based on variables with high predictive power as indicated by classification and regression tree analysis (Fig. 3). Figure a and b exhibit carbon payback periods for variables including and excluding wildfire dynamics, respectively.

length, suggesting that the role of natural disturbance within a system exerts strong control (Fig. 3). Unlike other natural disturbances (e.g. hurricanes, ice storms), wildfire risk can be managed. In biomass projects where fuel-reduction treatments are considered, the original driver for the treatments needs to be clearly defined because it directly influences the appropriate baseline condition. For example, if biomass is only a by-product of thinning that is already occurring, GHG emissions and derived carbon payback periods for bioenergy scenarios differ compared to scenarios where the presence of a biomass market triggers a decision to implement a fuel-reduction thinning (Walker *et al.*, 2013). The few studies in fire-prone regions where open burning of fuel-reduction treatment residues is common practice conclude that using the material for bioenergy results in immediate carbon benefits (Jones *et al.*, 2010; Springsteen *et al.*, 2011). Where a market facilitates the decision to thin, the carbon payback period is influenced by a suite of factors. The carbon costs associated with treatments (e.g. thinning and prescribed burning) have the potential to reduce mortality and emissions from subsequent wildfire when compared with the untreated forest condition (Hurteau *et al.*, 2008; North & Hurteau, 2011). However, the potential benefits (in terms of short payback periods) to be gained from reduced wildfire emissions following treatment are dependent on the probability of occurrence, size, and severity of wildfire as well as the growth response of trees retained during treatment (Campbell *et al.*, 2011; Hurteau *et al.*, 2014a). Given the influence of projected changes in climate on forest growth (Silva & Anand, 2013) and disturbance frequency and effect (Westerling *et al.*, 2011; Moritz *et al.*, 2012; Hurteau *et al.*, 2014b), disturbance dynamics are likely to become even more influential in evaluating biomass energy projects over meaningful temporal scales. Therefore, while simulating stochastic disturbance adds additional challenges to modeling efforts, in disturbance-prone areas, it is an integral component of both baseline and project scenario conditions.

Other influential attributes in determining carbon payback period can be broadly classified into decision criteria and regional market influences. Decision criteria attributes, including leakage and wood products LCA, require clearly defining the study boundary and present an opportunity for standardization of evaluation criteria. When the effects of wood harvest displacement to meet market demands are absent, the influence of market forces is left unaccounted and the actual effects of a project on the global carbon cycle are neglected. Likewise, accounting for the use and disposal of wood products can strongly influence conclusions about the carbon benefits of forest management (Lippke *et al.*, 2011). Creating a framework in which there is consensus on the specific boundaries for evaluation or inclusion of a range of boundaries will facilitate comparison across studies.

Attributes related to geographic location and local markets (e.g. dominant technology, fossil-fuel source) exert influence over the carbon payback period and pose a challenge for equitable comparison of forest biomass energy across large spatial scales. The dominant technology and its influence on carbon payback period are functions of conversion efficiency and are highly sensitive to the fossil-fuel source (McKechnie *et al.*, 2010). In our evaluation of dominant technology, electricity production vs. other technologies such as combined heat and power or heat only was the defining factor. This result was not surprising given the slightly low conversion efficiencies associated with producing electricity only from woody biomass combustion over fossil-fuel consuming systems (Schlamadinger & Marland, 1996). When other technologies are employed, such as combined heat and power, the overall conversion efficiency of woody biomass combustion systems increases (Richter *et al.*, 2009) and approaches that of fossil-fuel consuming combined heat and power systems; therefore, the carbon payback period is reduced. While decisions regarding dominant technology are in part influenced by location, the replacement fuel comparison is entirely a function of geographic location. Power sources and the emissions per unit of power generated vary by region (Chen, 2009). If the regional power mix is comprised primarily of natural gas, woody biomass energy will have a considerably longer carbon payback period (μ = 82 years, SD = 83, n = 21). However, if the regional energy mix is primarily from coal combustion, the carbon payback period is reduced (μ = 36 years, SD = 48, n = 21).

Author group was an influential attribute for classifying carbon payback period. The partitioning based on author groups is most likely attributable to the repeated application of modeling frameworks and software used within a confined circle of researchers. Models are a representation on how authors understand the system to be analyzed. Providing a host of results using various models is a common characteristic of complex systems where scientific consensus has not been reached. An example is the inclusion of 41 different climate models in the fifth assessment report of the Intergovernmental Panel for Climate Change (Flato *et al.*, 2013). This result validates how models are consistent within their applications but also how they can create 'half-predictable' outcomes based on their assumptions. This finding further reinforces the need to establish a common set of criteria for evaluation. In particular, specifying model components such as stochastic disturbances in general and wildfire in particular is a case in point.

Additional insights

Calculating a carbon payback period as a metric to describe the GHG impact of alternative scenarios is becoming standard practice outnumbering other metrics frequently employed such as tons of carbon displaced per energy unit of biomass fuel (e.g. (Hall *et al.*, 1991; Schmidt *et al.*, 2011), carbon emissions for various scenarios over a given timescale (e.g. (Domke *et al.*, 2008), or a carbon neutrality factor that measures GHG emissions in percent of a baseline scenario over a given period of time (e.g. Schlamadinger *et al.*, 1995; US Forest Service, 2009; Zhang *et al.*, 2010; Kilpeläinen *et al.*, 2012; Winford & Gaither, 2012). Carbon payback period was the principal metric in 26 of the 59 studies while nine studies used GHG savings in % over a fossil-fuel scenario over a given time. Other metrics such as CO_2 savings per ha (e.g. Dwivedi *et al.*, 2014) or CO_2 savings per MWh (e.g. KilpeläInen *et al.*, 2011) were infrequent. A conversation on the advantages and disadvantages of one metric over the others is largely absent.

For the majority of studies, we observed a high trust in models that was exhibited by the willingness of authors to report in 100+ year timespans as well as a frequent absence of uncertainty metrics when reporting results. We also observed no consistent pattern in the use of temporal scales for modeling. The temporal scale of analysis for all studies analyzed ranged from 20 (e.g. (Hudiburg *et al.*, 2011) to 10 000 years (Mitchell *et al.*, 2012) with a median of 240 years. The lowest temporal scale was applied by (Hudiburg *et al.*, 2011) to avoid the risk of 'overstretching data', that is owing to data uncertainty. No neutrality was achieved over these 20 years in this study. All other authors seemed to have enough confidence in their assumptions, datasets and models to investigate carbon fluxes over longer time scales although only a few cases included episodic carbon pulses that occur on large temporal and spatial scales such as wildfire (included in 8% or 14% of all studies), insect outbreaks or storm events. Most studies used hypothetical data (35% or 59% of all studies), only seven studies (12%) used field data. Among those studies that modeled neutrality over time on temporal scales surpassing 100 years, the share of studies using hypothetical data was even higher (67% or 30 of 45 studies). Uncertainties affecting other system elements such as baselines (Buchholz *et al.*, 2014a), product substitution (York, 2012; Bird, 2013), soil carbon (Buchholz *et al.*, 2014b), or market effects (Sedjo, 2013) were frequently underreported or excluded.

Setting assessment boundaries provide a major challenge when comparing bioenergy GHG emission studies and can result in incomplete accounting. For instance, we confirmed the observation of (Muench & Guenther, 2013) that most studies did not account for all upstream fossil-fuel emissions such as building machinery and facilities. Notably, a broader set of metrics to assess GHG implications using bioenergy systems was largely absent. The inclusion of non-CO_2 GHG relevant emissions (other reactive gases, biogenic aerosols, and factors such as methane or atmospheric particles), surface albedo only considered by (Guest *et al.* (2013), evapotranspiration or discounting approaches to account for the release of GHG emissions along a temporal scale (e.g. Cherubini *et al.*, 2011; Pingoud *et al.*, 2012) was not common practice. Nevertheless, our CART analysis suggests that a focus on top-priority system attributes such as wildfire dynamics, leakage, or wood products LCA can substitute for a more complete assessment that includes a maximum set of (ultimately less influential) attributes. This insight is supported by an observation of Holtsmark (2012), finding that complex global warming potential decay functions 'did not change the results fundamentally' compared to a model that used a simple accumulation model of CO_2 in the atmosphere.

While the CART analysis suggests some influence of plantation vs. natural forest management practices on carbon payback periods, this was only true for a small subset of cases. The full sample revealed no apparent differences in carbon payback periods between the two management types (Fig. 5). Reducing rotation lengths to increase profitability can be a major advantage of plantation over natural forest regimes (Cubbage *et al.*, 2010). Our results do not show that a switch from natural forest management regimes to plantation forestry provides

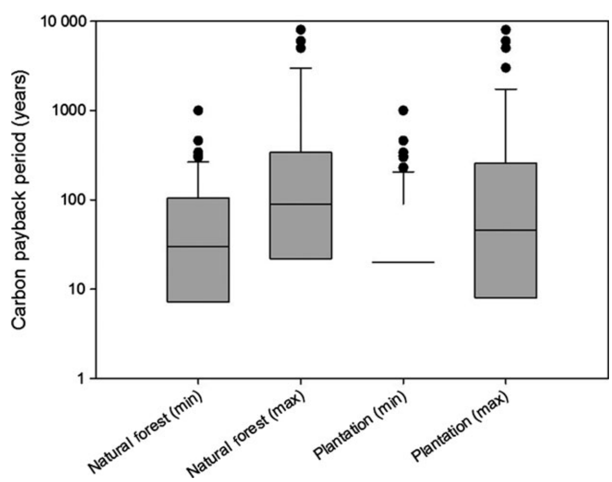

Fig. 5 Range of minimum and maximum carbon payback periods for natural and plantation forests.

a strong argument to reduce carbon payback period. Similarly, (Pyörälä *et al*., 2012) also concluded for boreal forests that shorter rotations do not always automatically produce more favorable emission balances on behalf of bioenergy. This result challenges the generalization by (Lamers & Junginger, 2013) that shorter rotations result in shorter carbon payback periods.

Recommendations

In summary, for carbon payback period calculations to provide operational insights to decision makers, future research should focus on creating consistent accounting principles including the consideration of stochastic disturbance, temporal scales, quantifying and reporting uncertainties, standardization of carbon pools evaluated, GHG emission metrics considered and baseline definition.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Figure S1. Carbon payback period in years for each case.
Table S1. The upper and lower bounds for the carbon payback period in years for each case within each study.
Table S2. Bioenergy carbon debt carbon payback periods by fossil fuel replaced and energy type.