Measurement matters in managing landscape carbon

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A B S T R A C T

Carbon stocks and emissions are quantified using many different measures and metrics, and these differ in their surrogacy, measurement, and incentive value. To evaluate potential policy impacts of using different carbon measures, we modeled and mapped carbon in above-ground and below-ground stocks, as well as fluxes related to sequestration, oxidation and combustion in the Ex Mega Rice Project Area in Central Kalimantan, Indonesia. We identify significant financial and carbon emission mitigation consequences of proxy choice in relation to the achievement of national emissions reduction targets. We find that measures of above-ground biomass carbon stock have both high measurement and incentive value, but low surrogacy for potential emissions or the potential for emissions reductions. The inclusion of below-ground carbon increased stocks and flows by an order of magnitude, highlighting the importance of protecting and managing soil carbon and peat. Carbon loss and potential emissions reduction is highest in the areas of deep peat, which supports the use of deep peat as a legislative metric. Divergence in patterns across sub-regions and through time further emphasizes the importance of proxy choice and highlights the need to carefully consider the objectives of the application to which the measure of carbon will be applied.

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1. Introduction

Land use and land cover change is responsible for a third of global anthropogenic greenhouse gas emissions over the last 150 years (Houghton et al., 2012), and ongoing deforestation and forest degradation is the major source of current greenhouse gas emissions in many tropical developing countries (Van Der Werf et al., 2009). Climate change mitigation and adaptation is now a strategic part of many national economies and environmental policies (C Kapoor and Ambrosi, 2008). This includes a strong emphasis on activities under the program for Reducing Emissions from avoided Deforestation and forest Degradation (REDD + ) and other similar voluntary mechanisms aimed to reduce greenhouse gas emissions in developing countries.

Information on carbon stocks and projections of future emissions over space and time is required at multiple stages of the development and implementation of climate change policy including carbon accounting (Lim et al., 1999) and land use planning (Achard et al., 2004). Specifically, it is needed to establish baselines (Lubowski et al., 2006), prioritize the location of emissions reduction or sequestration activities (Naidoo et al., 2008), and for the monitoring, reporting and verification (MRV) of such activities (Petrokovskiy et al., 2012).

The main pools of carbon in forested ecosystems are the stores of above- and below-ground living biomass, necromass (litter, and woody debris), and soil organic matter. Deforestation and degradation visibly impacts above-ground stores, however soils and particularly peat soils are also a significant source of emissions following deforestation and forest conversion (Houghton et al., 2012; Page et al., 2002). There are a multitude of methods for assessing above- and below-ground carbon stocks, and these have been extensively reviewed (Gibbs et al., 2007; IPCC, 2006; Ladd et al., 2013; Petrokovskiy et al., 2012; Qureshi et al., 2012; Vieilledent et al., 2012; Ziegler et al., 2012). All reviews conclude that comprehensive, field-derived carbon measures are labor intensive, time consuming, expensive, often destructive (Gibbs et al., 2007), and therefore generally prohibitive over extensive areas.

As a consequence, indirect methods of measuring carbon stocks and emissions, referred to herein as proxies, are common. Here we
Measurement-level proxies can be used to predict both measures of potential emissions and the potential for emissions reduction (Fig. 1). These proxies can be extrapolated or indirectly estimated over extensive areas. Measurement-level proxies include carbon stocks and fluxes of above- and below-ground carbon at a particular point in time. These proxies are substitutes for direct field measurements: they usually informollation collated from a number of field measurements that are extrapolated using additional landscape variables such as vegetation type (Couwenberg et al., 2011; Saatchi et al., 2007), elevation (Saatchi et al., 2007), rainfall (Saatchi et al., 2007), soil type (Kapos et al., 2008), and peat characteristics such as water level and subsidence (Fig. 1; Joosten and Couwenberg, 2009). Importantly, as these measurement-level proxies are of current processes, they can be verified at the time of estimation.

Metric-level proxies are typically derived from process models that combine many of the above mentioned measurement proxies and biophysical parameters, as well as assumptions regarding changes in these over time. Proxies at the level of metrics include both measures of potential emissions and the potential for emissions reduction (Fig. 1). These proxies can be used to predict biomass production and carbon dynamics over space and time (e.g. CENTURY; Parton et al., 1995) and the impacts of reforestation (e.g. 3-PG; Bryan and Crossman, 2013; Paterson and Bryan, 2012) and agricultural development (e.g. APSIM; Luo et al., 2013; Zhao et al., 2013). Typically calibrated against field data, a major strength of the process models used to develop metric-level proxies is their ability to forecast carbon sequestration and emissions under different scenarios of change (Crossman et al., 2011; Liu et al., 2009). Activities such as land-use planning necessarily deal with potential future emissions necessitating these forecast estimations (Couwenberg et al., 2010). The use of counterfactual baselines in such forecasts essentially mean that potential emissions reductions can never be verified (i.e. directly measured), and although potential emissions may be verified this necessarily must be post hoc, after decisions are made based on the available proxy information.

The performance of different carbon proxies has been the focus of past studies, particularly how well the proxy correlates with the true measurement, both spatially and temporally (i.e. its surrogacy value), and how easy or expensive it is to derive (i.e. its measurement value). For example, remotely sensed above-ground biomass (AGB) has been extensively compared to field-based measurements (Petrokofsky et al., 2012) and vegetation-based proxies for carbon flux have been compared with direct carbon flux measurements (Couwenberg et al., 2011). There has also been extensive comparison among metric-level proxies (Houghton et al., 2012). However, there has been little comparison between measurement and metric-level proxies and it is often assumed explicitly or implicitly that carbon stocks are an adequate proxy for the potential for emissions reduction (Chan et al., 2011, 2006; Egoh et al., 2010; Larsen and Harvey, 2010; Reyers et al., 2012; Wendland et al., 2010). When considering carbon proxies in a policy or planning context, it is also important to recognize that each proxy will differ in how easily the proxy is communicated and the extent to which it translates to actions and the other co-benefits it might encompass (i.e. its incentive value). This ‘framing’ of proxies can thus influence the overall performance of policies, even when the measurement or surrogacy values remain the same (Entman, 1993; Druckman, 2001).

The required performance of a proxy across these three dimensions (surrogacy, measurement, and incentive value) is dependent on the specific activity of interest. Land use planning undertaken by governments may place more importance on measurement and surrogacy value, whereas activities that rely on community involvement and acceptance may give greater importance to the incentive value of a proxy. The choice of proxy and how they are applied are likely to influence the perceived priority, cost-effectiveness, and impact of specific climate change mitigation or abatement activities in specific locations (Paterson and Bryan, 2012). Poor choices in this regard may result in inefficient and ineffective mitigation outcomes.

Here we explore the consequences of using different carbon proxies by modeling, mapping, and evaluating the surrogacy, measurement and incentive value of seven proxies of landscape carbon (Table 1) for the Ex Mega Rice Project region in Central Kalimantan, Indonesia. The study region is of considerable global interest due to continued high carbon emissions resulting from past land use change. We determine the financial and carbon emission mitigation consequences of proxy choice in relation to the achievement of Indonesia’s national emissions reduction targets, and discuss the performance of the different proxies, particularly in the context of their utility for informing and evaluating land use plans.

2. Materials and methods

2.1. Study region

The Ex Mega Rice Project (EMRP) region (Fig. 2) defines an area subject to an agricultural self-sufficiency and development policy implemented from 1996 to 1998 that cleared one million hectares of tropical lowland peat swamp forest and created 4000 km of canals for drainage and irrigation in Central Kalimantan, Indonesia (Page et al., 2009). The project failed to achieve its agricultural objectives, with subsequent agricultural land abandonment and ongoing degradation resulting in considerable negative consequences for hydrology and carbon emissions. After the peat lands were drained, a process of drying, oxidation, and irreversible collapse occurred (Wosten et al., 2008), increasing peat susceptibility to fire (Hooijer et al., 2006) and releasing significant amounts of greenhouse gases to the atmosphere (Page et al., 2002), particularly in extreme El Nino years (Ballhorn et al., 2009; Hooijer et al., 2010; Page et al., 2002). Widespread peat fires in the 1997 El Nino event attracted considerable international attention due to regional human health effects (Aditama, 2000) and the volume of carbon released into the atmosphere (Page et al., 2002). The land use changes across areas such as the EMRP
region have contributed to Indonesia’s position among the world’s top ten largest greenhouse gas emitters from 1995 to 2010 (WRI and CAIT 2.0, 2013).

2.2. Spatial modeling and mapping

We model seven proxies of carbon that could be used in the study region for carbon management (Table 1). Descriptions of base information of land use, land cover, and peat depth are described in Section 2.2.1. Carbon stocks are static, current estimates (as of 2008) based on prior land use, land cover, and peat depth (Section 2.2.2). Potential emissions are estimated based on a continuation of current management (Section 2.2.3), and the potential for emissions reductions are calculated by comparing this with a hypothetical scenario of carbon management (Section 2.2.4).

| Proxy | Description | Justification |
|-------|-------------|---------------|
| (1) Peat depth | Peat depth in cm, specifically noting the threshold of 300 cm | Current policy limits development on peat > 300 cm |
| (2) AGB carbon stock | Estimate of carbon (t C ha⁻¹) within AGB (live material only) | Commonly used measure for carbon accounting and land use planning |
| (3) Total carbon stock | Estimate of carbon (t C ha⁻¹) within AGB, below-ground biomass (BGB) and necromass (dead standing and fallen woody biomass), and soil | A more comprehensive estimate of the carbon stock |
| Potential emissions: change in AGB (4), or total carbon (5), measured against a static baseline (measured in t CO₂e) | Estimate of carbon emissions (t CO₂e) from respective carbon pools, relative to a static baseline set at year 0. Conversion to CO₂e using emission factors that differentiate between sources of emissions | This method estimates carbon change from a known and observable baseline |
| Potential emissions reduction: change in AGB (6), or total carbon (7), measured against a dynamic baseline (measured in t CO₂e) | Estimate of carbon emissions (t CO₂e) from respective carbon pools, relative to a dynamic baseline that projects a continuation of current land management. Conversion to CO₂e using emission factors that differentiate between sources of emissions | This method estimates carbon change from a hypothetical baseline, and calculates how carbon emissions differ between the two scenarios. Provides an estimate of the physical potential for emissions reduction |

Fig. 2. Location of the study region and administrative sub-regions (blocks A–E), current land use and land cover, and peat depth.
2.2.2. Carbon stocks

We quantified both AGB stocks (t C ha\(^{-1}\)), and total carbon stocks (including AGB, below-ground living biomass (BGB), necromass, and soil carbon; t C ha\(^{-1}\); Table 1). AGB carbon was allocated using a land cover proxy, on a 50 × 50 m grid resolution, aligned with land cover and peat depth. These were then scaled to a 100 ha hexagonal grid for further analysis. AGB stock was used to estimate BGB and necromass pools based on ratio factors drawn from the literature (Table C1). Soil carbon was determined based on soil type (terrestrial peat, mineral, or mangrove) and depth of (terrestrial) peat. Mineral soils were assumed to be fluvaquents and tropaquents (entisol) soils, and were assigned an average soil carbon value (375.24 t C ha\(^{-1}\) m\(^{-1}\); Wahyunto and Ritung, 2004). Peat soils are often denser on the surface due to compaction (Kool et al., 2006), and particularly when the overall depth is shallow (Wahyunto and Ritung, 2004). We therefore assigned a higher value, 980 t C ha\(^{-1}\) m\(^{-1}\), for the first 30 cm of peat for shallow peat soils (Wahyunto and Ritung, 2004). The remaining peat, 30 cm and deeper, was assigned 786.8 t C ha\(^{-1}\) m\(^{-1}\), the average of fibric, hemic, and sapric peat values (Wahyunto and Ritung, 2004). Areas with less than 30 cm of peat were considered to overlay mineral soils to a total depth of 30 cm. Mangroves were allocated a global average carbon value of 783.5 t C ha\(^{-1}\) and based on an average soil depth of 199.4 m (Donato et al., 2011).

2.2.3. Carbon flux and emissions

To estimate potential emissions, four main categories of carbon flux were defined: (1) peat oxidation in the absence of fire, (2) vegetation sequestration in the absence of fire, (3) carbon loss from peat due to fire events, and (4) loss from vegetation due to fire events. These were integrated into a process model to estimate carbon flux through time (Fig. C1), developed in R (R Core Team, 2012). The model was simulated on a 100 ha hexagonal grid, at yearly intervals in which either a fire occurred and carbon was lost due to combustion of biomass and peat, or a fire did not occur and carbon was sequestered in plant growth, and lost through (appric) peat oxidation.

The probability of fire was modeled using a generalized linear mixed effects (lme4: glmmer, R package; Bates et al., 2012) model to allow for the partitioning of variance due to both fixed effects (environmental variables) and random effects (the year, to account for El Niño events). The models included the following environmental variables: AGB; MODIS fire hotspot data for the years 2000–2006, which included one major El Niño event; distance to rivers and artificial canals (log transformed); the potential forest type; and the presence of agriculture (Table C2). AGB was back calculated for the years 2000–2005 based on the 2006 AGB value, and whether a fire occurred in each year at that location.

We developed two models of fire probability, with different assumptions regarding the amount of biomass burnt in fire events. This parameter is uncertain for tropical peat lands, and there are a range of values expressed in the literature for other ecosystems (Cochrane, 2003; IPCC GPG, 2006; Kasischke and Bruhwiler, 2002; Kasischke et al., 2005; Lü et al., 2006; Yokelson et al., 2007). We therefore assumed that a fire event would consume either 10% or 70% of the available AGB, regardless of soil type or existing land management (these mixed effects models are denoted herein as F10 and F70 respectively). Reduced fire probability is predicted with increasing AGB, increasing distance from canals and rivers, in areas of agricultural management, in mangroves, and in riparian forests (which mainly exist on mineral soils; Table C2). The strongest factor increasing fire probability was El Niño years, and forest types on peat soils. While there is the possibility that fire hotspot data can be biased against the short duration and low intensity fires common in agricultural management in some regions (due to the intermittent nature of satellite sampling; Langer and Siegert, 2009), we feel this data would likely capture most of the important fire events that burn through peat soils as these are generally of longer duration. Back calculation of AGB in the fire model results in a large loss of biomass in each fire event for the F70 model and therefore there is an even greater rate of reduction in fire probability with higher levels of AGB and with agricultural management under the F70 model (Table C2).

We then integrated the current carbon stocks, fire probability, and assumed land use scenarios into a process model to estimate potential emissions and emission reductions (Fig. C1). Time series for El Niño events at yearly intervals were derived for the period 1954–2004 (http://ggweather.com/enso/years.htm). Two thresholds were employed to classify a year as an El Niño event: agreement of three out of the four indices used to identify El Niño events, resulting in 11 events over the 50 year period (denoted S1) and agreement of at least a half of the indices, resulting in 20 events over the 50 year period (denoted S2). These two versions were used to both characterize the influence of this parameter on the results, as some predictions suggest climate change may increase the severity of the wet–dry cycle in this region (Collins et al., 2010; Kumagai and Porporato, 2012). These 50-year time series were allocated a random start year in each run, and cycled twice to give a 100-year series. Whether each grid cell was burnt in each year was determined stochastically, by evaluating a number drawn from a random uniform distribution against the modeled probability of fire. Peat consumption by fire was assumed to be 30 cm deep in unmanaged land, and 15 cm deep in managed agricultural areas, based on data from empirical estimation during burn events (Ballhorn et al., 2009), or the entire profile of peat if less than these thresholds.

For each year without fire, the vegetation in each grid cell experienced growth and there was a loss of carbon through peat oxidation, reflecting the continued impacts of drainage canals in the region. Peat oxidative loss can be estimated by the water table depth (Hooijer et al., 2006) and this was assumed to be 20, 40, 50, and 80 cm respectively for natural or restored, drained but forested, drained and deforested, and agricultural areas (Euroconsult Mott Macdonald et al., 2008), with a threshold of AGB carbon of 100 t ha\(^{-1}\) to distinguish forested from unforested areas on drained lands. We used an average oxidative loss of 3.041 t C ha\(^{-1}\) yr\(^{-1}\) for every additional 10 cm drainage depth (assuming an average of 50% carbon loss to oxidation; Couwenberg et al., 2010). The maximum peat available to be lost was assigned based on the carbon stock in the peat soils above mean sea level (at which burning and oxidation was assumed to cease). While peat lands may accumulate carbon in soil, this process was excluded as the level of the water table is generally not conducive for peat growth in the region (Page et al., 2009). We did not consider carbon loss or accumulation in the saline peat soils of mangroves. The maximum AGB was assigned based on the potential forest type and expected land use (Table C3). Growth in AGB (in the absence of fire) up to a maximum allowed under the assumed land use and land cover was assumed to be 13.5 t dry biomass ha\(^{-1}\) for up to 20 years (IPCC GPG, 2006), and 3.7 t dry biomass ha\(^{-1}\) thereafter (IPCC GPG, 2006).
represents a more reasonable planning horizon, and most patterns observed at 40 years are similar to those at the end of a 100 year time period.

2.2.4. Potential for emissions reduction

In order to measure the potential for emissions reduction, we compared the results of two scenarios using the carbon process model described above: that of maintaining the current management, and a hypothetical scenario assuming complete fire control and no agricultural management. Current management is comprised of areas with agricultural production, and areas where no particular management occurs (including, drained and deforested land in the southern section of the region, and partially drained and forested areas in the northern section). The hypothetical comparison involves the assumption of natural forest restoration, but no widespread and substantial canal damming and peat restoration work, and as such we assume maximum water table depth is limited to 40 cm on previously drained lands, based on empirical observations in the region (Euroconsult Mott Macdonald et al., 2008). This represents a relatively conservative estimate of the maximum possible carbon storage value for this study region (the least emissions from peat and greatest sequestration in vegetation) and we acknowledge that canal damming may be utilized in the process of both restoration and fire management. This comparison however provides an indication of the physical potential for emissions reduction (Table 1).

2.3. Proxy correlation and hotspot congruence

Correlation among the seven carbon proxies was assessed using Spearman’s rank test with a significance test corrected for spatial autocorrelation (i.e. to account for trends due to spatial proximity rather than the parameters of interest; Clifford et al., 1989; Dutilleul et al., 1993; Osorio et al., 2012). To further reduce the impact of spatial autocorrelation, a bootstrapping technique, with 10 subsamples (n=1000) randomly selected without replacement from the full dataset was employed to calculate average Spearman’s Rho (the degree of correlation) and significance values (Gos and Lavorel, 2012). This analysis was conducted in R and contributed packages (SpatialPack::modified.test; Osorio et al., 2012). We describe correlation results as weak if absolute values of Spearman’s Rho were 0.2–0.3, moderate 0.3–0.6, and strong if 0.6 or over, using a significance level of α=0.05.

Hotspots were defined as the areas representing the upper 30th and 10th percentile threshold for each proxy individually. Hotspots were chosen to represent the areas of highest value, for example the areas that held the greatest stock of carbon, or could potentially deliver the greatest emissions reduction. Hotspot congruency was assessed using Cohen’s Kappa. Cohen’s Kappa estimates adjust observations of agreement accounting for that expected by chance (Cohen, 1960; Czaplewski, 1994; Gamer et al., 2012). The value of the Kappa statistic ranges from a minimum of negative one to a maximum of one, with a value of one indicating perfect similarity, zero indicating expected similarity due to chance, and negative one indicating no similarity. Values greater than 0.6 are considered to represent substantial overlap, values between 0.2 and 0.4 to indicate minimal overlap, while equivalent negative values show analogous level of disassociation (Landis and Koch, 1977). Cohen’s Kappa was calculated in R and contributed packages (irr::kappa2; Gamer et al., 2012).

2.4. Consistency of patterns at different temporal and spatial scales

Carbon emissions are expected to be temporally and spatially dynamic. To explore these dynamics we evaluated the similarity of patterns (within proxies) over time periods of 5, 10, 20, 40 and 100 years. Previous studies also highlight the potential variability of carbon stocks and emissions at different spatial scales (Anderson et al., 2009). The EMRP is divided into five management blocks (blocks A–E; Fig. 2), each with a substantially distinct social-ecological history. To assess the consistency of observed patterns of correlation and congruence at finer spatial extents we repeated the analyses for each management block (A–E) separately, and compared results with the patterns observed at the regional level.

2.5. Impact on efficiency of achieving emissions reduction targets

In 2009, Indonesia committed to reduce overall greenhouse gas emissions by 26% from the business as usual by 2020 and up to 41% with international support (Presidential Regulation No. 61, 2011). If we assume the business as usual case to be a continuation of current management, we calculate these targets to be 26% and 41% of the potential emissions of this scenario, or 3136 and 4943 M t CO2e respectively. We assumed a hypothetical land use planning scenario for the EMRP area where the location of climate change mitigation activities was selected using each of the seven proxies for stocks and emissions (Table 1), that is, we selected areas that represented the top 26th and 41st percentiles for each proxy. We evaluated the outcomes in terms of the estimated emissions reduction that would be achieved, the efficiency of emissions reduction (emissions reduction per hectare), and the potential gross financial benefits at a carbon price of US$ 9.2 per tonne (Peters-Stanley et al., 2012).

3. Results

3.1. Values and spatial patterns

Carbon stored in total carbon stocks (including AGB, BGB, and soil carbon) in the EMRP area exceeded that stored in only AGB by approximately an order of magnitude (2749 M t C compared to 129 M t C; Table D1). AGB potential emissions across the study region were predicted to be 30–65% that of the AGB potential emissions reductions after 40 years (Table D1), as potential emissions do not account for the additional sequestration in growing biomass allowed for by the control of both fire and reforestation of currently cleared agricultural and degraded land. Total carbon potential emissions (accounting for both above and below-ground sources) were estimated to be 95–98% of potential emissions reductions over the same time period (Table D1), suggesting the additional sequestration in AGB is offset by the unavoidable emissions from peat oxidation.

If it is assumed that there is a 10% reduction of AGB biomass in each fire event (the F10 model) then this resulted in potential AGB emissions that were four times greater than if it is assumed that there is a 70% reduction in AGB biomass (the F70 models; Table D1; Section 2.2.3). Doubling the incidence of El Niño events (i.e. S2 models compared with S1 models) increased AGB emissions estimates (Table D1). Sub-regional blocks with different environmental features and historic conditions showed distinct differences in carbon value. Largely still forested and overlaying deep peat, Block E dominates both AGB and total carbon stock measurements (Figs. 3 and 4; Table D2). Block C contains large areas of peat and therefore has large total carbon stocks, but extensive deforested areas result in lower AGB stock values compared to Block E. Block D has also experienced substantial deforestation, and the lack of deep peat deposits result in this block having the lowest value of both AGB and total carbon stocks in the study region (Table D1).

Allocation of AGB potential emissions among blocks largely reflected that of AGB stocks. Total potential emissions and
emissions reductions values were similarly patterned to total stocks across all models (Figs. 3 and 4). Hotspots for these proxies were more heavily skewed towards Blocks A and C, with only 5–15% occurring in Block E over all models (Table D2). Total carbon proxy hotspots had over 94% overlap with deep peat areas. AGB proxies had less correspondence with deep peat areas, with only a 6–28% overlap overall (Table D3).

3.2. Proxy correlation and congruence

AGB carbon stock was not correlated with total carbon stock (Table D4). While much of the remaining forest lies over more inaccessible deeper peat profiles in Block E, the deepest peats support forests with lower biomass, and a high proportion of the peat domes of Block C are cleared. AGB carbon stocks were strongly positively correlated with AGB potential emissions (Table D4). Total carbon stock showed much more consistency of pattern across models compared to AGB: total carbon stocks were significantly positively correlated with both total carbon potential emissions and potential for emissions reduction in all models (Rho = 0.48–0.96, P < 0.01; Table D4), but showed only weak correlations in limited cases with AGB potential emissions and potential for emissions reduction.

The level of congruence between the upper 10th and 30th percentile hotspots for AGB carbon proxies and deep peat areas reflected those expected by chance across all models (Kappa = 0.15 to 0.02, with deep peat areas overlapping 8–29% of the hotspots for these; Table D3). There was substantial overlap between deep peat areas and hotspots for total carbon proxies (Fig. 4; Table D3).

Fig. 3. Carbon stock, potential emissions and the potential for emissions reduction measured over a 40-year time period using either AGB or total carbon stocks, for model F70-S2. Negative potential emissions reflect areas of high sequestration. Results for all models can be seen in Figs. D1–D4.

Fig. 4. Hot spots of carbon proxies for model F70-S2. Potential emissions and emission reductions are measured over a 40-year time period. Results for all models can be seen in Figs. D1–D4.
3.3. Consistency of patterns at different temporal and spatial scales

Total carbon potential emissions were less temporally consistent than for AGB potential emissions (Rho = 0.66–0.79 and Rho = 0.81–0.93 respectively, when comparing year 5 values to year 100; Fig. D5), however the strong influence of peat fires ensured the correlation of total carbon potential emissions reduction was more temporally consistent (Rho = 0.65–0.80) than that of the equivalent AGB proxy (Rho = 0.50–0.62; Fig. D5).

The correlation and congruency results were relatively consistent across blocks for the F10 models, with Block D being the major exception. Largely cleared, and without deep peat deposits, Block D showed positive correlations between the majority of proxies tested (Tables D4–D6). For the F70 models there was more variation among Blocks, though this is usually limited to the strength and evidence for correlations rather than the direction of the observed trends (Tables D4–D6).

3.4. Impact on efficiency of achieving emissions reduction targets

The greatest potential emissions reductions and financial benefit are seen if the decision rule is to manage and protect all the deep peat areas (Table 2 and Table D7). However, this is largely due to the large area managed, and is achieved less efficiently than if the proxy employed represents total potential emissions reduction or total potential emissions. Prioritizing areas with the greatest total carbon stocks would achieve emissions reduction targets, however at 68–74% of the efficiency of directly prioritizing areas representing the greatest potential for emissions reduction. The efficiency, in terms of potential carbon emissions reduction per area, of targeting areas where the overall potential for emissions reduction is greatest would be approximately two to three times that achieved through targeting the areas with the greatest AGB carbon stocks (Table 2). The latter is the most poorly performing decision rule in terms of carbon outcomes, meeting only 32–38% of the emissions reduction targets, while targeting total carbon stocks would meet 68–74%, targeting total potential emissions would achieve 97% of the targets, and targeting deep peat areas would far exceed the emission reduction targets. These conclusions are based on the assumption that all policies are equally effective on a per area basis, which may not be the case, as their incentive value differs (as discussed below in Section 4).

4. Discussion

We have demonstrated that proxies for carbon stocks and emissions exhibit differing spatial patterns, and this will have significant implications for the use of different carbon metrics in carbon management and land use policy. In particular, the use of AGB carbon stock proxies for informing where mitigation activities should occur could significantly reduce the benefits of emission reduction schemes. In our study AGB stock and potential emissions, while substantial, were dwarfed by the potential carbon stored and released from burning and carbon peat, the densest source of terrestrial carbon stock (Petrokovsky et al., 2012). Total carbon stock and emissions were more than an order of magnitude larger than their AGB counterparts, and in the rare cases where AGB and total carbon metrics were correlated the relationships were mostly inverse (i.e. negative Spearman’s Rho values). The one exception to this was in the one sub-region that is largely cleared and does not include substantial peat deposits (Block D). This reinforces the significant impact that the ongoing process of peat oxidation (e.g. due to drainage) and fires has on the emission of greenhouse gases in this system, and therefore the importance of protecting remaining undeveloped tropical peat deposits. Our results also highlight important implications for the implementation of REDD+ policy if it fails to account adequately for high carbon soils such as tropical lowland peat swamp forest.

AGB carbon stock was a good predictor of potential emissions from AGB, indicating that areas with extensive forest cover are likely also to be areas with high carbon loss if no positive action is taken to prevent this occurring. However, AGB stocks were not a consistent surrogate for potential AGB emissions reduction: this is determined by both avoidance of loss from current stocks and the potential for vegetation sequestration. By factoring in the potential for emissions sequestration, greater emissions reduction will be predicted in moderately degraded areas in some models as the process model assumes denser, more mature forests are likely to experience lower rates of sequestration than fast growing secondary forests (IPCC, 2006). However, this pattern is only seen in models for which the probability of fire is more strongly influenced by AGB (i.e. F70 models where 70% of biomass is assumed to be burnt in each fire event). In comparison, total carbon stocks were reasonable predictors of areas where the potential for emissions reduction is highest over much of the study region, and therefore could potentially have a high surrogacy value. While prioritizing areas with the greatest total carbon stocks is likely not

Table 2

The impact of choice of carbon proxy on the efficiency of emissions reduction and financial benefits of climate change mitigation. Results are for the F70-S2 model, and the results for all models can be seen in Table D7.

| Target (%) | Policy | 40 year Potential emissions reduction (M t CO2e) | Per cent of potential emissions reduction target (%) | Area (ha) | Efficiency (1000 t CO2e potential emissions reduction per ha) | Potential benefit (M USD, based USD 9.2 per t CO2e) | Benefit per ha (USD) |
|-----------|--------|-----------------------------------------------|-----------------------------------------------|----------|------------------------------------------------|-----------------------------------------------|---------------------|
| 26        | AGB stock | 1004                                          | 32                                            | 168,300  | 6.0                                             | 9233                                           | 54,859                           |
|           | Total stock | 2135                                          | 68                                            | 122,600  | 17.4                                           | 19,644                                         | 160,226                          |
|           | Total potential emissions | 3047                                          | 97                                            | 133,000  | 22.9                                           | 28,037                                         | 210,802                          |
|           | Total potential emissions reduction | 3136                                          | 100                                           | 137,600  | 22.8                                           | 28,852                                         | 209,681                           |
|           | Deep peat      | 7525                                          | 240                                           | 446,730  | 16.8                                           | 69,232                                         | 154,976                           |
| 41        | AGB stock | 1866                                          | 38                                            | 281,400  | 6.6                                            | 17,170                                         | 61,016                           |
|           | Total stock | 3657                                          | 74                                            | 209,600  | 17.4                                           | 33,649                                         | 160,539                          |
|           | Total potential emissions | 4812                                          | 97                                            | 232,900  | 20.7                                           | 44,267                                         | 190,070                          |
|           | Total potential emissions reduction | 4943                                          | 100                                           | 240,900  | 20.5                                           | 45,473                                         | 188,765                           |
|           | Deep peat      | 7525                                          | 152                                           | 446,730  | 16.8                                           | 69,232                                         | 154,976                           |
to meet the emissions reduction targets, due to a smaller target area, it would be achieved at similar efficiencies obtained by targeting areas of deep peat (\(>3\) m) as per current policy.

We identify deep peat areas as a useful carbon proxy in the study region; protection of all deep peat regions could deliver on emissions reductions targets, albeit less efficiently than targeting potential emissions reductions directly and requiring 1.5–3 time more land area. A regulatory approach to protecting deep peat may therefore be a useful policy direction in Indonesia and elsewhere. The identification and mapping of deep peat locations is relatively straightforward and would provide a basis for land use planning regulations (Jaenicke et al., 2008). While currently the main legislative mechanism in Indonesia for peat land conservation is one that limits agricultural land development in peat ecosystems with a depth greater than three meters (Republic of Indonesia, 1990), this does not however give adequate protection from fires which are the predominant drivers of emissions in this region (Couwenberg et al., 2010; Houghton et al., 2012; Murdiyarso et al., 2010; Page et al., 2009). Nor does it provide any incentive or instruction for management of surrounding shallower, yet still hydrologically-connected peat land, the management of which is likely to be a critical determinant of the success of deep peat conservation.

The performance of a carbon proxy also encompasses the costs of monitoring, reporting, and verification and the time lag for responses to be accurately detected. Proxies for AGB carbon stock are often measured remotely or through land use/land cover conversions. These proxies can be field validated, and consequently measures of AGB carbon stocks have high measurement value. However, considerable uncertainties still exist, including the inaccurate measurement of variables, the use of incorrect allogentic models, inadequate sampling regimes, and poor representation of the sampling network (Butt et al., 2013; Petrokofsky et al., 2012). Greater uncertainties exist in the measurement of emission dynamics of BGB and soil carbon stocks, especially those associated with tropical peat lands. Typically, the estimation of emissions is based on a land-use proxy stock-difference approach, with unclear treatment of soil carbon (Rai et al., 2011; Luck et al., 2009; Nelson et al., 2009), as opposed to the gain-loss process based model used in this study, and suggested as a preferable approach for soil carbon, particularly for peat soils (Murdiyarso et al., 2010).

Emission estimates from peat fires have large uncertainties, because of the highly variable mass of peat combusted and the quantity of greenhouse gases emitted varying with fire severity, water table, peat moisture content, and fire history (Murdiyarso et al., 2010). Our results suggest that the frequency of El Niño events (varied almost 1-fold in this study) is overshadowed by the parameter controlling biomass loss in fire events, highlighting the importance of resolving uncertainties regarding peat land emissions due to fire. These uncertainties mean that absolute results from this study should be taken as indicative only: we have designed these models to illustrate potential impacts of proxy choice, and further sensitivity analysis on key values and model structure would be required for further inference to occur.

Land use plans are designed to be enduring over mid-long time periods therefore temporally consistent proxies are also desired. We found patterns for all potential emission and emission reduction proxies used in this study were reasonably consistent over time. This reflects a strong dominance of peat, rather than AGB, in determining carbon dynamics in this region. A caveat of this study is the assumption that all parameters will remain constant over the 100 year period. While we have integrated some possible ecological feedbacks (though specifying fire frequency as a function of vegetation biomass), for simplicity we did not include, for example, dynamic impacts of climate change. Climate change predictions for Borneo suggest an increased seasonality of rainfall, with dry seasons becoming drier and wet seasons wetter (Kumagai and Porporato, 2012), but there is considerable uncertainty surrounding impacts on El Niño (Collins et al., 2010), which is a key driver of climate and dry season fires in the region. Our results suggest increased frequency of El Niño events will increase potential emissions, but also the potential for emissions reductions if fires are controlled. Other impacts of climate change in this region that would be important to consider are likely substantial impacts on low lying areas from sea level rise.

Research from the sociology, psychology, and political sciences has shown that the way in which an issue is ‘framed’ can profoundly influence decision making (Druckman, 2001). Hence the psychological appeal of a proxy can be an important consideration, for example if the uptake of incentive schemes depends on the proxy communicating the importance of a particular process (Entman, 1993). Even if a proxy has both high measurement and surrogacy values, it may have low incentive value, for example if the proxy reflects a process that one has little control over (Gibbs et al., 2007) or if the measure is intended to incentivize change but fails to gain traction (Entman, 1993). The performance of a proxy also depends on how clearly the concept can be communicated and how well it reflects the impacts of actions in a reasonable time scale.

The AGB carbon stock proxy relates to a visible and relatively easily monitored action (i.e. actions that ensure protection or growth of biomass) and therefore has high incentive value. The peat depth proxy can be easily communicated as it is simple in concept and is generally constant through time. These characteristics reinforce its potential in a regulatory framework. However, the peat depth proxy does not speak to actions and this reduces its incentive value: peat depth is unlikely to increase due to actions, and the implications of the choice of depth threshold (such as three meters) are unclear. It is also uncertain as to how collapsed peat domes (i.e. particularly those with an original height of greater than three meters and a collapsed height of less than three meters) ought to be managed. Therefore for the development of future land use plans that require actions such as rewetting and fire management (rather than simply restricting development), and for ongoing monitoring, the peat depth proxy may not be particularly useful. In these cases, water table depth may be a useful proxy for the effectiveness of rewetting activities (CKPP, 2008; Jaenicke et al., 2010).

The spatial variation of stocks, potential emissions and the potential for emissions reduction across the administrative blocks reflects different biophysical and historical management characteristics. It is therefore likely that a single policy action or strategy is unlikely to capture the full potential for emissions reduction across the study region. While an initial policy of limiting development on deep peat areas may limit the negative impacts of poor management of these areas, it would by definition not cover sub-regions without deep peat, and any incentive or disincentive to support this policy would thereby bias particular areas. While this may be acceptable, direct action taken to manage carbon emissions or improve stocks will require greater community support and engagement than a regulatory approach. Furthermore, decisions regarding management need to account for implications of, and trade-offs between a full range of environmental, economic, and social considerations. For example, equity between sub-regions will become more important in the case of direct action, particularly given the high rates of poverty and displacement. This would place a greater emphasis on selection of a carbon proxy that distributes mitigation actions throughout the landscape, and facilitates the rapid identification of responses to management actions (such as AGB stock or water table levels).
Our methods for calculating carbon proxies are not aligned to the Kyoto Protocol (IPCC, 2006) nor to voluntary carbon standards, as we needed to balance a desire for simplicity with a requirement to derive the best possible estimates of carbon for this specific study region. In particular, our stock measures considered the carbon value of the entire profile of peat soils, rather than limiting to the top 30 or 100 cm, as we considered this to be more reflective of the total potential for emissions. Further, our model does not distinguish natural from anthropogenic disturbance and re-vegetation. This can be difficult to classify when both anthropogenic and natural factors contribute to, for example, fire and regeneration of forest in the region. In Indonesia, where standards are still under development, we are optimistic that studies such as ours will inform the creation of rigorous measurement standards. Our aim was to identify and compare carbon proxies for application in land use planning and therefore we sought to develop carbon proxies with utility beyond the task of carbon accounting. Land use planning aims to seek multiple objectives. Most carbon accounting defaults to conservative estimates, for example, AGB carbon stock must meet a certain definition of forest to be considered under the metric. This is not appropriate for land use planning as the evaluation of different land uses necessitates accurate information on all values derived from alternative land uses. Using conservative proxies in such applications will devalue a parcel of land or broader land use category from a carbon stocks and emissions reduction perspective.

5. Conclusion

Our study highlights the need to assess the use of different carbon proxies depending on the desired application. While the use of carbon proxies is widespread, few studies have compared and evaluated measurement- and metric-level proxies, let alone the implications of their use. Our results show that carbon stock measures based on AGB carbon alone fail to account for over 90% of the total carbon stock in the EMRP. Further, the different spatial patterns observed between AGB stocks and the potential for emissions reduction mean that prioritization of mitigation actions based on an AGB focused proxy would fail to meet emission reduction targets. This has important implications for studies and policies that utilize AGB stock measures as a basis for planning mitigation activities, and further for regional or global policies that do not adequately account for the substantial carbon deposits and emissions in tropical peat lands. With land use and land cover change being a major contributor to global greenhouse gas emissions, careful consideration of proxy performance is critical to facilitate effective and efficient implementation of climate change mitigation policies.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.ecoser.2014.07.007.

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