Forest Ecology and Management 593 (2025) 122840

Contents lists available at ScienceDirect

Forest Ecology and Management

journal homepage: www.elsevier.com/locate/foreco

Total ecosystem carbon stocks of tropical peat forests and greenhouse gas emissions from their disturbance

J. Boone Kauffman [a,b,*], Maria Fernanda Adame [c], Wahyu Catur Adinugroho [d], Gusti Anshari [e,f], Imam Basuki [g], Daniel Donato [h], Adi Gangga [i], Daniel Murdiyarso [j,k], Rasis Putra Ritonga [l], Matthew Warren [m], Nisa Novita [n]

[a] Illahee Sciences International, Corvallis, OR 97330, USA
[b] Department of Fisheries, Wildlife, and Conservation Sciences, Oregon State University, Corvallis, OR 97331, Australia
[c] Australian Rivers Institute, Griffith University, Nathan, QLD 4111, Australia
[d] Research Center for Ecology and Ethnobiology, National Research and Innovation Agency (BRIN), Bogor, Indonesia
[e] Dept of Soil Science, Tanjungpura University, Pontianak 78124, Indonesia
[f] Magister of Environmental Science, Tanjungpura University, Pontianak 78124, Indonesia
[g] Wildlife Works Indonesia, Wisma GKBI, 12th Floor, Suite 1203 Jl. Jenderal Sudirman Kav. 28, Jakarta 10210, Indonesia
[h] School of Environmental and Forest Sciences, University of Washington, Seattle, WA 98195, USA
[i] Yayasan Konservasi Alam Nusantara, Graha Iskandarsyah Lt.3, Jl. Iskandarsyah Raya, Kebayoran Baru, Jakarta, Indonesia
[j] Center for International Forestry Research - World Agroforestry, Jl. CIFOR, Situgede, Bogor 16115, Indonesia
[k] Department of Geophysics and Meteorology, IPB University, Bogor 16680, Indonesia
[l] Yayasan Konservasi Alam Nusantara, Graha Iskandarsyah Lt.3, Jl. Iskandarsyah Raya, Kebayoran Baru, Jakarta, Indonesia
[m] Food and Agriculture Organization of the United Nations, Rome, Italy
[n] Yayasan Konservasi Alam Nusantara, Graha Iskandarsyah Lt.3, Jl. Iskandarsyah Raya, Kebayoran Baru, Jakarta, Indonesia

ARTICLE INFO

Keywords:
Blue carbon Freshwater wetlands
Land cover change
Social carbon costs
Tropical ecology
Supratidal ecosystems
Wetlands degradaton

ABSTRACT

Because of their unique biodiversity and inordinately large carbon stocks, tropical peat forests are considered key wetland ecosystems for conservation and restoration. Despite this recognition continued deforestation and land cover change result in these ecosystems becoming significant sources of greenhouse gases. There is a strong need for accurate quantification of carbon stocks and emissions at scales relevant for participation in carbon markets and nationally determined contributions. Based upon analyses of 125 forests in 4 continents (Asia, Oceania, the Americas) there was a broad range in peat depths (19–1414 cm) with total ecosystem carbon stocks (TECS) ranging from 172 to 9379 Mg C ha^{-1} (mean of 2137 Mg C ha^{-1}). Among the 47 sampled sites known to be tidally-influenced (i.e., blue carbon ecosystems), TECS ranged from 206 to 5591 Mg C ha^{-1} with a mean of 1979 Mg C ha^{-1}. Those sites with deep peats (> 7 m depth) have a mean TECS of 4620 ± 395 Mg C ha^{-1} and we know of no ecosystems with an equivalent ecosystem carbon stock. Peat soils composed a mean of 86 % of TECS, and peat depths were strongly correlated with soil carbon stocks at continental and global scales ($R^2 > 0.80$) suggesting inventories that include measurement of peat depth can accurately estimate carbon stocks. Degradation of peat landscapes comes with high ecological and social costs including the largest greenhouse gas emissions from any forest land use globally. The social carbon costs to future generations associated with the conversion of tropical peat forests to oil palm plantations is conservatively estimated to be nine times the value of the palm oil generated from the conversion. Such costs and values of the tropical peat forests underscore the importance of the conservation and restoration of these wetlands for future generations – an important element of sustainability.

1. Introduction

Tropical peat forests – wetland tropical ecosystems dominated by trees growing over water-saturated, largely organic soils – are increasingly recognized for providing many important ecosystem services, including functioning as global hotspots of biological diversity, key

* Corresponding author at: Illahee Sciences International, Corvallis, OR 97330, USA
E-mail address: Boone.kauffman@oregonstate.edu (J.B. Kauffman).

https://doi.org/10.1016/j.foreco.2025.122840
Received 31 December 2024; Received in revised form 20 May 2025; Accepted 21 May 2025
Available online 6 June 2025
0378-1127/

regulators of biogeochemical cycles, and regulating water flows (Page et al., 2022; Harrison et al., 2020). Among these ecosystem services is their role in affecting the global carbon cycle and influencing climate change regulation and mitigation (Ribeiro et al., 2021; Leifeld and Menichetti, 2018; Leifeld et al., 2019). Tropical peat forests are known to be among the world's most productive (13.2 Mg C ha^{-1} yr^{-1}; Basuki et al., 2019). There are vast amounts of carbon stored in peatlands, resulting from the accumulations of soil organic matter over millennia. However, estimates in both peatland area and the quantity of carbon stored varies widely. Estimates of peatland area ranges from ≈ 0.4–1.7 million km^2 of the tropics (Page et al., 2011; Gumbricht et al., 2017) and carbon-storage estimates range from 75 to 288 Gt C, or 12–45 % of global peatland carbon (Dargie et al., 2017; Page et al., 2011; Warren et al., 2017b).

Because tropical peat forests store an immense amount of C, they are priority candidates for climate change mitigation strategies (Murdiyarso et al., 2013; Novita et al., 2023). Carbon stored in peat forests is high in part because these ecosystems develop under unique environmental/hydrological conditions that results in saturated soils for most, or all of the year (Cobb et al., 2017). Land uses such as logging, fire, and/or draining results in shifts in these environmental/hydrological conditions and significant and rapid losses of carbon stocks (Basuki et al., 2021, Dadap et al., 2022, Ribeiro et al., 2021). These conversions likely have major climate impacts, as rates of deforestation in peat forests are among the highest of any tropical forest types in the world (e.g., 2.2 % per year between 2009 and 2019) for Southeast Asia where many tropical peat forests are concentrated (Miettinen et al., 2011; Lestari et al., 2024). As such, their conservation and restoration can be important pathways of natural climate solutions (Humpenöder et al., 2020; Tan et al., 2022; Novita et al., 2023). For example, conserving

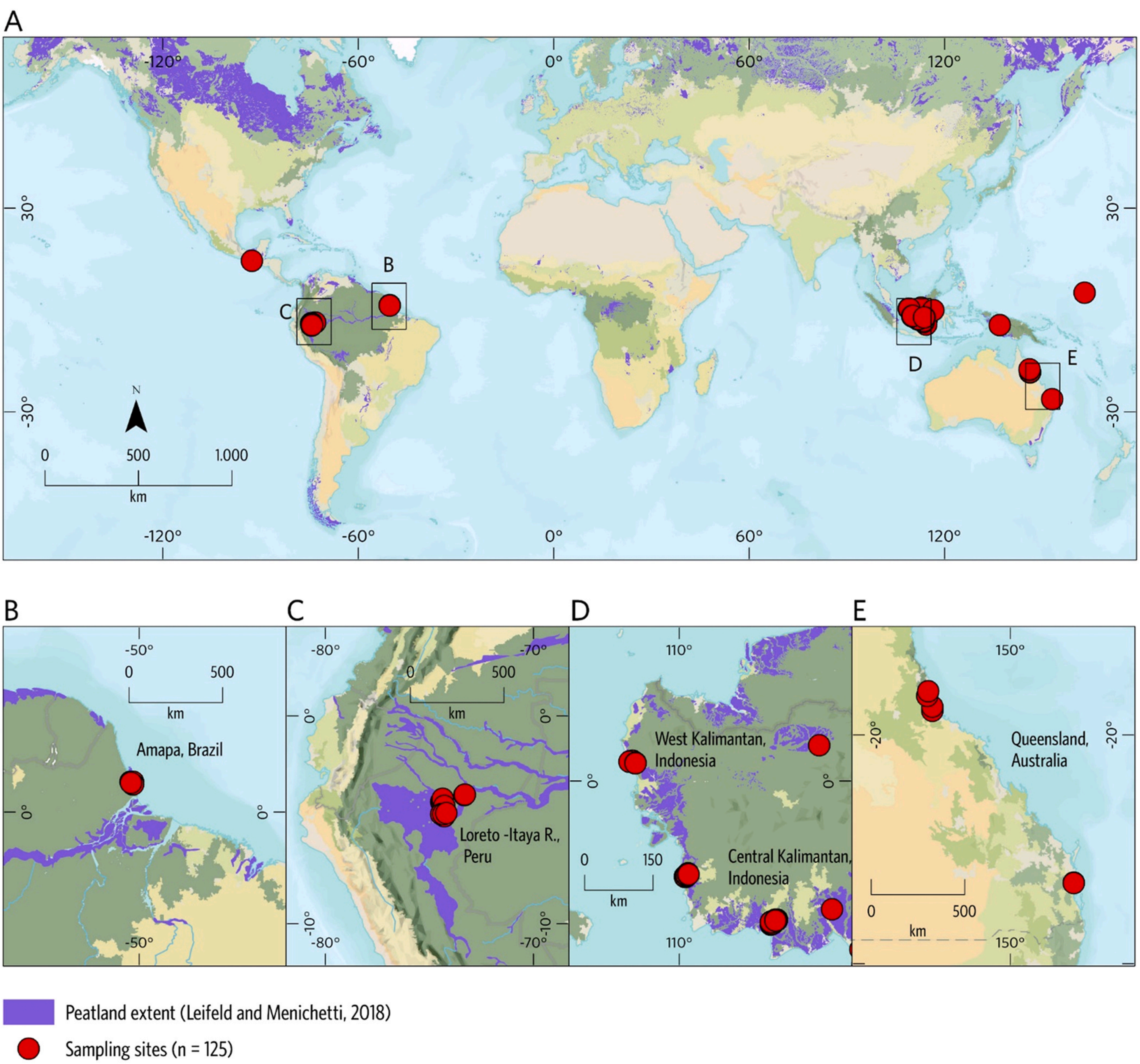

Fig. 1. The locations of the sampled peat forest sites included in this study. The top map (A) is the global distribution of all sampled carbon stocks. Study areas include SE Asia with sample sites in West, Central, and East Kalimantan, Indonesia (n = 79); Oceania with sites in Papua, Indonesia, western Australia, and Kosrae, FSM (n = 24); the Americas with sites in the lower Amazon, Brazil, upper Amazon, Peru and Mexico (N = 22). The subset maps include: (B) sampling sites in Amapa, Brazil; (C) sampling sites in Peru; (D) sampling sites in West and Central Kalimantan; and (E) sampling sites in western Australia.

remaining tropical peat forests and restoring those degraded by past land use could contribute about 75 % of the mitigation potential generated from the forest sector in Indonesia (Novita et al., 2023).

Given the widespread occurrence of tropical peat forests, their high productivity and large carbon stocks, and anthropogenic threats to their existence, it is of value to synthesize information on carbon stocks throughout the tropical peatland biome. For example, participation in global carbon markets requires accurate measurements of carbon stocks, rates of sequestration, and emissions associated with land use at the site scale (IPCC, 2014; Kauffman et al., 2016). But like all forest ecosystems, carbon stocks and fluxes can greatly vary from one forest stand to the next. The preliminary objective of this study was to synthesize data of carbon stocks and emissions that have been collected using comparable and comprehensive approaches (e.g., see Kauffman et al., 2016). In this analysis, we compiled data on total ecosystem carbon stocks (TECS) of intact forests, degraded forests, and agricultural sites in tropical peatlands across 4 continents (Fig. 1). We limited inclusion in this analysis to studies where carbon stocks were collected in a comprehensive, replicated, and accurate manner. From these data we quantified the mean and range of global and continental carbon stocks of tropical peat forests. We also addressed a sub-objective of quantifying ecosystem carbon stocks of peat forests which are tidally influenced and therefore considered to be blue carbon ecosystems (Adame et al., 2024; Krauss et al., 2018). The second objective was to examine the possibility of predicting carbon stocks using variables that may be easily collected via remote sensing or simple measurements in the field. Finally, our third objective was to calculate changes in carbon stocks due to land use and the potential greenhouse gas (GHG) emissions from land cover change. From these data we ascertained the potential social carbon costs from forest degradation and compared these costs to the value of commodities arising from land use.

2. Methods

2.1. Peat forest definitions and site selection

Definitions of "peat soils" and therefore peatlands vary among scientists and the ecosystems in which they work. This may contribute to uncertainty and wide variability in reporting both the extent and size of ecosystem carbon stocks. Organic matter concentration and thickness of organic horizons are the two main components used to define peat soils and definitions of peatlands and peat soils differ by the minimum thickness and the concentration threshold (IPCC, 2014). The United States Department of Agriculture (USDA) Soil Taxonomy Classification categorizes peat soils as Histosols that contain more than 30 % organic matter in a 40 cm organic layer within the upper 50 cm of the soil surface (Soil Survey Staff, 2022). Maltby and Immirzi (1993) define peat soil thresholds of 50 % organic matter and 30 cm peat depth. In tropical ecosystems, peat soils have been defined as those with a concentration > 65 % of organic matter and at least 50 cm thickness (Rieley and Page, 2005). Joosten and Clarke (2002) reduced those thresholds to 30 % of organic matter and 30 cm thickness. Andriesse (1988) defined peats as organic soils with more than 50 % organic matter in the upper 80 cm of the soil. Finally, Indonesia defines peat as soils containing an organic horizon at least 50 cm deep, with a minimum organic matter content of 65 % and minimum carbon content of 12 % (BSN, 2013). Regardless of the definition, it is important to know the depth, bulk density, and carbon concentration of peat layers to determine soil carbon pools. In this study we included sites with peat depths ranging from 19 to > 1400 cm. A few of the sites with shallow peat horizons would not fall into the definitions of peat forests above. However, they are included here as local land managers and scientists classified and managed them as tropical peat forests.

Sites selected for sampling were limited to those where total ecosystem carbon stocks were sampled using adequate replication and plot sizes in the field and where soil carbon was quantified in the laboratory using induction furnace methods (see Kauffman et al., 2016). This study includes 125 sites where aboveground carbon stocks and belowground carbon stocks of the entire soil profile were quantified (see companion database published by Kauffman et al., 2024b). Most of the sampled sites were in Indonesia (N = 95) which spanned two continents (Asia and Oceania). Other countries where peat forests were sampled included Brazil, Peru, Mexico, Australia, and the Federated States of Micronesia.

2.2. Carbon stocks

The field approaches to quantify carbon stocks at all sampled sites were similar (Figure S1). For example, at each sampled peatland site, six plots were established 20–50 m apart along a randomly established transect. In addition, data necessary to calculate total ecosystem carbon stocks derived from measures of standing tree biomass, understory vegetation and litter, downed wood (dead wood on the forest floor), and soils were collected at each site (Kauffman et al., 2016).

2.2.1. Trees

Standing live and dead trees were measured in each of the six plots, usually within a 10 m-radius (Figure S1). The plot radius was increased or decreased depending on tree density and the structure of the forests of a given region. For example, in the extremely dense but low-statured peatlands of the Lower Amazon, a plot radius of 7 m was sufficient to quantify biomass and carbon stocks of the tree component (Kauffman et al., 2024a). Within each subplot, the diameter of all trunks/main stems (live and dead) that were > 5 cm at 1.3 m aboveground (diameter at breast height; DBH) or above the buttress was measured. Two-meter-radius nested subplots in the center of each 10 m plot were used to sample small trees with a DBH of < 5 cm diameter. Tree mass and carbon pools of aboveground biomass were determined using regression equations where tree diameter was the dependent variable. Standing dead trees were included in aboveground biomass calculations. For each dead tree, the DBH was measured and assigned to one of three decay classes following recommendations of Kauffman et al. (2016): Status I - dead trees without leaves, Status II - dead trees without secondary branches, and Status III - dead trees without primary or secondary branches. Biomass of Status I dead trees was estimated to be 97.5 % of a live tree, class II - 80 % of a live tree, and class III - 50 % of a live tree (Kauffman et al., 2016).

Belowground root biomass for trees was calculated using regression equations where aboveground biomass or tree diameters were the independent variables (Kauffman et al., 2016; Sierra et al., 2007). Tree carbon content was calculated by multiplying biomass by 0.48 for aboveground and 0.39 for belowground biomass (i.e., the mean carbon concentration of plant tissues; Kauffman et al., 2016).

2.2.2. Understory vegetation and litter

Samples of the forest floor and vegetation were collected in microplots (e.g., 50 × 50 cm) within each plot to determine biomass and carbon mass on a dry weight basis. Sample mass from the was then scaled to a per-hectare basis. Carbon mass of these components was determined by multiplying the mass by the carbon concentration. Novita (2016) reported that the mean carbon concentration of forest litter in Tanjung Puting, Indonesia, was 48.4 ± 0.4 %. Therefore, a biomass-to-carbon conversion factor of 0.48 was used.

2.2.3. Downed wood

We used the planar intersect technique parameterized for peat forests to calculate the mass of dead and downed wood (Kauffman et al., 2016). Within each sampled plot, four 14 m transects were established. The first was established in a direction that was offset 45° from the azimuth of the main transect. The other three were established 90° clockwise from the first transect. Along each transect, the diameter of any downed wood intersecting the transect was measured (Figure S1).

Downed wood $\geq$ 2.5 cm but $<$ 7.5 cm in diameter at the point of intersection was measured along the last 5 m of the transect. Downed wood $\geq$ 7.5 cm in diameter at the point of intersection was measured from the second meter to the end of the transect (12 m length in total). Large downed wood was separated into two decay categories: sound and rotten. Wood was considered rotten if it visually appeared decomposed and broke apart when impacted. We assumed that the C concentration of downed wood was 50 % (Kauffman et. al. 2016).

2.2.4. Soil carbon

At each plot, fixed-volume soil samples were collected for bulk density and nutrient concentration using either a specialized peat auger or one consisting of an open-faced cylindrical chamber with a 6.4 cm radius (Kauffman et al., 2016). These augers allow efficient collection of cores from soils in peat forests with minimal disturbance. One core of the entire soil profile was taken at (or close to) each subplot center (N = 6 cores per sampled vegetation stand).

The thickness of the organic (peat) horizons and the depth of the entire soil profile were measured during soil extraction. Samples to determine bulk density and C concentration were collected throughout the soil profile based upon depth and soil composition. Soil samples were collected at depths of 0–15 cm, 15–30 cm, 30–50 cm, 50–100 cm and thereafter, at least every 2 m in depth for the deepest peats. In the laboratory, soil bulk density was determined by measuring the dry weight of samples divided by their known volumes. The carbon concentration was determined using induction furnaces (carbon analyzers).

2.3. Total carbon stocks, emissions, and social costs

We determined the total ecosystem carbon stocks (TECS; i.e., the sum of the carbon pools found in trees, roots, soils, wood, and litter) at continental and global scales and for Indonesia alone. Further, we described ecosystem carbon characteristics of the tidally-influenced sites to determine the carbon stocks of these blue carbon ecosystems. We also determined TECS based on soil depth. Sites were partitioned into depth classes of $<$ 0.5 m, 0.5–2 m, 2–4 m, 4–7 m, and $\geq$ 7 m. Classes were determined based on natural breaks in the data, classifications of peat depths, and adequate sample sizes to conduct statistical analyses.

Carbon stock losses and hence potential cumulative greenhouse gas emissions were estimated at locations where measures of both intact and degraded peatlands exist (e.g., Basuki, 2017; Kauffman et al., 2024a; Novita et al., 2021). We determined the potential emissions from conversion of peat forests as the difference in carbon stocks between the intact sites and those converted to other uses such as pasture, or oil palm (a stock-change approach; IPCC, 2003; Kauffman et al., 2017). The ecosystem carbon losses are reported CO_2 equivalent basis (CO_2e) obtained by multiplying C loss values by 3.67, the molecular ratio of CO_2 to C. This approach assumes that the declines in carbon stocks due to deforestation/conversion largely comes from emissions associated with biomass burning or aerobic decomposition recognizing that some carbon losses may arise from erosional losses or groundwater transport (Kauffman et al., 2017). But the emissions estimates are likely conservative as carbon loss is converted to CO_2e and some carbon would likely be emitted as methane CH_4) which has a higher global warming potential (IPCC 2013).

The emissions due to land cover change were also expressed in terms of Social Carbon Costs (SCC). Valuing the conservation of tropical forests and wetlands as compared to values of products arising through land use/land cover change is necessary to make sustainable long-term land use planning decisions. A frequently used cost-benefit metric for assessing climate policy is the social cost of carbon, which estimates in dollars the long-term damage done by emitting one additional ton (Mg) of CO_2 equivalent GHGs in a given year (Rennert et al., 2022; Aldy et al., 2021). SCC calculations draw on climate science, economics, demography, and other disciplines and are used by governments and other decision-makers in cost-benefit analyses. In the USA, the government used a SCC of \$51/Mg for CO_2 (IWG 2021). Applying recent, peer-reviewed advances in climate, economic, and demographic science, Rennert et al. (2022) calculated a mean SCC of \$185/ Mg CO_2 (2020 US dollars at a near-term risk-free discount rate of 2 %). These values are likely underestimates as they do not account for factors such as damage to biodiversity, forest loss through increased wildfires and tropical storm severity, labor productivity, conflict, and migration (Rennert et al., 2022).

Included in the objectives of this research was exploration through regression analysis of relatively simple field measurements that could be employed to predict the total, or soil carbon stocks at continental and global scales. We also conducted these analyses for Indonesia alone. We determined the strength of relationships of tree biomass with TECS and soil depth with total soil carbon stocks to determine if these easily measured variables could be utilized to accurately predict the carbon stocks thereby avoiding difficult and costly laboratory analyses.

Testing for significance between the carbon stocks of peat forests between continents and between different soil depths was accomplished through analysis of variance. If significant, a least significant difference multiple comparison test was used to determine where differences existed.

3. Results

The global mean TECS of sampled tropical peat forests was 2137 $\pm$ 149 Mg C ha^{-1} with a median of 1847 Mg C ha^{-1} (Table 1, Fig. 2). There was a tremendous range in soil and carbon stock properties. For example, peat depths of sampled peatlands ranged from 19 to 1414 cm and the range in TECS was 172–9379 Mg C ha^{-1}, Fig. 2a). The sites with the lowest TECS were degraded sites of the Peruvian and Brazilian Amazon ($<$ 200 Mg C ha^{-1}; Table 1). The largest TECS of peat forests were those of deep peats measured in West and Central Kalimantan, Indonesia.

Of the 125 sampled sites, 95 were from Indonesia, where the mean TECS was 2591 Mg C ha^{-1} with a range of 358–9379 Mg C ha^{-1}, Fig. 2b, Table S1). The lowest carbon stocks in Indonesia were shallow peat forests of Central Kalimantan and Papua. The sampled peat forests of Southeast Asia (N = 58) were strictly from sites sampled on the island of Borneo, Indonesia. Here, the mean TECS was 2826 Mg C ha^{-1}. The Southeast Asian peat forests were significantly greater ($P \leq 0.05$) than those forests of Oceania (1489 Mg C ha^{-1}) and the Americas (1567 Mg C ha^{-1}; Table 1).

As is quite apparent, the vast majority of the carbon stocks in peat forests are stored in the soil profile comprising a mean of 86 % of the TECS (Fig. 3). The tree component composed a mean of 10 % of the TECS while other sampled pools in the ecosystem comprised $<$ 2 % of the TECS. Examining only the plant pools, we found that aboveground tree mass comprised 70 % of plant-based carbon pools (Fig. 3). Root mass comprised 15 %, downed wood comprised 11 %, and litter/surface vegetation comprised 4 % of the plant C pools. Vegetation did comprise a larger proportion of the TECS in the sites with shallower peats and smaller carbon stocks. For example, aboveground components comprised a mean of 20 % of the TECS in shallow peat forests of the Americas where the median peat depth was 62 cm (Table 1).

There were 47 sites sampled known to be tidally-influenced forests. These blue carbon ecosystems were encountered in the Americas, Oceania, and Asia. They had a broad range in TECS from 206 to 5591 Mg C ha^{-1} with a mean of 1979 Mg C ha^{-1} (Table 1, Figure S3). Similar to all peat forests, soils composed the vast majority of the TECS. Peat depths ranged from 19 to 953 cm (Table 1). Those tidal forests with the lowest TECS were from the lower Amazon, Brazil (Kauffman et al., 2024), while the largest TECS in tidal forests were those from coastal areas in West Kalimantan, Indonesia (Basuki et al., 2019, 2021).

Determination of carbon loss or greenhouse gas emissions from land use/land cover change requires site-specific measurements. At global

Table 1
Characteristics of the carbon stocks of intact and converted tropical peat forests. All stocks data are reported as Mg C ha^{-1}. TECS is the total ecosystem carbon stock, TAGCS is the total aboveground carbon stock, TBGCS is the total belowground carbon stock. Soil and peat depths are reported in cm. The % Aboveground and % Belowground are the proportions of TECS found in either aboveground or belowground pools. All sites (peatland and forests) are combined data from Southeast Asia, the Americas and Oceania. Forests include primary, secondary and logged forests. Converted sites are those where forests have been replaced by agriculture or abandoned agriculture. Tidal forests are those that are tidally influenced (blue carbon ecosystems).

	TECS	TAGCS	TBGCS	Tree	Downed wood	Surface/ litter	Total Soil	Belowground plant	Total soil depth (cm)	% Abovegd	% Belowgd	Peat depth (cm)
All peatland sites												
Sample Size	125	125	125	103	97	61	125	104	125	125	125	115
Mean	2137	102	2037	91	14	5	2023	18	390	0.09	0.91	359
SE	149	7	148	7	1	0	147	1	26	0.01	0.01	31
Min	172	2	118	0	0	1	109	0	20	0.00	0.35	19
Max	9379	430	9099	430	52	18	9047	55	1414	0.65	1.00	1414
Median	1847	90	1737	82	12	5	1704	17	295	0.05	0.95	241
All forests												
Sample Size	100	100	100	79	73	41	100	80	100	100	100	91
Mean	2113	122	1992	116	16	6	1975	23	373	0.10	0.90	336
SE	172	7	170	7	1	0	170	1	29	0.01	0.01	35
Min	172	16	118	31	1	2	109	7	30	0.01	0.35	19
Max	9379	430	9099	430	52	18	9047	55	1414	0.65	0.99	1414
Median	1772	107	1668	99	13	5	1646	21	268	0.06	0.94	231
All converted peatlands sites												
Sample Size	25	25	25	24	24	20	25	24	25	25	25	24
Mean	2235	21	2214	9	8	4	2213	2	456	0.02	0.98	445
SE	288	4	289	3	2	1	289	1	58	0.00	0.00	64
Min	206	2	204	0	0	1	202	0	20	0.00	0.92	20
Max	4389	78	4384	53	35	9	4384	15	783	0.08	1.00	783
Median	2566	12	2555	3	5	4	2555	1	603	0.01	0.99	606
Oceania (only forests)												
Sample Size	24	24	24	20	17	nd	24	21	24	24	24	18
Mean	1489	127	1362	126	18	nd	1343	21	260	0.13	0.87	137
SE	148	17	152	20	3	nd	152	2	21	0.03	0.03	33
Min	281	31	180	31	2	nd	179	6	100	0.03	0.35	19
Max	2818	430	266	430	50	nd	2650	43	490	0.65	0.97	405
Median	1495	113	1378	111	16	nd	1356	20	244	0.07	0.93	50
Americas (forests)												
Sample Size	18	18	18	18	18	12	18	18	18	18	18	18
Mean	646	82	564	71	7	6	548	16	193	0.18	0.82	109
SE	97	4	97	4	1	1	96	1	29	0.02	0.02	20
Min	172	55	118	37	1	2	109	9	71	0.05	0.62	28
Max	1567	112	1496	101	23	8	1483	25	530	0.38	0.95	280
Median	430	83	358	71	6	6	343	16	156	0.16	0.84	62
Southeast Asia (all sites)												
Sample Size	79	79	79	61	58	49	79	61	79	79	79	73
Mean	2769	104	2668	91	17	5	2655	19	487	0.06	0.95	491
SE	194	9	193	9	2	0	192	2	36	0.01	0.01	39
Min	533	5	354	0	0	1	354	0	20	0.00	0.63	20
Max	9379	280	9099	246	52	18	9047	55	1414	0.37	1.00	1414
Median	2488	97	2337	89	14	5	2311	20	406	0.04	0.97	442
Southeast Asia (forests)												
Sample Size	58	58	58	41	38	29	58	41	58	57	57	53
Mean	2826	133	2696	130	20	6	2680	27	476	0.07	0.93	478
SE	247	9	244	8	2	1	243	2	44	0.01	0.01	49
Min	533	16	354	46	4	2	354	11	30	0.01	0.63	27
Max	9379	280	9099	246	52	18	9047	55	1414	0.37	0.99	1414
Median	2263	133	2155	115	20	5	2142	24	400	0.04	0.96	383
Tidal forests (Blue Carbon)												
Sample Size	47	47	47	43	40	24	47	44	44	47	47	41
Mean	1983	98	1889	85	9	6	1874	16	407	0.11	0.89	377
SE	224	13	227	13	1	0.5	228	2	44	0.02	0.02	56
Min	206	2	180	0	0	1	165	0	100	0.00	0.35	19
Max	5591	430	5467	430	33	10	5452	43	953	0.65	1.00	953
Median	1626	81	1481	67	7	5	1452	14	210	0.04	0.97	129

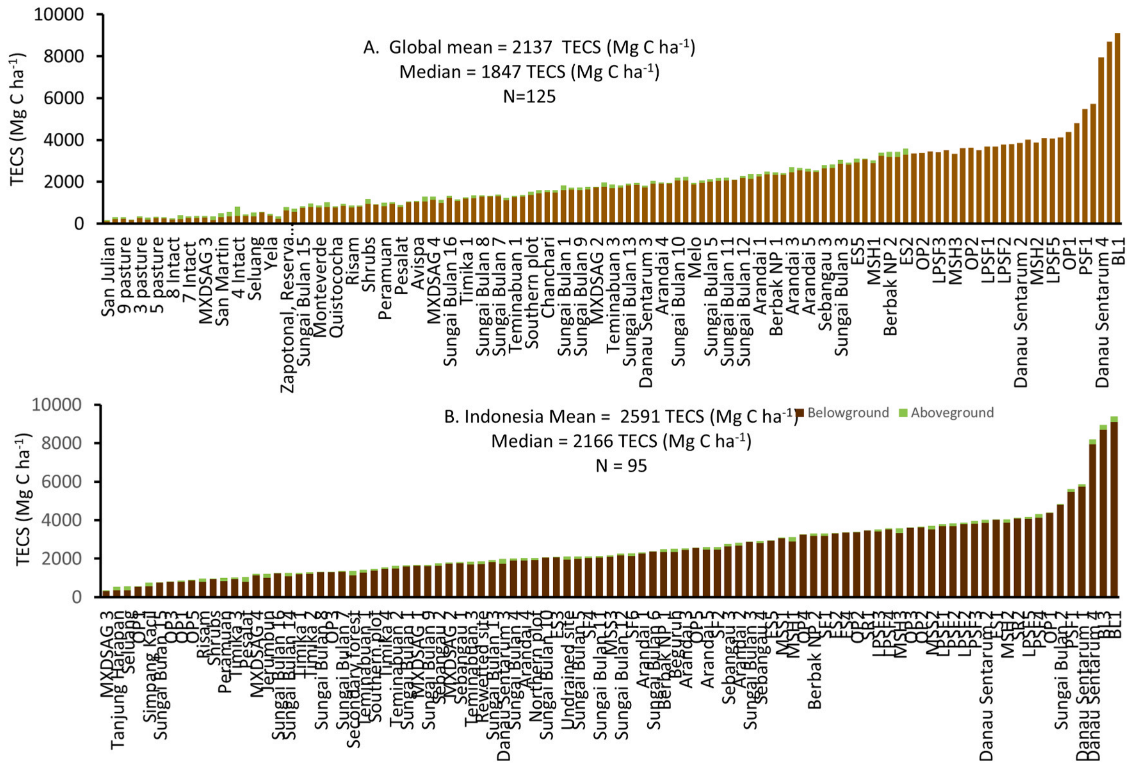

Fig. 2. A: The range of total ecosystem carbon stocks (Mg C/ha) of tropical peat forests sampled in Southeast Asia, Oceania, and the Americas. B: The range of total ecosystem carbon stocks (Mg C/ha) of tropical peat forests sampled in Indonesia.

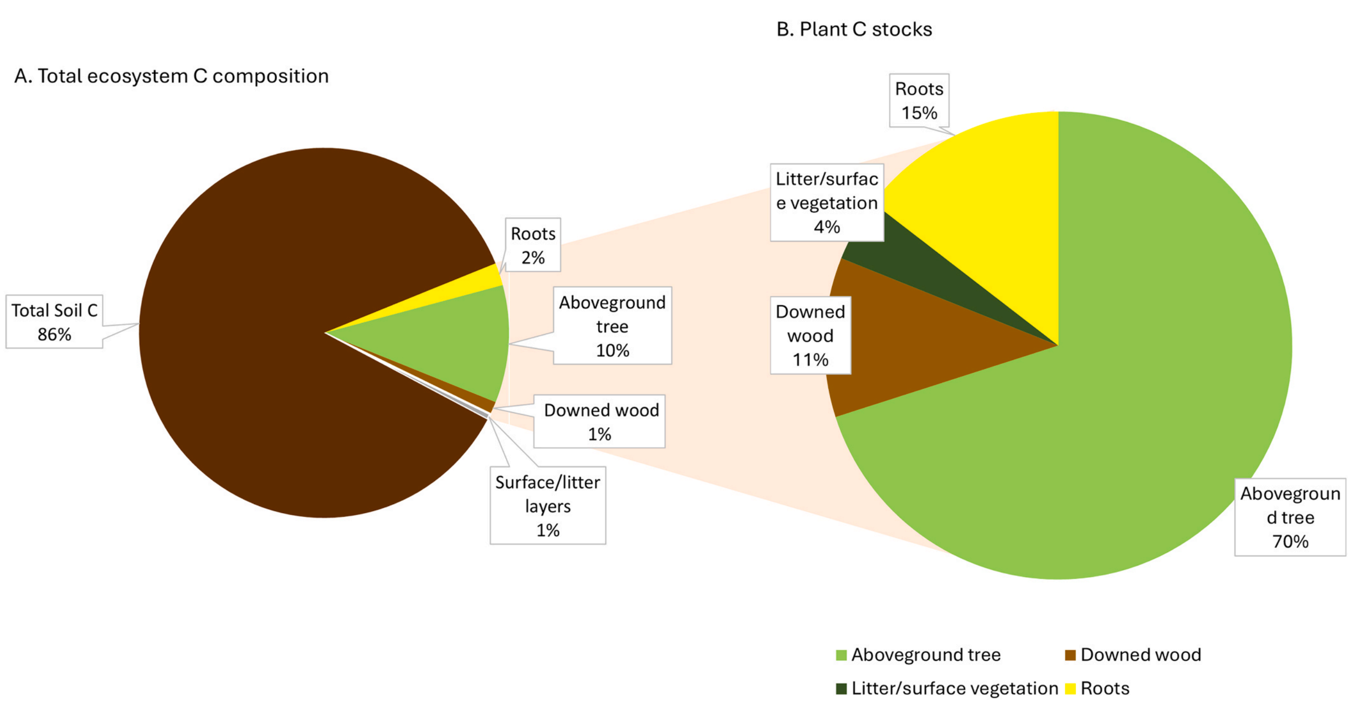

Fig. 3. The distribution of carbon among aboveground and belowground pools in tropical peat forests. The chart on the left (A) is the distribution of total ecosystem carbon stocks while the chart on the left (B) is the distribution of plant carbon stocks.

scales, there was no difference in the TECS between intact forests and converted/degraded peatland ecosystems (Table 1). This can be explained by the broad range of TECS of the peatlands which, at global scales, masks differences between intact forest and degraded sites (Fig. 2a; Table 1). However, there were significant differences ($P \leq 0.001$) in the aboveground biomass of intact (122 Mg C ha^{-1}) and degraded/converted sites (21 Mg C ha^{-1}; Table 1).

3.1. Predicting carbon stocks in tropical peat forests

There was a weak relationship between the aboveground carbon stocks and TECS (R^2 =0.06; Fig. 4). Such a poor relationship does not facilitate accurate estimates of ecosystem carbon stocks of peat forests based on aboveground measurements alone. This was not surprising since aboveground stocks only comprise ≈ 12 % of the TECS (Fig. 4). While land use is readily apparent through changes in aboveground structure and mass, this suggests that TECS cannot be easily measured via remote sensing of forest structure or land cover types.

We found a strong linear relationship between peat depth and total soil carbon stocks at both continental and global scales ($R^2 > 0.77$) and when sampling only for Indonesia ($R^2 = 0.81$; Fig. 5, Figure S2). Comparing the results of the graphs and equations displayed in Fig. 5 clearly show differences in peat characteristics among the different continents.

Using the regression equations displayed in Fig. 5, we developed predictive estimates of the mean total soil carbon stocks at the continent, Indonesia, and global level and then compared these predictions to the field measurements (Fig. 6). The predictive equations appeared to be quite accurate for Indonesian forests (i.e., a 1 % difference between measured and predicted total soil carbon results). Regression equations were also reasonably accurate for Southeast Asia forests (5 % difference), Oceania forests (4 % difference) and for all sites (global – 6 % difference; Fig. 6). Using the continent-specific equation to predict the carbon stocks of peat forests of the Americas resulted in an estimate of 495 Mg C ha^{-1} compared to the direct measure of 548 Mg C ha^{-1}, i.e., a 10 % difference, Table 1). However, using the global equation did not yield an accurate estimation of total soil C for peat forests of the Americas. Clearly, the use of the continent-specific models provided more accurate estimates.

The relationships between peat depth and TECS are readily apparent when comparing sites partitioned by depth classes (Table 2). We found significant differences in TECS between the sampled depths ($P = 0.10$–0.05; Table 2). At the extremes, shallow peat forests (≤ 0.5 m) have a mean TECS of 988 Mg C ha^{-1} while the mean TECS of peat forests ≥ 7 m was 4620 Mg C ha^{-1}.

4. Discussion

It is well known that the carbon stocks of peat forests could very well be the largest carbon stocks on Earth (Griscom et al., 2020; Page et al., 2004; Ruwaimana et al., 2020). The mean TECS of tropical peat forests greatly exceeds means of other ecosystems known to have significant carbon stocks (Fig. 7). For example, the TECS is about twice the mean of temperate peat forests or mangroves. The deep peats (> 7 m depth) have a mean TECS of 4620 ± 395 Mg C ha^{-1}and we know of no ecosystems with an equivalent ecosystem carbon stock. Even shallow peats (< 0.5 m) contain significant carbon stocks. We found that the mean TECS of shallow peats was 825 Mg C ha^{-1}globally, and 988 Mg C ha^{-1} for Indonesia alone (Table 2). This is important as some countries, notably Indonesia, do not include shallow peats (< 0.5 m depth) in their national inventories of peatlands (BSN 2013, MOEF Indonesia, 2019). Nevertheless, even these shallow peatlands are significant carbon stocks made evident by comparing them to other tropical ecosystems (Table 2; Fig. 7).

There are currently few published default values for tidal forests in the tropics (Murdiyarso et al., 2024). The tidally-influenced peat forests are considered "blue carbon" ecosystems along with mangroves, salt marshes, and seagrass communities (Adame et al., 2024; Krauss et al., 2018). The tidal peat forests contain the largest carbon stocks of any blue carbon ecosystem (Fig. 7, Table 1). The global mean TECS of mangroves is less than half of that of tidal peat forests (856 Mg C ha^{-1}; Kauffman et al., 2020). The mean TECS of salt marshes is 255 Mg C ha^{-1} IPCC, (2014)) and is 194 Mg C ha^{-1} for seagrass communities (Fourqurean et al., 2012).

The global mean TECS of the sampled sites was 2137 Mg C ha^{-1}. This mean is reflective of our sampling where most of our sites were in Asian Indonesia. We found that the TECS of Asian Indonesian forests (2826 Mg C ha^{-1}) were significantly greater than those of Oceania and the Americas (1489 and 646 Mg C ha^{-1} respectively, Table 1, Fig. 6). The deeper peats in the Indonesian forests (mean of 451 cm) compared to those of American peat forests (mean of 62 cm) results in the dramatic differences in the TECS of these two regions. In addition, peat forests of Africa are conspicuously missing from this study. Dargie et al. (2017) reported there were 145,500 km^2 of peatland area with a mean peat

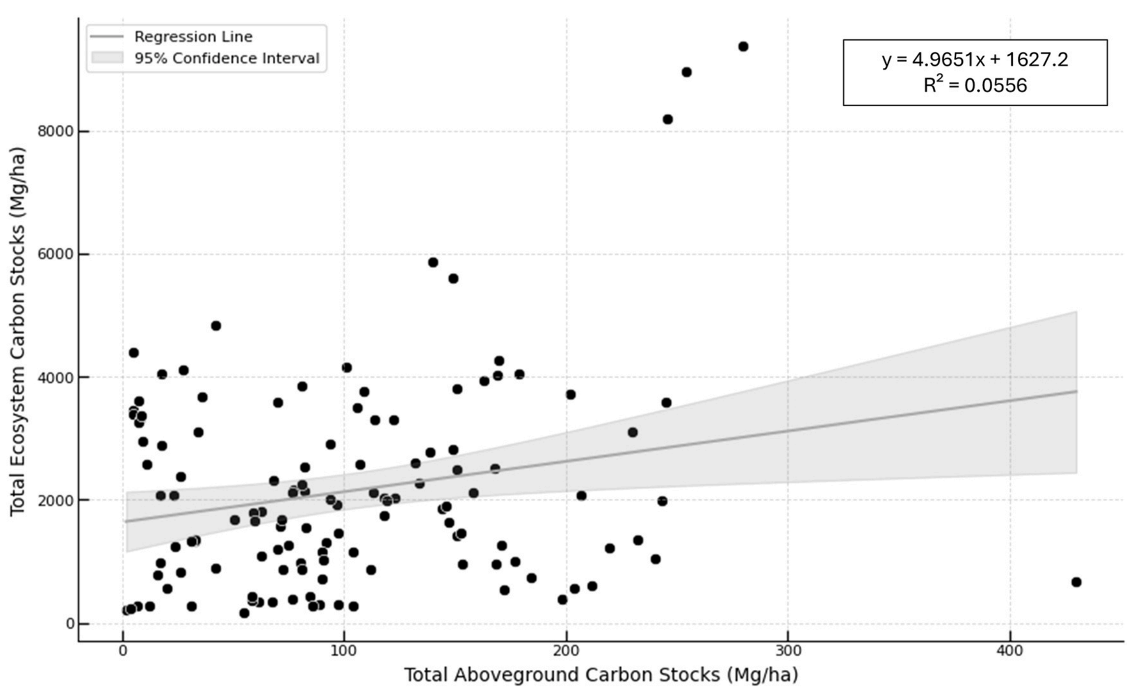

Fig. 4. The relationship of total ecosystem carbon stocks with the aboveground carbon stocks.

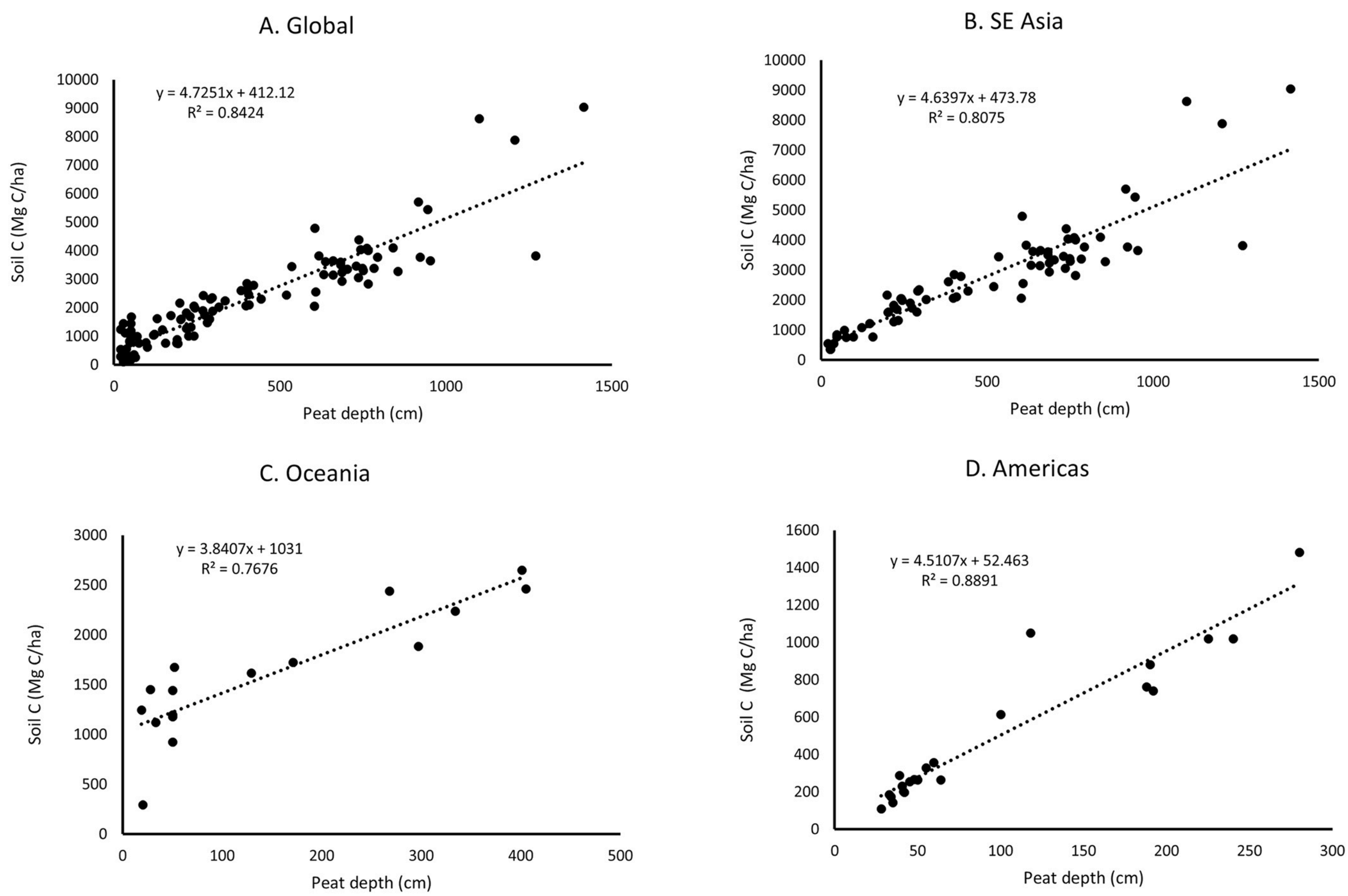

Fig. 5. The relationship of peat depth (cm) with total soil carbon stocks (Mg C/ha) for peat ecosystems the world (A), Southeast Asia (B), Oceania (C), and the Americas (D).

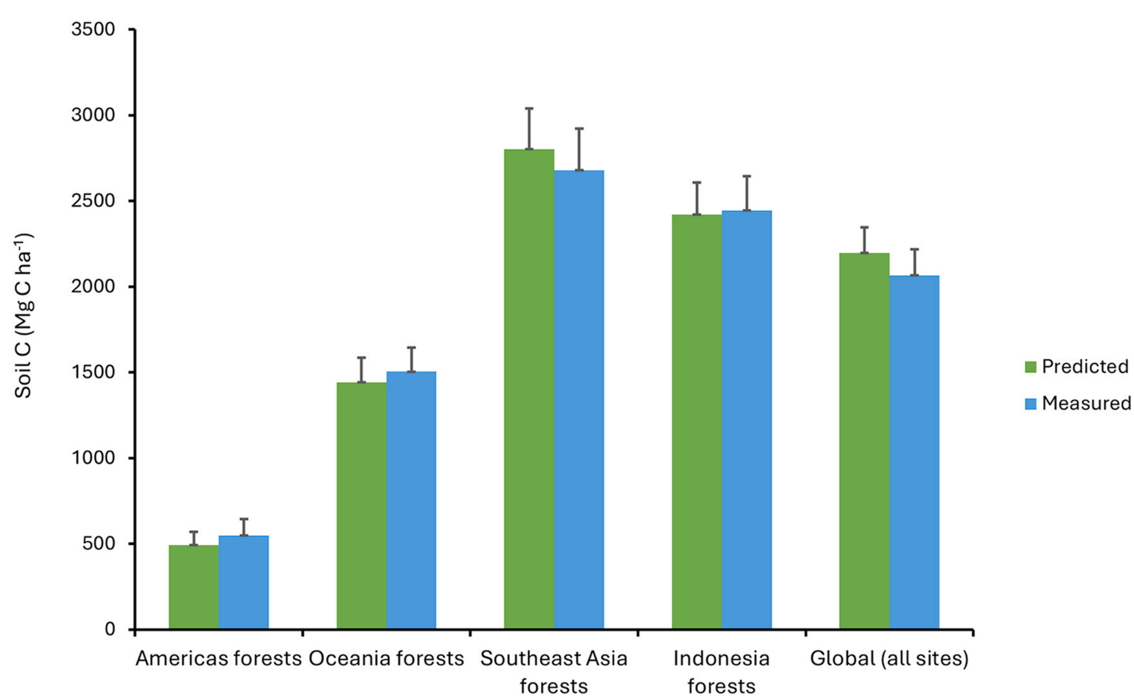

Fig. 6. A comparison of measured soil carbon stocks (Mg C ha^{-1}) with predicted soil carbon stocks based upon the relationship of peat depth with total soil carbon in tropical peat forests and broken down into continents. Southeast Asia sites include Kalimantan, Indonesia sites while Oceania includes Papua, Indonesia, Australia, and The Federated States of Micronesia. Indonesia forests are sites from both Papua and Kalimantan. Predicted soil C stocks for each continent and Indonesia were derived from equations in Fig. 5 and Figure S2.

Table 2
The total mean, standard error (SE), and sample size (N) of ecosystem carbon stocks (Mg C ha^{-1}) of sampled peat forest sites (global and only for Indonesia) partitioned according to their ranges in peat depth (m). Different letters represent a significant difference among forests of different depth classes.

Global (all sampled sites)					
Depth class	Mean	SE	N	P = 0.05	P = 0.10
0–0.5 m	825	122	29	a	a
0.5–2.0 m	1306	198	19	a	b
2.0–4.0 m	1958	100	24	b	c
4.0–7.0 m	3162	156	19	c	d
> 7.0 m	4620	395	22	d	e
Indonesia only					
Depth class	Mean	SE	N	P = 0.05	P = 0.10
0–0.5 m	988	95	16	a	a
0.5–2.0 m	1419	139	11	a	b
2.0–4.0 m	2056	94	21	b	c
4.0–7.0 m	3162	156	19	c	d
> 7.0 m	4620	395	22	d	e

depth of 2.4 m in the Congo basin with a mean TECS of 2186 Mg C ha^{-1}. Using the global equation in Fig. 5A which includes forests with peat depths ranging from 19 to > 1400 cm we calculate the mean C stock in central Africa to be 1650 Mg C ha^{-1}. Additional sampling in Africa and other under-represented areas would improve understanding of both the global and continental ranges of carbon stocks of tropical peat forests.

The large carbon stocks of peat forests provide a strong rationale for the conservation and protection of these wetlands for climate change mitigation (Fig. 7; Novita et al., 2022; Griscom et al., 2020). Further, converting tropical peat forests to other land uses such as oil palm, tree plantations, or agriculture results in the largest greenhouse gas emissions of any land use (Fig. 8). Carbon losses (greenhouse gas emissions) through land cover change in peat forests range from 393 to 4525 Mg CO_2e ha^{-1}. From the data presented in Fig. 8, the mean potential GHG emissions from peat forest loss in Indonesia is estimated to be 2935 Mg CO_2e ha^{-1}. These emissions are 4–10 times that of emission losses resulting from the conversion of upland tropical forests. Further, following deforestation these sites will continue to be sources of GHGs during phases of active land use as well as through recurring peat fires in abandoned sites (Murdiyarso et al., 2010; Basuki et al., 2021; Warren et al., 2017a).

4.1. Developing cost-effective approaches to carbon stock quantification

One of the barriers to participating in carbon markets is the fact that conventional measurements accurately quantifying ecosystem carbon stocks are costly, require specialized laboratory equipment, and are labor intensive. Finding solutions that can improve the effectiveness and efficiency of the quantification of carbon stocks is needed. When quantifying carbon stocks, the IPCC (2014) and modules from Verra (2024) for above above-ground carbon stocks assessment both for baseline (including VMD 0001, 0006, 00070042) and monitoring (VMD 0046) suggest that attention should be focused on those components of the ecosystem that comprise ≥ 5 % of the TECS. The results of this study show that only soil profiles and the aboveground tree component exceed 5 % of the TECS (Fig. 4). Quantifying litter/surface vegetation and downed wood mass can be costly and cumbersome (Kauffman et al., 2016) yet they comprise only 1–2 % of the TECS. As such, applied projects requiring accurate estimates of carbon stocks should focus on adequate replication and measurement of the entire peat profile and tree carbon stocks. The carbon density of peat (the product of bulk density and % C) is relatively constrained for all tropical peatlands. For example, the carbon density in both the very shallow peats of the lower Amazon, Brazil and the very deep peats of East Kalimantan Indonesia are very similar (i.e., C density ranges of 0.02–0.06 g cm^3 at both sites; Kauffman et al., 2024a; Basuki et al., 2021). As such, the measurement of soil depth, which is an effective predictive variable for soil carbon stocks, should be a part of any tropical peat forest inventory where quantification is necessary (Agus et al., 2011; Farmer et al., 2014).

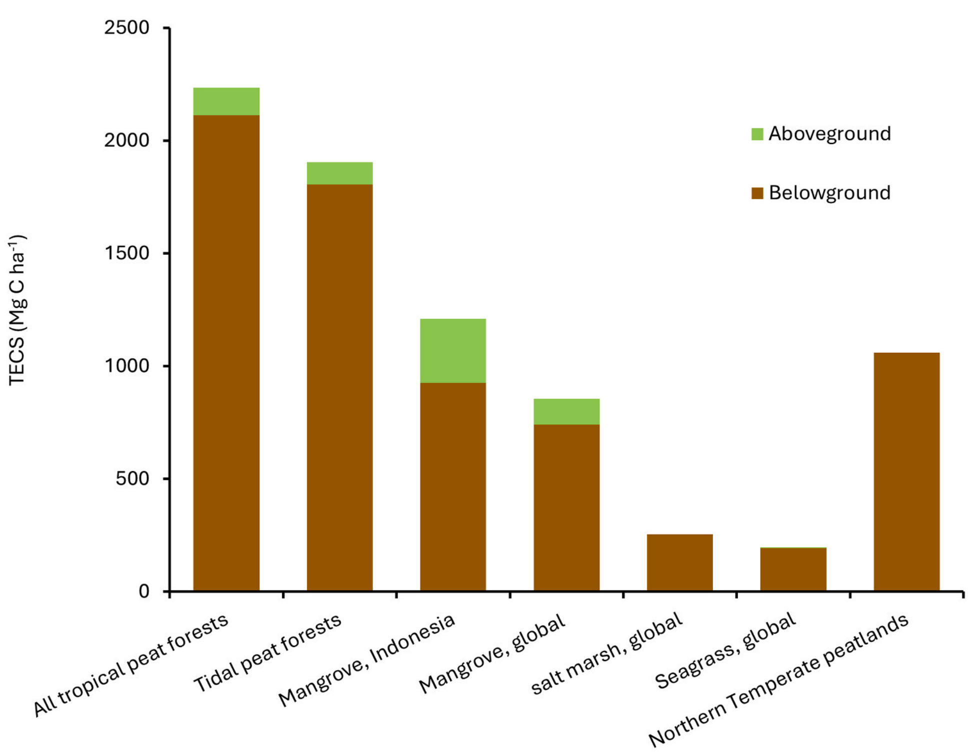

Fig. 7. Mean total ecosystem carbon stocks of tropical peatlands and other wetlands (blue carbon) ecosystems of the world. The data for the tropical peat forest and tidal peat forests are from this study. Mangroves are from Kauffman et al. (2020). Data from salt marshes are from IPCC (2014) and seagrass are from Fourqurean et al. (2012).

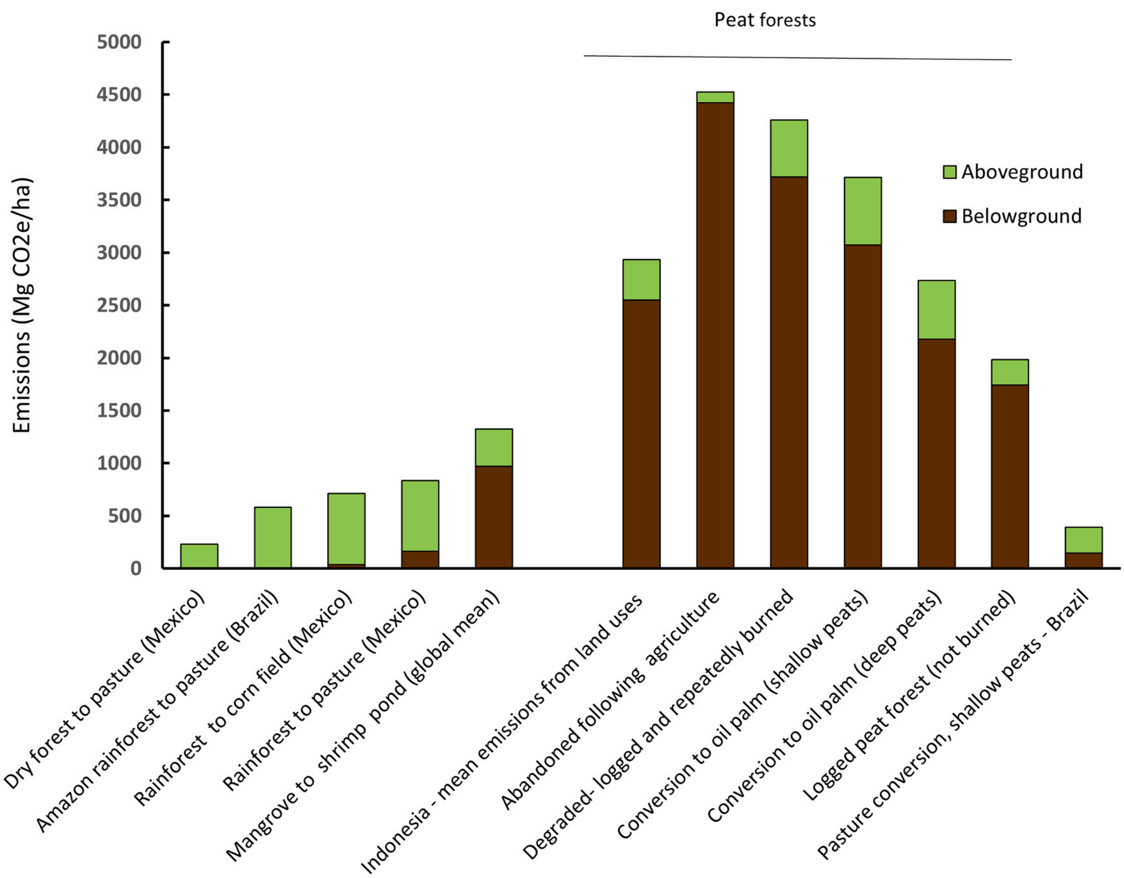

Fig. 8. Mean potential greenhouse gas emissions (Mg CO_2e ha^{-1}) from perturbations of selected tropical ecosystems of the world. Data from non-peat forests are from Kauffman et al. (2017). Emissions from abandoned peat forests and oil palm on shallow peats are from Novita (2016). Emissions from conversion-abandoned forest, conversion to oil palm on deep peats, and logged peat forest are from Basuki (2017). Emissions from pasture conversion – Brazil are from Kauffman et al. (2024a). Emissions were determined via a stock-change approach (IPCC, 2003; Kauffman et al. 2016; Kauffman et al. 2024a).

4.2. Social carbon costs of deforestation

Following the conversion of shallow peat forests to cattle pasture in the lower Amazon, Kauffman et al. (2024a) reported the social carbon costs (SCC) arising from the degradation of coastal Amazon peatlands was as high as $2742 USD ha^{-1} $year^{-1}$. Social carbon costs from the conversion of peat forest to oil palm is even higher. The SCC relating to GHG emissions from the mean carbon loss in converted Indonesian peat forests is $149,685 ha^{-1} using the IWG (2021) value and $542,975 ha^{-1} using the Rennert et al. (2022) value. This would be an annual SCC of $598 ha^{-1} to $21,719 ha^{-1} for the life of the plantation. Assuming an annual palm oil production of 3 Mg ha^{-1} yr^{-1} with a plantation life of 25 years (Woittiez et al., 2017), and a palm oil value of $815 Mg^{-1} would yield a gross value of all oil produced of $61,125 ha^{-1} over the lifetime of the plantation (an annual mean of $2445 ha^{-1}). It is quite apparent that the social carbon costs to future generations greatly exceed near-term economic benefits from the conversion of tropical peat forests, and associated emissions generate a higher SCC than other tropical ecosystems. Costs are conservatively estimated to be as high as nine times that of the value coming from the palm oil. Such social costs and the values of the tropical peat forests of the world underscore the importance of the conservation and restoration of these wetlands for future generations who will experience the worst impacts of climate change.

CRediT authorship contribution statement

Maria Fernanda Adame: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Nisa Novita:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **J Boone Kauffman:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Rasis Putra Ritonga:** Writing – review & editing, Writing – original draft, Software, Project administration, Methodology, Formal analysis, Data curation. **Matthew Warren:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Adi Gangga:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation. **Daniel Murdiyarso:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **Imam Basuki:** Writing – review & editing, Writing – original draft, Resources, Methodology, Formal analysis. **Donato Dan:** Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Investigation, Formal analysis. **Wahyu Catur Adinugroho:** Writing – review & editing, Writing – original draft, Resources, Investigation, Formal analysis. **Gusti Anshari:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of Competing Interest

J Boone Kauffman reports financial support was provided by Illahee Sciences International LLC. J Boone Kauffman reports a relationship with Illahee Sciences International LLC that includes:. All authors declare no competing interests If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Funding for this project came from the Yayasan Konservasi Alam Nusantara (The Nature Conservancy Indonesia) from Bezos Earth Fund under Peatland Playbook and Prototyping award. Many of the original studies were funded by the US Agency for International Development which greatly contributed to the scientific understanding of the dynamics of wetland forests and climate change. We wish the thank all the dedicated technicians from throughout the world who participated in the collection of these data in both the field and laboratory.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.foreco.2025.122840.

Data availability

Data are available in Kauffman et al., 2024b (Figshare)

References

Adame, M.F., Kelleway, J., Krauss, K.W., Lovelock, C.E., Adams, J.B., Trevathan-Tackett, S.M., Noe, G., Jeffrey, L., Ronan, M., Zann, M., Carnell, P.E., 2024. All tidal wetlands are blue carbon ecosystems. BioScience 74, 253–268. https://doi.org/10.1093/biosci/biae007.

Agus, F., Hairiah, K., Mulyani, A., 2011. Measuring carbon stock in peat soils, I. ed. World Agroforestry Center-ICRAF, SEA Regional Office dan Balai Besar Penelitian dan Pengembangan Sumberdaya Lahan Pertanian, Bogor.

Aldy, J.E., Kotchen, M.J., Stavins, R.N., Stock, J.H., 2021. Keep climate policy focused on the social cost of carbon. Science 373, 850–852. https://doi.org/10.1126/science.abi7813.

Andriesse, J.P., 1998. Nature and management of tropical peat soils. Food and Agriculture Organization of The United Nations. FAO Soils Bull. 59. ⟨https://www.fao.org/4/x5872e/x5872e00.htm⟩.

Badan Standardisasi Nasional (BSN). 2013. Pemetaan Lahan Gambut Skala 1:50.000 Berbasis Citra Penginderaan Jauh. SNI 7925:2013 (in Bahasa Indonesia). Jakarta, Indonesia.

Basuki, I., Kauffman, J.B., Peterson, J., Anshari, G., Murdiyarso, D., 2019. Land cover changes reduce net primary production in tropical coastal peatlands of West Kalimantan, Indonesia. Mitig. Adapt. Strateg. Glob. Change 24, 557–573.

Basuki, I., Kauffman, J.B., Peterson, J.T., Anshari, G.Z., Murdiyarso, D., 2021. Land cover and land use change decreases net ecosystem production in tropical peatlands of West Kalimantan, Indonesia. Forests 12, 1587. https://doi.org/10.3390/f12111587.

Basuki, I. 2017. Carbon dynamics in response to land cover change in tropical peatlands, Kalimantan, Indonesia. Ph.D. Dissertation. Oregon State University, Corvallis, Oregon USA. DOI:10.13140/RG.2.2.16650.21447.

Cobb, A.R., Hoyt, A.M., Gandois, L., Eri, J., Dommain, R., Abu Salim, K., Kai, F.M., Haji Su'ut, N.S., Harvey, C.F., 2017. How temporal patterns in rainfall determine the geomorphology and carbon fluxes of tropical peatlands. Proc. Natl. Acad. Sci. 114 (26), E5187–E5196. https://doi.org/10.1073/pnas.1701090114.

Dadap, N.C., Cobb, A.R., Hoyt, A.M., Harvey, C.F., Feldman, A.F., Im, E.S., Konings, A.G., 2022. Climate change-induced peatland drying in Southeast Asia. Environ. Res. Lett. 17 (7), 074026. https://doi.org/10.1088/1748-9326/ac7969.

Dargie, G.C., Lewis, S.L., Lawson, I.T., Mitchard, E.T., Page, S.E., Bocko, Y.E., Ifo, S.A., 2017. Age, extent and carbon storage of the central Congo Basin peatland complex. Nature 542 (7639), 86–90. https://doi.org/10.1038/nature21048.

Farmer, J., Matthews, R., Smith, P., Langan, C., Hergoualc'h, K., Verchot, L., Smith, J.U., 2014. Comparison of methods for quantifying soil carbon in tropical peats. Geoderma 214–215 177–183. https://doi.org/10.1016/j.geoderma.2013.09.013.

Fourqurean, J.W., Duarte, C.M., Kennedy, H., Marbà, N., Holmer, M., Mateo, M.A., Apostolaki, E.T., Kendrick, G.A., Krause-Jensen, D., McGlathery, K.J., Serrano, O., 2012. Seagrass ecosystems as a globally significant carbon stock. Nat. Geosci. 5, 505–509.

Griscom, B.W., Busch, J., Cook-Patton, S.C., Ellis, P.W., Funk, J., Leavitt, S.M., Lomax, G., Turner, W.R., Chapman, M., Engelmann, J., Gurwick, N.P., 2020. National mitigation potential from natural climate solutions in the tropics. Philos. Trans. R. Soc. B 375 (1794), 20190126, 1794.

Gumbricht, T., Roman-Cuesta, R.M., Verchot, L., Herold, M., Wittmann, F., Householder, E., Herold, N., Murdiyarso, D., 2017. An expert system model for mapping tropical wetlands and peatlands reveals South America as the largest contributor. Glob. Change Biol. 23, 3581–3599. https://doi.org/10.1111/gcb.13689.

Harrison, M.E., Ottay, J.B., D'Arcy, L.J., Cheyne, S.M., Anggodo, Belcher, C., Cole, L., Dohong, A., Ermiasi, Y., Feldpausch, T., Gallego-Sala, A., 2020. Tropical forest and peatland conservation in Indonesia: Challenges and directions. People Nat. 2, 4–28. https://doi.org/10.1002/pan3.10060.

Humpenöder, F., Karstens, K., Lotze-Campen, H., Leifeld, J., Menichetti, L., Barthelmes, A., Popp, A., 2020. Peatland protection and restoration are key for climate change mitigation. Environ. Res. Lett. 15, 104093. https://doi.org/10.1088/1748-9326/abae2a.

Interagency Working Group on Social Cost of Greenhouse Gases (IWG), 2021. Technical support document: social cost of carbon, methane, and nitrous oxide interim estimates under Executive Order 13990, https://www.whitehouse.gov/wp-content/uploads/2021/02/TechnicalSupportDocument_SocialCostofCarbonMethaneNitrousOxide.pdf.

IPCC (Intergovernmental Panel on Climate Change), 2003. Good practice guidance for land use, landuse change, and forestry. Hayama, Japan: Institute for Global Environmental Strategies.

IPCC, 2014. 2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands, Hiraishi, T., Krug, T., Tanabe, K., Srivastava, N., Baasansuren, J., Fukuda, M. and Troxler, T.G. (eds). Published: IPCC, Switzerland.

Joosten, H. and Clarke, D., 2002. Wise Use of Mires and Peatlands. International Mire Conservation Group and International Peat Society. Greifswald, Germany. 303p.

Kauffman, J.B., Adame, M.F., Arifanti, V.B., Schile-Beers, L.M., Bernardino, A.F., Bhomia, R.K., Donato, D.C., Feller, I.C., Ferreira, T.O., Jesus Garcia, M.C., MacKenzie, R.A., Megonigal, J.P., Murdiyarso, D., Simpson, L., Hernandez Trejo, H., 2020. Total ecosystem carbon stocks of mangroves across broad global environmental and physical gradients. Ecol. Monogr. 00 (00), e01405, 10.1002/ecm.1405.

Kauffman, J.B., Arifanti, V.B., Basuki, I., Kurnianto, S., Novita, N., Murdiyarso, D., Donato, D.C. and Warren, M.W., 2016. Protocols for the measurement, monitoring, and reporting of structure, biomass, carbon stocks and greenhouse gas emissions in tropical peat swamp forests. Working Paper 221. Bogor, Indonesia: CIFOR. https://doi.org/10.17528/cifor/006429.

Kauffman, J.B., Arifanti, V.B., Hernandez Trejo, H., Jesus Garcia, M., Norfolk, J., Cifuentes, M., Hadriyanto, D., Murdiyarso, D., 2017. The jumbo carbon footprint of a shrimp: carbon losses from mangrove deforestation. Front. Ecol. Environ. 2017 15 (4). https://doi.org/10.1002/fee.1482.

Kauffman, J.B., Novita, N., Basuki, I., Adame, M.F., Murdiyarso, D., Gangga, A., et al., 2024b. Database total ecosystem carbon stocks of tropical peat forest and greenhouse gas emissions from their disturbance. Figshare. Dataset. https://doi.org/10.6084/m9.figshare.25996036.v1.

Kauffman, J.B., Souza, F.M., Costa, R.F., da Silva, A.E.B., Ferriera, T.O., Megonigal, J.P., Ritonga, R., Gangga, A., Novita, N., Pacheco, C.F.O., Bernardino, A.F., 2024a. Conversion of tropical forests to water buffalo pastures in lower Amazonia: Carbon losses and social carbon costs. Ecosphere 15 (12), e70055. https://doi.org/10.1002/ecs2.70055.

Krauss, K.W., Noe, G.B., Duberstein, J.A., Conner, W.H., Stagg, C.L., Cormier, N., Jones, M.C., Bernhardt, C.E., Graeme Lockaby, B., From, A.S., Doyle, T.W., 2018. The role of the upper tidal estuary in wetland blue carbon storage and flux. Glob. Biogeochem. Cycles 32 (5), 817–839 https://doi.org/10.1029/ 2018GB005897.

Leifeld, J., Menichetti, L., 2018. The underappreciated potential of peatlands in global climate change mitigation strategies. Nat. Commun. 9 (1), 1071. ⟨https://www.nature.com/articles/s41558-019-0615-5?fromPaywallRec=false⟩.

Leifeld, J., Wüst-Galley, C., Page, S., 2019. Intact and managed peatland soils as a source and sink of GHGs from 1850 to 2100. Nat. Clim. Change 9 (12), 945–947.

Lestari, N.S., Rochmayanto, Y., Salminah, M., Novita, N., Asyhari, A., Gangga, A., Ritonga, R., Yeo, S., Albar, I., 2024. Opportunities and risk management of peat restoration in Indonesia: lessons learned from peat restoration actors. Restor. Ecol. 32 (1), e14054. https://doi.org/10.1111/rec.14054.

Maltby, E., Immirzi, P., 1993. Carbon dynamics in peatlands and other wetland soils. Regional and global perspectives. Chemosphere 27, 999–1023.

Miettinen, J., Shi, C., Liew, S., 2011. Deforestation rates in insular Southeast Asia between 2000 and 2010. Glob. Change Biol. 17 (7), 2261–2270. https://doi.org/10.1111/j.1365-2486.2011.02398.x.

MOEF Indonesia, 2019. Peraturan Direktur Jenderal Pengendalian Pencemaran Dan Kerusakan Lingkungan Nomor: P.1/Ppkl/Pkl/Pkg/Pkl.0/1/2019 Tentang Pedoman Pelaksanaan Peraturan Menteri Lingkungan Hidup Dan Kehutanan Nomor P.14/Menlhk/Setjen/Kum.1/2/2017 Tentang Tata Cara Inventarisasi Dan Penetapan Fungsi Ekosistem Gambut. https://pkgppkl.menlhk.go.id/v0/wp-content/uploads/2020/02/Perdirjen-P.1-PPKL-0-2019-Pelaksanaan-Permen-14-Tahun-2017-18-Desember-2018.pdf.

Murdiyarso, D., Hergoualc'h, K., Verchot, L.V., 2010. Opportunities for reducing greenhouse gas emissions in tropical peatlands. Proc. Natl. Acad. Sci. 107 (46), 19655–19660. https://doi.org/10.1073/pnas.0911966107.

Murdiyarso, D., Kauffman, J.B., Verchot, L.V., 2013. Climate change mitigation strategies should include tropical wetlands. Carbon Manag. 4 (5), 491–499. https://doi.org/10.4155/cmt.13.46.

Murdiyarso, D., Swails, E., Hergoualc'h, K., Bhomia, R., Sasmito, S.D., 2024. Refining greenhouse gas emission factors for Indonesian peatlands and mangroves to meet ambitious climate targets. Proc. Natl. Acad. Sci. 121 (17). https://doi.org/10.1073/pnas.2307219121.

Novita, N., 2016. Carbon stocks and soil greenhouse gas emissions associated with forest Conversion to oil palm plantations in Tanjung Puting tropical peatlands, Indonesia. PhD Diss, Oregon State University, Corvallis, OR USA. https://ir.library.oregonstate.edu/concern/graduate_thesis_or_dissertations/4j03d427z.

Novita, N., Kauffman, J.B., Hergoaulc'h, K., Murdiyarso, D., Hendry-Tryanto, D., Jupesta, J., 2021. Carbon Stocks from Peat Swamp Forest and Oil Palm Plantation in

Central Kalimantan, Indonesia. Chapter 10. In: Djalante, et al. (Eds.), Climate Change Research, Policy and Actions in Indonesia. Springer Nature Switzerland AG. https://doi.org/10.1007/978-3-030-55536-8_10.

Novita, N., Subarno, Lestari, N.S., Anshari, G.Z., Lugina, M., Yeo, S., Malik, A., Asyhari, A., Putra, C.A.S., Gangga, A., Ritonga, R.P., Albar, I., 2023. Natural climate solutions in Indonesia: wetlands are the key to achieve Indonesia's national climate commitment. Environ. Res. Lett. 17 (11), 114045.

Page, S.E., Mishra, S., Agus, F., Anshari, G., Dargie, G., Evers, S., Jauhiainen, J., Jaya, A., Jovani-Sancho, A.J., Laurén, A., Sjögersten, S., 2022. Anthropogenic impacts on lowland tropical peatland biogeochemistry. Nat. Rev. Earth Environ. 3, 426–443.

Page, S.E., Rieley, J.O., Banks, C.J., 2011. Global and regional importance of the tropical peatland carbon pool. Glob. Change Biol. 17 (2), 798–818. https://doi.org/10.1111/j.1365-2486.2010.02279.x.

Page, S.E., Wust, R.A.J., Weiss, D., Rieley, J.O., Shotyk, W., Limin, S.H., 2004. A record of Late Pleistocene and Holocene carbon accumulation and climate change from an equatorial peat bog (Kalimantan, Indonesia): Implications for past, present and future carbon dynamics. J. Quant. Sci. 19, 625–635. https://doi.org/10.1002/jqs.884.

Rennert, K., Errickson, F., Prest, B.C., Rennels, L., Newell, R.G., Pizer, W., Kingdon, C., Wingenroth, J., Cooke, R., Parthum, B., Smith, D., 2022. Comprehensive evidence implies a higher social cost of CO2. Nature 610 (7933), 687–692. https://doi.org/10.1038/s41586-022-05224-9.

Ribeiro, K., Pacheco, F.S., Ferreira, J.W., de Sousa-Neto, E.R., Hastie, A., Krieger Filho, G. C., Alvalá, P.C., Forti, M.C., Ometto, J.P., 2021. Tropical peatlands and their contribution to the global carbon cycle and climate change. Glob. Change Biol. 27 (3), 489–505. https://doi.org/10.1111/gcb.15408.

Rieley, J.O. and Page, S.E., eds., 2005. Wise Use Guidelines for Tropical Peatlands. Wageningen, The Netherlands: Alterra. 237 p. ISBN 90327-0347-1.

Ruwaimana, M., Anshari, G.Z., Silva, L.C.R., Gavin, D.G., 2020. The oldest extant tropical peatland in the world: a major carbon reservoir for at least 47,000 years. Environ. Res. Lett. 15, 1–16. https://doi.org/10.1088/1748-9326/abb853.

Sierra, C.A., del Valle, J.I., Orrego, S.A., Moreno, F.H., Harmon, M.E., Zapata, M., Colorado, G.J., Herrera, M.A., Lara, W., Restrepo, D.E., Berrouet, L.M., Loaiza, L.M., Benjumea, J.F., 2007. Total carbon stocks in a tropical forest landscape of the Porce region, Colombia. For. Ecol. Manag. 243, 299–309.

Soil Survey Staff., 2022. Keys to Soil Taxonomy. 13th ed. Natural Resources Conservation Services. Washington DC: United States Department of Agriculture. 360 pp.

Tan, Z.D., Carrasco, L.R., Sutikno, S., Taylor, D., 2022. Peatland restoration as an affordable nature-based climate solution with fire reduction and conservation co-benefits in Indonesia. Environ. Res. Lett. 17 (6), 064028. https://doi.org/10.1088/1748-9326/ac6f6e.

Verra., 2024. The Verified Carbon Standard Program Methodologies. Verra https://verra.org/methodologies-main/. Accessed 29 August 2024.

Warren, M., Frolking, S., Dai, Z., Kurnianto, S., 2017a. Impacts of land use, restoration, and climate change on tropical peat carbon stocks in the twenty-first century: implications for climate mitigation. Mitig. Adapt. Strateg. Glob. Change 22, 1041–1061.

Warren, M., Hergoualc'h, K., Kauffman, J.B., Murdiyarso, D., Kolka, R., 2017b. An appraisal of Indonesia's immense peat carbon stock using national peatland maps: uncertainties and potential losses from conversion. Carbon Balance Manag. 12 (1), 12. https://doi.org/10.1186/s13021-017-0080-2.

Woittiez, L.S., van Wijk, M.T., Slingerland, M., van Noordwijk, M., Giller, K.E., 2017. Yield gaps in oil palm: a quantitative review of contributing factors. Eur. J. Agron. 83, 57–77. https://doi.org/10.1016/j.eja.2016.11.002.