SUPPLEMENTARY INFORMATION

Protecting irrecoverable carbon in Earth's ecosystems

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List of Supplementary Materials

Ecosystem delineation and manageability of carbon stocks

While many ecosystems play an important role in cycling and storing carbon, our objective in this analysis was to identify those ecosystems containing carbon that is pertinent to human management decisions for climate mitigation. We started by delineating major categories of terrestrial, coastal and marine, and freshwater ecosystems and then narrowing the list to ecosystems containing carbon that is manageable through direct, localized human activities (i.e., the carbon content of the ecosystem could either increase or decrease depending on localized human decisions). We considered an ecosystem's carbon to be 'manageable' only if the localized action was widely applicable with current technology (i.e., not requiring geoengineering technology projected to be available at some future date) and if increasing the ecosystem's carbon content would not have other adverse impacts (e.g., ocean acidification).

Terrestrial ecosystems

To delineate terrestrial ecosystems, we started with Dinerstein et al's 15 terrestrial biomes[1]: boreal forests/taiga; temperate broadleaf and mixed forests; temperate conifer forests; tropical and subtropical coniferous forests; tropical and subtropical dry broadleaf forests; tropical and subtropical moist broadleaf forests; Mediterranean forests, woodlands and scrub; deserts and xeric shrublands; temperate grasslands, savannas, and shrublands; tropical and subtropical grasslands, savannas and shrublands; montane grasslands and shrublands; flooded grasslands and savannas; mangroves; tundra; and rock and ice. These biomes were chosen as the starting point because they represent a discrete list of ecosystem types, with climate and other biophysical factors driving differentiation in terms of carbon storage. Tropical and subtropical coniferous forests; flooded grasslands and savannas; and Mediterranean forests, woodlands, and scrub were excluded due to low data availability and limited geographic coverage: 0.5%. 0.9% and 2.4% of terrestrial land, respectively[1].

Other terrestrial ecosystems were eliminated from further consideration due to their irrelevance to local carbon management:

- **Rock and ice** was excluded because its carbon content is not of recent biotic origin and is not responsive to direct human management.
- **Deserts and xeric shrublands** were excluded because, although the saline aquifers below deserts may store a significant amount of carbon – perhaps around 1,000 Gigatonnes (Gt) – that has been leached from soils by past irrigation and accumulated in groundwater[2]. Dissolved CO_2 can only be re-released from storage if this groundwater is discharged into surface water systems or if it is pumped to the surface for subsequent irrigation where, in both cases, turbulence will release dissolved CO_2 to the atmosphere. However, discharge from these aquifirs is low and the cited total storage already accounts for the aquifir's relative CO_2 gains and losses. Irrigation represents the only potential conduit within the purview of human management and is unlikely given that the saline groundwater is often toxic to crops[2].
- **Tundra** ecosystems cover an estimated 1,878 million hectares of the Earth's surface and the permafrost – the remnants of plants and animals accumulated in frozen soil – within them stores an estimated 1,300 Gt of carbon[3,4], twice as much carbon as is currently in the atmosphere. This carbon can be released to the atmosphere if these frozen soils thaw, increasing mineralization by microbes that convert it to carbon dioxide (CO_2) and methane (CH_4). A portion of this carbon is likely to be released under the current climate warming trajectory[4]. However, though humans have indirect control over the level of thawing that occurs through global anthropogenic emissions, there are no proven direct, localized land-use management activities that can affect the carbon content of tundra ecosystems.

Coastal and marine ecosystems

To delineate coastal and marine ecosystems, we used the systems delineated in Howard et al 2017[5]. They were: mangroves, tidal marshes, seagrasses, coral reefs, kelp forests, and the open ocean. Again, a few coastal and marine ecosystems were eliminated from further consideration due to their irrelevance to local management:

- **Kelp forests** are so quickly consumed by marine fauna that relatively little carbon (at most 0.13 Gt globally) can be considered part of a long-term sink. Though we may be able to expand the extent of kelp forests, doing so would have little effect on global carbon stores[5].
- **Coral reefs** do not store significant carbon. Reef growth through calcification occurs when calcium carbonate ($CaCO_3$) precipitates out of the water column onto the reef structure, releasing a small amount of CO_2 to the atmosphere; the opposite happens with reef dissolution. With future conditions of ocean acidification, many reefs are expected to enter a net dissolution phase, capturing CO_2 but ultimately destroying the reefs[5].
- **The open ocean** contains 38,000 Gt carbon[6] and serves as a major carbon sink as CO_2 in the atmosphere reacts with seawater and gets pumped into the ocean's deep waters (the "solubility pump", a chemical process) and as marine organisms sequester CO_2 through photosynthesis, beginning with phytoplankton (the "biological pump"). Additional organic matter is also transported to the open ocean through rivers[7], but this effect is smaller than either the solubility pump or the biological pump. All told, oceans have absorbed 40% of the CO_2 humans have added to the atmosphere since the dawn of the industrial era[8]. However, the rate of CO_2 uptake by the ocean is dependent mainly on the concentration of CO_2 in the atmosphere, and the open ocean is not responsive to direct carbon management except through unproven and highly risky strategies such as fertilizing the ocean with iron[9]. Additionally, unlike in coastal and terrestrial ecosystems, uptake of carbon in the oceans has

a negative biological consequence: ocean acidification, which is harmful to marine creatures[10].

Freshwater ecosystems

For freshwater ecosystems, we considered lakes, rivers/streams, and peatlands. Peatlands were further delineated as tropical, temperate, and boreal. Peat is the accumulation of organic material that occurs when water prevents the remains of dead plants and mosses from decomposing due to the absence of oxygen. Peat may occur within a forest, grassland, savanna, or wetland and therefore overlaps spatially with the Dinerstein biome delineations. We decided to assess peatlands separately despite the spatial overlap because of their huge carbon reserves, unique carbon dynamics, and low recoverability, since some peatlands take millennia to form[11].

Lakes, rivers and streams were excluded because it is unclear whether they represent an additional carbon sink. While these freshwater ecosystems play an important role in the global carbon cycle, receiving an estimated 2.7-5.1Gt of carbon annually from terrestrial ecosystems; of this, between 0.7-3.9 Gt is respired back to the atmosphere, 0.9 Gt is transported to the ocean, and 0.2-0.6 Gt is retained and buried in sediments[7,12-14]. The carbon that does make it into sediments can remain there for 10,000 years or more, and over time the world's lakes have accumulated an estimated 820 GtC[15], mostly in shallow sediments[12]. Carbon burial in freshwater sediments is an order of magnitude greater than carbon burial in the ocean[16]. However, it is unclear whether freshwater ecosystems represent an additional carbon sink, or whether they are simply the resting point for carbon that would have otherwise been stored in terrestrial ecosystems or the ocean floor[17].

Ecosystems considered in subsequent analysis

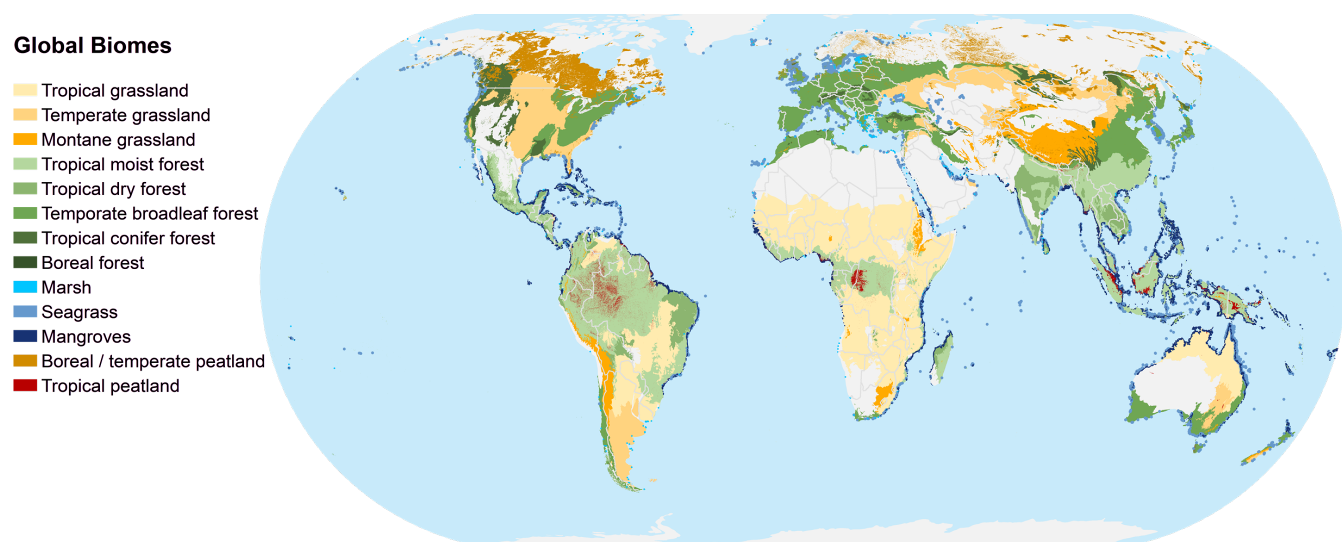
The remaining ecosystems we considered against the subsequent criteria were:

- Boreal forests/taiga (abbreviated as "Boreal forest")
- Temperate broadleaf and mixed forests ("Temperate broadleaf forest")
- Temperate conifer forests

- Tropical and subtropical dry broadleaf forests (“Tropical dry forest”)
- Tropical and subtropical moist broadleaf forests (“Tropical moist forest”)
- Temperate grasslands, savannas, and shrublands (“Temperate grassland”)
- Tropical and subtropical grasslands, savannas and shrublands (“Tropical grassland”)
- Montane grasslands and shrublands (“Montane grassland”)
- Mangroves
- Seagrasses
- Tidal marshes (“Marshes”)
- Boreal peatlands (“Boreal peatlands”)
- Temperate peatlands (“Temperate peatlands”)
- Tropical peatlands (“Tropical peatlands”)

Supplementary Figure 1 shows the geographic distribution of the ecosystems considered in this analysis. The subsequent analysis is spatial only to the extent that we sometimes used this ecosystem delineation to calculate average values by ecosystem based on point data.

Supplementary Figure 1: Ecosystem delineation map



Notes: This map was created by overlaying the manageable Dinerstein biomes[1] with coastal ecosystem layers (Bunting et al 2018 for mangroves[18], UNEP-WCMC 2018 for seagrasses[19], and Mcowen et al 2017 for marshes[20]) and peatlands (using PeatMAP[21]).

Magnitude of vulnerable carbon stocks

Initial biomass (aboveground and belowground carbon)

Forests

We derived average aboveground biomass carbon (AGC) values for forests from the Forest C database (ForC-db), an open access global carbon database that contains previously published data on ground-based measurements of ecosystem-level C stocks and annual fluxes in forests globally[22]. ForC-db contains >23,000 records from >3,300 sites. We used values for biome average aboveground biomass carbon per hectare. Coordinates were given for all sites in ForC-db and we used these coordinates to tag each site to a Dinerstein biomes, as discussed above. We averaged values by geographic area to reduce the impact of heavily sampled areas on the mean values.

Because the carbon storage of forests differs significantly by age[23,24] and because there are large areas of secondary forest across the planet due to deforestation and subsequent regrowth, we delineated the major forest ecosystem types as either 'young' (<100 years since natural regeneration or replanting initiated) or 'old' (≥100 years) to capture differences in carbon storage per hectare and based on the cutoff for secondary forest versus old-growth stands used in Suarez et al 2019[25]. We used the 'stand age' at the time of measurement (ForC-db compiles this based on the age as reported in the original publication or calculated based on the date of initiation of forest regrowth).

We derived average belowground biomass carbon (BGC) values for forests using a root-to-shoot conversion based on Mokany et al 2006[26]. Forest root-to-shoot ratios were adjusted to align with the Dinerstein ecoregions and differentiated based on the aboveground carbon content, using low, medium, or high delineations based on the ranges shown in Table S1. We calculated BGC for each of the ForC-db sites that reported an AGC value and then averaged the BGC per ecosystem.

Supplementary Table 1: Root-to-shoot conversion rates for estimating belowground carbon

Ecosystem	Aboveground C Range ($MgC\ ha^{-1}$)	Root-to-shoot ratio
Boreal forest	<35.3	0.392[a]
Boreal forest	≥35.3	0.239[a]
Temperate broadleaf forest	<35.3	0.456[a]
Temperate broadleaf forest	35.3-70.5	0.226[a]
Temperate broadleaf forest	>70.5	0.241[a]
Temperate conifer forest	<23.5	0.403[a]
Temperate conifer forest	23.5-70.5	0.292[a]
Temperate conifer forest	>70.5	0.201[a]
Tropical moist forest	<58.8	0.205[a]
Tropical moist forest	≥58.8	0.235[a]
Tropical dry forest	<9.4	0.563[a]
Tropical dry forest	≥9.4	0.275[a]
Tropical grassland	All	1.887[a]
Temperate grassland	All	4.224[a]
Montane grassland	All	4.504[b]
Mangroves	All	0.580[c]
Seagrasses	All	2.650[d]
Marshes	All	1.098[c]

Sources: [a] Mokany et al. 2006[26] [b] Used Mokany value for 'cool temperate grasslands' [c] Average R:S ratio across all mangrove subtypes in the IPCC Wetlands Supplement[27] [d] Midpoint value from Purvaja et al. 2018[28]

Grasslands

For grasslands, AGC density was tabulated separately within each off the three grassland biomes from a global map of grassland herbaceous biomass carbon density[29]. Grassland BGC density was then calculated using the corresponding root-to-shoot ratios reported in Table S1. These estimates only account for the herbaceous (i.e. grass) biomass within these ecosystems and thereby exclude the biomass of trees and shrubs that may also be located within grassland areas.

Coastal ecosystems

For coastal ecosystems our average AGC and BGC density values were derived from a literature review. The results of all biomass analyses and the coastal ecosystem literature review are summarized in Table S2 below.

Peatlands

Peatlands are excluded from this table because they underly other land-use classes and their AGC and BGC is therefore captured under other ecosystem types.

Supplementary Table 2: Mean aboveground and belowground carbon densities across ecosystems

Ecosystem	Mean AGC (MgC ha^{-1})	Min. AGC (MgC ha^{-1})	Max. AGC (MgC ha^{-1})	Mean BGC (MgC ha^{-1})	Min. BGC (MgC ha^{-1})	Max. BGC (MgC ha^{-1})	Count
Boreal forest	56.9	0.7	141.9	14.3	0.3	33.9	83
Temperate broadleaf forest (young)	67.6	2.1	242.0	16.7	1.0	58.3	106
Temperate broadleaf forest (old)	116.1	17.4	720.5	28.3	7.9	173.6	65
Temperate conifer forest (young)	76.2	4.1	246.0	17.0	1.7	49.5	34
Temperate conifer forest (old)	119.4	22.7	360.9	25.2	7.7	72.5	70
Tropical moist forest (young)	72.9	5.0	287.2	16.7	1.0	67.5	64
Tropical moist forest (old)	154.7	22.7	361.5	36.3	4.8	84.9	153
Tropical dry forest (young)	31.8	0.7	56.4	8.9	0.1	15.5	5
Tropical dry forest (old)	96.9	14.0	162.6	26.7	3.8	44.7	12
Temperate grassland	0.8	0.1	1.6	3.6	0.2	6.8	NA
Tropical grassland	1.0	0.1	1.6	1.8	0.4	3.2	NA
Montane grassland	0.6	0.01	1.6	2.6	0.05	7.2	NA
Mangroves	89.5	2.6	236.0	51.9	1.5	136.9	30
Seagrasses	0.8	<0.1	5.6	2.1	<0.1	17.8	251
Marshes	5.0	0.1	31.2	5.5	.1	34.3	409

Notes: 'Count' represents the number of geographic areas on which the mean value was based, if available. BGC values were calculated based on the root-to-shoot ratios specified in Table S1 unless otherwise specified. Peatlands excluded from this table because peatlands underly other aboveground land-uses. We captured peatlands SOC only. "Young" refers to forests <100 years old and "old" is ≥100 years old. This was a meaningful distinction in all forest types except boreal.
Sources: ForC database for all forest values[22]; Xia et al. 2014[29] for grasslands (min and max values here refer to the 0.01 and 99.9 percentiles); Kaufmann et al. 2017[30] for mangrove AGC values; Fourqurean et al. 2012[31] for seagrass AGC and BGC; Byrd et al. 2018[32] for tidal marshes AGC.

Soil organic carbon (SOC)

Forests and grasslands

Summarizing average soil organic carbon (SOC) density values per biome required a different approach. To maximize methodological consistency across ecosystems and holistically represent the spatial variation within each, we tabulated SOC carbon stocks from the SoilGrids250v2 gridded soils database[33] (hereafter "SoilGrids"). SoilGrids maps are produced at a 250m spatial resolution for the globe using a machine learning algorithm that is trained by relating more than 150,000 soil profiles to nearly 160 remotely sensed covariate grids. SoilGrids provides accurate depth-specific SOC estimates for most ecosystems, with a few exceptions (see boreal, below). The global root mean square error of SoilGrids SOC predictions is 32.8 MgC ha^{-1}, indicating tight agreement with corresponding field measurements. While a small number of alternative global soil maps exist and were considered, none report a quantitative accuracy assessment to which we could compare. Independent comparisons, though, suggest that SoilGrids' predictions are likely closest to reality [34]. We considered the effects of land use changes on SOC stocks to a depth of 30 cm for forests and grasslands.

Within each ecosystem, we summarized a representative sample of the initial (i.e. pre-conversion), depth-specific SOC stocks that underlie the primary natural land cover from the SoilGrids maps. A series of masks were applied to each SOC grid in Google Earth Engine (GEE)[35] to exclude non-representative areas from each tabulation. We began by masking each SOC grid to the biome's extent. Since our analysis only considers the effects of the changes to the primary vegetation type within each biome, we then masked each grid to the extent of that land cover (e.g. tree covered areas of forested biomes and herbaceous and shrubland classes of grasslands biomes) using the ESA CCI land cover map for the year 2010[36], which was used to represent land cover within the SoilGrids algorithm[33]. Lacking a map of forest age, we were not able to further differentiate SOC in "old" vs. "young" forests in our stock tabulations and thus assumed no significant difference. Finally, since peat soils (Histosols) were examined separately, we removed grid cells that SoilGrids identified as probable Histosols (prob. ≥ 95%) to avoid double counting.

Summaries of SOC stocks were then generated from the remaining SOC grid cells within each biome's extent using GEE. We determined the median stock density of each relevant SoilGrids depth increment (0-5cm, 5-15cm, 15-30cm). In addition, we also generated percentile estimates (p = 0.1%, 1.0%, 2.0%, 2.5%, 5.0%, 10.0%, 25.0%, 75.0%, 90.0%, 95.0%, 97.5%, 99.0%, 99.9%) of each depth increment to which we could fit probability distributions and quantify/propagate uncertainty associated with the stock's spatial variation. Probability distributions were fit using the *rriskDistributions* package[37] in the R statistical computing environment[38]. In the rare case of a bimodal distribution, the distribution was approximated using a monotone cubic Hermite spline. Depth specific median and percentile estimates were integrated by depth to report estimates of these metrics for the upper 30 cm of soil.

Corresponding information on clay content and mean annual temperature was required to model land use induced SOC stock changes in some ecosystems and were similarly tabulated from additional maps using the masking procedure described above. We used depth-specific maps of soil clay content from SoilGrids and a map of mean annual temperature (1970-2000) from the WorldClim2 dataset to represent these variables[39].

In the organic rich soils of the boreal region, SoilGrids is known to overestimate SOC stocks[34] due to a lack of representative bulk density data[40]. For this reason, we instead used a modified, though less resolved version of SoilGrids in which this issue has been resolved to tabulate boreal SOC stocks to depth of 30 cm[31]. These grids were only used for stock tabulations in the boreal forest ecosystem since the primary anthropogenic land use change here was assumed to not significantly influence SOC stocks (see below) and thus more resolved, depth-specific estimates and matching soil property information were not necessary. These modified grids were, however, subject to the same masking procedure described above such that our estimates only consider stocks in forested areas and exclude peatland areas to avoid double counting.

Coastal ecosystems and peatlands

SoilGrids does not explicitly cover coastal ecosystems or peatlands. The SOC values for mangroves were thus derived from Sanderman et al. 2018[41]; values for seagrasses and tidal marshes were derived from the IPCC Wetlands Supplement 2013, Table 4.11[27]. The values for peatlands were derived from Page et al. 2011 for tropical peatlands and Christensen et al. 2004 for temperate and boreal peatlands[42,43]. For coastal ecosystems and peatlands, we considered SOC down to 1 m as the relevant depth vulnerable to the most common anthropogenic disturbances[44,45].

Supplementary Table 3: Average initial soil organic carbon stocks by ecosystem

Ecosystem	Average SOC (MgC ha^{-1})	Min. SOC (MgC ha^{-1})	Max. SOC (MgC ha^{-1})	Depth considered
Boreal forest	193	130	302	30 cm
Temperate broadleaf forest	137	80	214	30 cm
Temperate conifer forest	138	89	207	30 cm
Tropical moist forest	92	56	151	30 cm
Tropical dry forest	67	44	123	30 cm
Temperate grassland	73	31	151	30 cm
Tropical grassland	40	18	152	30 cm
Montane grassland	101	42	202	30 cm
Mangroves	361	86	729	100 cm
Seagrasses	108	9	829	100 cm
Marshes	255	16	623	100 cm
Boreal & temperate peatlands	500	392	1,531	100 cm
Tropical peatlands	504	424	1,357	100 cm

Sources/ Notes: Forest and grasslands values are the median; all other values are the mean. Boreal forests estimates come from Sanderman et al. 2017[46]. Mangrove estimates come from Sanderman et al. 2018[41]. Seagrasses estimates come from Fourqurean et al. 2012[31]. Marshes estimates come from the 2013 IPCC Wetlands Supplement[27]. Tropical peatlands estimates come from Page et al. 2011[39]. Temperate and boreal peat estimates come from Christensen et al. 2004[43]. All other estimates come from SoilGrids and exclude Histosols (peat). The min and max represent the 1st and 99th percentile of mapped values, respectively, which we think is a good proxy for the true range.

Vulnerability of initial carbon stocks

Across ecosystems, we assessed the likely amount of the initial carbon that would be lost per hectare in a typical conversion event, expressed as a percentage of the initial stock. The 'typical' conversion event was considered to be the most common driver of ecosystem loss, considering events that would alter the land cover (e.g., forest to soy field or clear-cut) as a maximum feasible loss event, as opposed to activities that might reduce the carbon content but not constitute full conversion (e.g., forest degradation due to charcoal collection or selective logging). Our assumptions about the typical conversion events that would result in carbon loss are defined in Table S4. In tropical forests, agriculture drives the vast majority of deforestation, while in temperate and boreal regions, the main anthropogenic driver is forestry[47]. Grassland conversion is also largely driven by agriculture[48] while coastal ecosystem loss is driven by aquaculture, agriculture, and coastal development[45]. Peatland conversion is largely driven by agriculture[11]. These common drivers were used to estimate the maximum 'vulnerable carbon' per hectare by major ecosystem type. We assumed complete conversion to a different land-use rather than degradation, however, we recognize that degradation through activities such as selective logging is a major driver of carbon loss in tropical forests, accounting for additional biomass losses on the order of 47-75% of deforestation[49].

Supplementary Table 4: Assumed % vulnerable carbon per hectare by ecosystem type due to typical conversion

Ecosystem	**% of initial biomass typically lost in conversion**	**% of initial SOC typically lost in conversion**	**Typical / assumed conversion event**
Boreal forest	100%	0%	Forestry
Temperate broadleaf forest	100%	0%	Forestry
Temperate conifer forest	100%	0%	Forestry
Tropical moist forest (young)	100%	18%	Agriculture
Tropical moist forest (old)	100%	23%	Agriculture
Tropical dry forest (young)	100%	18%	Agriculture
Tropical dry forest (old)	100%	23%	Agriculture
Temperate grassland	100%	39%	Agriculture
Tropical grassland	100%	23%	Agriculture
Montane grassland	100%	34%	Agriculture
Mangroves	100%	81%	Aquaculture / development
Seagrasses	100%	72%	Aquaculture / development
Marshes	100%	60%	Aquaculture / development
Boreal Peat / Temperate Peatlands	NA	27%	Agriculture
Tropical Peatlands	NA	89%	Agriculture

We separated our analysis by biomass and SOC, assuming that 100% of the biomass was potentially vulnerable in a conversion event. This follows IPCC Tier 1 methodology for forest land[50] and is also consistent with the assumption made in other estimations of carbon flux to the atmosphere associated with biomass loss in forests[51-53]. We applied the same 100% assumption to grasslands and coastal ecosystems as the maximum but reasonable amount of 'vulnerable carbon' by ecosystem.

In contrast to biomass, ecosystem conversion to a human appropriated land-use does not typically result in complete loss of the SOC stock. Instead, a fraction of the initial SOC stock is often lost following conversion due to changes in the ecosystem carbon balance that result from both biomass removal and physical disruption of otherwise-stable, carbon-containing soil aggregates. The relative magnitude of these losses has been related to both the type of ecosystem converted and its subsequent land use, among other factors, by numerous meta-analyses[54,55], and their findings are commonly used to model expected changes to the size of the initial SOC stock resulting from specific land use changes[56,57]. Likewise, we used this approach to model expected losses from the initial SOC stocks tabulated in each biome as described above. In the event of forestry/logging being the main driver of loss, we assumed that no (0%) of the SOC was vulnerable based on studies that show no significant change in SOC for harvested temperate forests (more details in subsequent section)[58,59]. This is a conservative assumption given uncertainties about SOC disturbance due to logging/ harvesting.

Boreal Forests SOC

We assumed that timber harvest of boreal forests – when followed by forest regeneration – induced no signification change in the magnitude of their underlying SOC stocks. While data is limited, we found multiple studies suggesting that such a transition had no meaningful effect on mineral SOC stocks and a minimal transient effect of forest floor carbon[60,61] – the organic layer containing litter and woody debris at the soil surface. For these reasons, we assumed no net change due to land use change and/or subsequent recovery in our analyses.

Temperate Forests SOC

Similar to boreal forests, introduced forestry was assumed to have no significant long-term effect on temperate forest SOC. In a meta-analysis of 75 studies reporting 432 SOC response ratios for harvested temperate forests, Nave et al. (2010) report no significant SOC change in forest mineral soils[58]. A recent analysis of SOC responses in harvested temperate forests found that forest floor carbon losses due to conventional harvest were offset by SOC accumulation in deeper mineral soils[59]. When SOC changes were integrated to a depth of 20 cm or more, this study found no statistically significant effect of conventional harvest. We therefore assumed for this analysis that temperate forest SOC is not lost to any significant degree upon harvest, by far the most common cause of conversion in temperate forests[47]. This is the assumption driving the 'irrecoverable carbon' calculation.

Conversion of temperate forests to cropland is relatively rare (e.g., Lark et al. 2015)[48] but represents a more drastic change to the local carbon cycle that leads to significant SOC losses., To get as sense of the potential implications of this sort of land use change, we also modeled SOC responses expected when temperate forests are converted to cropland. We used a carbon response function (CRF; see implementation details in "Temperate Grassland SOC") for forest conversion to cropland from Poeplau et al. 2011[42] to model the SOC response of this transition as described above. This analysis is captured in Table S6.

Temperate Grasslands SOC

The most common driver of loss of temperate grasslands is conversion to agriculture, which often causes SOC losses. We modeled these losses using a carbon response function (CRF) – a simple statistical model that predicts SOC emissions associated with specific land use transitions based on the empirical effects of environmental covariates over a user-specified duration. This CRF was derived in a meta-analysis of 95 published studies conducted throughout the temperate zone[55]. CRFs have been used by others to estimate SOC emissions from land use change[56,57]. The CRF used in this analysis predicts the proportional change relative to an initial SOC stock based on soil clay content (%), mean annual temperature (MAT; °C), soil depth (meters), and the time (*t*) since conversion (years).

The CRF was applied to depth-specific SOC estimates following the general approach of Spawn et al. 2019[57]. We quantified total changes expected as a result of land use change by setting *t* equal to 30 years since, according to these models, stocks stabilize after 17 years on average[42], and we aimed to capture the full effect of conversion events. To quantify uncertainty associated with the modeled SOC stock change, we used a bootstrapping procedure that resampled (n = 10,000) the probability distributions of SOC, clay and MAT (described previously), as well as those representing the error associated with CRF coefficients. Probability distributions for CRF coefficients were created from mean and standard error estimates (obtained from Poeplau et al. 2011 and reported in Table S10 of Spawn et al. 2019) and were assumed to be normally distributed. All distributions were sampled without replacement to generate novel distributions of (i) expected SOC change (ii) the post conversion SOC stock, from which we report the median and spread.

Tropical Forest and Grasslands SOC

CRFs were not available for tropical ecosystems so we instead used emissions factors (EFs) representing the average total SOC loss resulting from specific land use changes. These EFs (Table S6) were derived in a meta-analysis of 385 studies conducted throughout the tropics[54]. We used EFs describing changes resulting from the conversion of (i) primary forests, (ii) secondary forests, and (iii) natural grasslands to cropland. Since each EF was based on observations from different average maximum depths (36 to 44cm) and since our analysis only considers changes in these systems to a depth of 30cm, we calibrated each EF to reflect expected changes in the upper 30cm of the soil profile by fitting an exponential function derived from global SOC change data (Figure S8 in Sanderman et al. 2017[46]), such that the average change to the literature reported sample depth was equal to the literature reported EF. As a result, EFs used for the entire 30cm profile were slightly less than those reported in the meta-analysis[54].

As with the temperate grassland SOC loss calculation, we used a bootstrapping procedure (n = 10,000) to quantify uncertainty associated with modeled tropical SOC changes. In addition to probability distributions of depth-specific SOC densities, distributions were also fit to the mean, standard error and range estimates of the literature reported EFs by assuming a truncated normal distribution bounded by the given EF's reported minimum and maximum estimate[54]. Distributions describing the time since LUC and sample depth were also created and assumed to be normally distributed. All distributions were sampled without replacement to generate novel distributions of (i) expected SOC change and (ii) the post-conversion SOC stock from which we report the median and spread.

Coastal Ecosystems SOC

SOC loss rates from coastal ecosystems were estimated through literature review. The mangrove SOC loss value of 81% was derived from a study that compared ecosystem carbon stocks from 30 relatively undisturbed mangrove forests and 21 adjacent shrimp ponds or cattle pastures[30]. Another study across 25 mangrove sites in the Indo-Pacific found 25-100% SOC loss in mangroves following disturbance, with the lower end applying to moderate soil disturbance and the upper end applying to heavier activities such as shrimp aquaculture[62]; the 81% derived from Kauffman et al. falls towards the upper end of this range[30]. SOC loss in seagrasses remains uncertain, as it is unclear whether the entire top meter of soil is remineralized in the event of seagrass loss, however, one study in Jervis Bay, Australia which examined a seagrass area disturbed 50 years prior found that 72% of the SOC was lost[63]. (This study looked at just the top 30 cm of soil). Finally, the tidal marsh SOC loss assumption was derived from a study of salt marsh conversion in the Scheldt estuary in the Netherlands[64].

Peatlands

We considered the top meter of peatland SOC to determine the maximum vulnerable carbon in a conversion event. The 1 m drainage depth is consistent with the IPCC Wetlands Supplement[27] and with studies of peatlands emissions converted to palm oil in Southeast Asia that found likely drainage depths to be between 0.8 and 1.1 meters[44]. Our goal was to capture the full effects of a conversion event to estimate 'vulnerable carbon'. While *all* carbon in peatlands might be lost eventually, good data on this does not exist, so we looked at subsidence over 30 years, assuming that peatlands converted to palm oil, for example, would not be restored within several decades. This gives us a realistic but conservative estimate of the proportion of SOC in peatlands that would be vulnerable in a typical conversion event. In tropical peatlands, we estimate that 89% of the original SOC is vulnerable. This percentage is based on average annual loss of 15 MgC ha^{-1}

following a conversion event, reaching 450 MgC ha^{-1} within 30 years (and compared to the the original 504 MgC ha^{-1} as captured in Table S4). The 15 MgC ha^{-1} is an expert estimate of carbon loss based on IPCC emissions factors of 11-20 MgC ha^{-1} per year for plantations on tropical peatlands as well as documented subsidence rates of tropical peat of 4-5 cm / yr following conversion events[44]. For temperate and boreal peatlands, rate of carbon loss is somewhat lower, and we estimate that 27% of the original soil carbon is vulnerable following a conversion. This is again based on IPCC ranges, from which we assumed a conservative annual loss of 4.5 MgC ha^{-1}, reaching 135 MgC ha^{-1} over 30 years (compared to the original 500 MgC ha^{-1} as captured in Table S3). If drainage is stopped and/or restoration is initiated soon after conversion, some of the carbon loss can be prevented, however, this avoided emissions scenario is rare in peatlands, and beyond the scope of this analysis.

Recoverability of ecosystem carbon stocks

To determine carbon recoverability for each ecosystem, we used average sequestration rates for biomass and soils. Though these could be assessed for any timeframe, for the purposes of Figures 2 and 5 in the main text, we looked at recoverability over 30 years as a key illustrative example given the need to reach net-zero emissions by mid-century. Recovery can include natural regeneration (reducing threats and allowing the ecosystem to recover on its own) as well as active restoration / planting. The deficit between the 'vulnerable carbon' and the carbon that can subsequently be recovered within 30 years is considered the 'irrecoverable carbon'.

Biomass recovery

Forest biomass (AGC and BGC) rates are based on 2,790 observations of carbon accumulation in forests across 450 sites[65]. To assess recoverable carbon within 30 years, we applied a best fit linear equation of forest carbon with respect to either stand age or log of stand age, whichever provided a better fit, and looked at the carbon density at year 30 (Table S5).

Supplementary Table 5: Average biomass recovery in 30-year-old forests

Ecosystem	Biomass recovery in 30 years ($MgC\ ha^{-1}$)
Boreal forest	43.2
Temperate broadleaf forest	50.3
Temperate conifer forest	48.5
Tropical moist forest	94.4
Tropical dry forest	65.5

For grassland ecosystems, where peak biomass is achieved prior to 30 years of recovery, we assumed that the sequestration rate was equal to the total stock observed in these ecosystems divided by the biomass turnover time. Total stocks were taken to be those tabulated above from the Xia et al. 2014 grassland aboveground biomass carbon density map[25] and corresponding root-to-shoot ratios. Turnover times were taken from an ecosystem specific meta-analysis[66] whereby we assumed that root biomass turnover is representative of total grassland biomass stocks since roots comprise the majority of the total stock, and that montane grasslands were representative of those reported as “boreal grasslands”. Mangrove biomass sequestration rates are not well-constrained, so to estimate mangrove biomass recovery, we multiplied our best expert estimate (by co-author Jen Howard) of annual sequestration by 30 years. The other coastal ecsoystems, seagrasses and marshes store the vast majority of their carbon in their soils, and even an estimate of annual sequestration was not available; however given the low initial biomass values, we assumed full biomass recovery within 30 years for these coastal ecosystems.

Supplementary Table 6: Average biomass recovery rates in grasslands and mangroves

Ecosystem	Biomass sequestration rate (MgC ha^{-1})	Source(s) for sequestration rate	Biomass recovery over 30 years (MgC ha^{-1})
Temperate grassland	1.95	Xia et al 2014 & Gill & Jackson 2000[29,66]	Full recovery
Tropical grassland	2.36	Xia et al 2014 & Gill & Jackson 2000	Full recovery
Montane grassland	0.50	Xia et al 2014 & Gill & Jackson 2000	Full recovery
Mangroves	2.69	Expert estimate	80.7
Note: Peatlands were excluded from this table because peatlands underly other aboveground land-uses. Annual sequestration rates for seagrasses and marshes are not well documented but we assumed full recovery.			

Soil organic carbon recovery

We determined whether SOC lost during the initial conversion could be fully recovered through subsequent restoration by applying restoration CRFs and EFs to the post-conversion SOC stock determined previously.. Due to a lack of globally consistent emissions factors, we divided our analysis into temperate and tropical zones to conform with data availability.

Boreal Forests

As mentioned previously, we assume no net change to initial boreal forest SOC stocks following wood harvest, so they were not considered in these calculations.

Temperate Forests

As mentioned previously, we assume no net change to temperate forest SOC stocks following wood harvest in the main assessment of ‘irrecoverable carbon’, but we did model forest recovery from row-crop cultivation using a representative CRF from Poeplau et al. 2011 as described above to determine the additional ‘irrecoverable carbon’ in temperate forests should agriculture the driver of forest loss.

Temperate Grasslands

Similar to the method used to determine SOC losses due to temperate grassland conversion, we used CRFs describing SOC gains resulting from restoration of croplands to grassland[42] to determine how much of the vulnerable carbon could be recovered within 30 years if the ecosystem reverted to the previous land use. Like the previous conversion CRF, this restoration CRF considers MAT and clay content in its predictions of SOC gain which were again represented using WorldClim2 and SoilGrids, respectively. The CRF was applied to the previously determined post-conversion SOC as before using a bootstrapping procedure to propagate and quantify uncertainty associated with the spatial variation of SOC and its covariates and the uncertainty of the model coefficients. This procedure resulted in a novel distributions of (i) SOC gain and (ii) post-restoration SOC stocks, from which we report the median and spread.

Tropical Forests and Grasslands

Emissions factors (EFs) were, likewise, used to determine expected gains to the post conversion SOC stocks of tropical ecosystems due to restoration. Once again, these EFs were taken from the meta-analysis of Don et al. 2011[43] and represent the average total SOC gain (%) resulting from restoration of croplands to either (i) secondary forest or (ii) grasslands. While EFs don't allow for the explicit consideration of change over a specified time period, those used represent the mean of observed changes of grassland and forest restoration, 22 (SE = 5) and 32 (SE = 7) years, respectively, after restoration was initiated and thus largely conform with our definition of irrecoverable carbon.

We applied these EFs to the previously determined post-conversion SOC stocks for the corresponding tropical ecosystems. Once again, EFs were adjusted such that they represent change to a depth of 30 cm as and were applied to the SOC estimates using the same bootstrapping procedure to propagate and quantify uncertainty associated with the spatial variation of SOC and the uncertainty of the depth correction and the EF estimate. This procedure resulted in a novel distributions of (i) SOC gain and (ii) post-restoration SOC stocks, from which we report the median and spread (Table S6).

Supplementary Table 7: Summary of modelled SOC loss due to conversion for agriculture and potential restoration by ecosystem

Ecosystem	Original median SOC (mean absolute deviation) (MgC ha^{-1})	Median % SOC lost in disturbance (mean absolute deviation)	Median SOC after disturbance (mean absolute deviation) (MgC ha^{-1})	Median % SOC that could be recovered with restoration (mean absolute deviation)	Median SOC after recovery (mean absolute deviation) (MgC ha^{-1})	Median % irrecoverable SOC (mean absolute deviation)
Temperate broadleaf forest (young)	137 (±20)	-34 (±19)	88 (±29)	22 (±14)	106 (±31)	19 (±19)
Temperate broadleaf forest (old)	137 (±20)	-34 (±19)	88 (±29)	22 (±14)	106 (±31)	19 (±19)
Temperate conifer forest (young)	138 (±18)	-16 (±16)	113 (±27)	11 (±11)	124 (±26)	9 (±15)
Temperate conifer forest (old)	138 (±18)	-16 (±16)	113 (±27)	11 (±11)	124 (±26)	9 (±15)
Tropical moist forest (young)	92 (±13)	-18 (±12)	74 (±15)	45 (±7)	92 (±22)	0 (±19)
Tropical moist forest (old)	92 (±13)	-23 (±15)	70 (±17)	45 (±7)	92 (±24)	0 (±22)
Tropical dry forest (young)	67 (±8)	-18 (±12)	54 (±11)	45 (±7)	67 (±16)	0 (±19)
Tropical forest (old)	67 (±8)	-23 (±15)	51 (±12)	45 (±7)	67 (±18)	0 (±22)
Temperate grassland	73 (±16)	-39 (±6)	43 (±11)	59 (±26)	68 (±18)	6 (±13)
Tropical grassland	40 (±9)	-23 (±15)	30 (±9)	45 (±7)	40 (±13)	0 (±22)
Montane grassland	101 (±22)	-34 (±5)	66 (±16)	25 (±16)	85 (±21)	16 (±10)

Notes: Any modeled values less than 0% were changed to 0% to reflect full recovery of the C content in 30 years. The median % C recovery over 30 years is relative to the pre-conversion SOC stock. A model for boreal SOC loss was not available, but not material to our analysis because boreal forests are primarily threatened by forestry / logging and unlikely to be converted to agriculture.

Coastal Ecosystems and Peatlands

SOC recovery rates for coastal ecosystems and peatlands were estimated based on literature review.

Supplementary Table 8: Average soil carbon recovery rates by major ecosystem type

Ecosystem	**Typical SOC sequestration rate (MgC ha^{-1} yr^{-1})**	**% carbon recovery over 30 years**	**Source / explanation**
Mangroves	1.68	33%	Taillardat et al 2018[67]
Seagrasses	0.83	51%	
Marshes	2.42	68%	
Boreal / Temperate Peatlands	0	0%	Peatland restoration following disturbance may reduce emissions but will not lead to net sequestration[27]
Tropical Peatlands	0	0%	
Notes: For coastal ecosystems, % recovery is estimated based on the SOC sequestration rate x 30 years / the average original carbon density.			

Global estimates of irrecoverable carbon

We estimated the typical amount of ‘irrecoverable carbon’ per hectare by subtracting the ‘recoverable carbon’ from the ‘vulnerable carbon’. The summary numbers in Table S8 below inform Figure 2 in the Main Text.

Supplementary Table 9: Average irrecoverable carbon density 30 years following loss, by ecosystem

Ecosystem	Irrecover-able biomass carbon	Irrecover-able SOC	Vulnerable but recoverable biomass carbon	Vulnerable but recoverable SOC	Biomass carbon not vulnerable to disturbance	SOC not vulnerable to disturbance	Total average carbon
Boreal forest	28.0	0.0	43.2	0.0	0.0	193.0	**264.2**
Temperate broadleaf forest (young)	33.3	0.0	50.3	0.0	0.0	137.0	**220.6**
Temperate broadleaf forest (old)	94.1	0.0	50.3	0.0	0.0	137.0	**281.4**
Temperate conifer forest (young)	44.7	0.0	48.5	0.0	0.0	138.0	**231.2**
Temperate conifer (old)	96.1	0.0	48.5	0.0	0.0	138.0	**282.6**
Tropical moist forest (young)	0.0	0.0	91.4	0.0	0.0	92.0	**183.4**
Tropical moist forest (old)	96.6	0.0	94.4	22.0	0.0	70.0	**283.0**
Tropical dry forest (young)	0.0	0.0	40.7	13.0	0.0	54.0	**107.7**
Tropical dry forest (old)	58.3	0.0	65.5	16.0	0.0	51.0	**190.8**
Temperate grassland	0.0	5.0	4.4	25.0	0.0	43.0	**77.4**
Tropical grassland	0.0	0.0	2.8	10.0	0.0	30.0	**42.8**
Montane grassland	0.0	16.0	3.2	19.0	0.0	66.0	**104.2**
Mangroves	90.4	242.0	51.0	50.4	0.0	68.6	**502.4**
Seagrasses	0.0	52.9	2.9	24.9	0.0	30.2	**110.9**
Marshes	0.0	80.4	10.5	72.6	0.0	102.0	**265.5**
Boreal /temperate peatlands	NA	135.0	NA	0.0	NA	365.0	**500.0**
Tropical peatlands	NA	450.0	NA	0.0	NA	54.0	**504.0**

Note: All values are in MgC ha^{-1}.

We then estimated the amounts of irrecoverable carbon and vulnerable-but-recoverable carbon in manageable ecosystems globally. These estimates are based on the global geographic extent of each ecosystem (generated using the Dinerstein biomes crossed with ESA land classes as described above, or literature review in the case of coastal and peatland ecosystems) and the average values of irrecoverable carbon and vulnerable but recoverable carbon by hectare and should be considered indicative values. Because our geographic extent numbers only consider the primary landcover in each biome (e.g., forested land classes within the boreal forest biome), our estimates of global irrecoverable carbon are conservative.

Supplementary Table 10: Global irrecoverable carbon and vulnerable but recoverable carbon 30 years following loss, by ecosystem

Ecosystem	**Global geographic extent (1000 km^2)**	**Irrecoverable carbon density (MgC ha^{-1})**	**Global irrecoverable carbon (Gigatonnes, estimated)**	**Vulnerable but recoverable carbon density (MgC ha^{-1})**	**Global vulnerable but recoverable carbon (Gigatonnes, estimated)**
Boreal forest	10,700	27	30	44	47
Temperate broadleaf forest	4,960	82	41	49	24
Temperate conifer forest	2,410	87	21	47	11
Tropical moist forest	11,700	66	77	113	132
Tropical dry forest	842	33	2.8	79	6.7
Temperate grassland	7,000	5	2.5	29	15
Tropical grassland	5,080	0	0	13	9.0
Montane grassland	2,600	16	4.2	22	5.8
Mangroves	145	335	4.9	99	1.5
Seagrasses	450	36	1.6	44	1.3
Marshes	210	88	1.8	76	1.7
Boreal peatlands	3,609	135	49	0	0
Temperate peatlands	587	135	2.5	0	0
Tropical peatlands	185	450	26	0	0
Total			**264**		**256**
Note: Because global geographic extent of forest ecosystems could not be delineated by 'young' and 'old', we used typical values across all age classes by ecosystem. The geographic extent of coastal ecosystems was derived from Howard et al, 2017[5] and peatlands from Leifeld et al, 2018[11].					

Recent loss rates

We used recent loss rates in each ecosystem based as documented in the literature to estimate the amount of irrecoverable carbon and vulnerable but recoverable carbon that could be at risk of release to the atmosphere over the next decade if recent loss rates continued. Timeframes differed slightly based on available data. For all forests and mangroves, we looked at annual average loss rates between 2000-2012. Other ecosystems are not tracked as consistently, so we used historical loss rates as available in the literature. These are documented in Table S11. Loss rates are indicative only and not necessarily predictive of future risk.

Supplementary Table 11: Historical/recent loss rates by ecosystem and carbon at risk

Ecosystem	% loss / year	Source
Boreal forest	0.18%	Based on Hansen et al. 2013;[68] 2000-2012 loss rates at 25% tree cover, refined using Curtis et al. 2018 to exclude tree cover loss due to wildfire[47] (not considered an anthropogenic driver)
Temperate broadleaf forest	0.35%	
Temperate conifer forest	0.28%	
Tropical moist forest	0.45%	
Tropical dry forest	0.58%	
Temperate grassland	0.14%	Based on Ramankutty et al. 1999[69] reported loss rate of 0.7 M ha per year (1980-1990), as cited in Griscom et al. 2017[70]
Tropical grassland	0.14%	Based on Ramankutty et al. 1999 reported loss rate of 1 M ha per year (1980-1990), as cited in Griscom et al. 2017
Montane grassland	0.14%	Assumed same loss rate as temperate and tropical grasslands
Mangroves	0.13%	Based on Global Mangrove Watch loss rates from 2000-2012[70]
Seagrasses	0.95%	Based on Waycott et al. 2009;[71] loss rates from 1980-2000.
Marshes	0.25%	Estimated based on Bridgham 2006;[72] 25% marsh loss since the 1800s (we assumed most loss occurred in the last century).
Boreal peatlands	0.0%	Based on recent loss rates reported Leifeld et al, 2019[73] (1990 to now)
Temperate peatlands	0.0%	
Tropical peatlands	0.6%	

Time to recovery

While 30 years was the key timeframe considered in our analysis, the recoverability criterion may be applied over any timeframe. To estimate the average number of years to recovery of vulnerable carbon by ecosystem (as shown in Table 2 in the Main Text), we used average biomass and soil sequestration rates and/or models (the same ones described above) to find the length of time necessary for all previously lossed carbon to be fully recovered after restoration is initiated. We used average vulnerable carbon densities by ecosystem, or the typical amount of carbon lost per hectare in the most common conversion event. In forest ecosystems, where more biomass carbon that SOC is originally vulnerable to loss during a conversion, the time to recovery is driven primarily by the biomass. Conversely, in grasslands and coastal ecosystems, the vulnerable biomass carbon would typically recover fully before the vulnerable SOC, so time to full recovery is driven by SOC. For peatland ecosystems, sequestration rates are extremely slow and not well-constrained, so our time to recovery is conservative and based on an expert estimate (by co-author Susan Page). To recover completely, tropical peatlands not only need to reestablish hydrological functioning but also vegetation cover that is capable of sequestering carbon and transferring it to an accumulating peat layer, and there is no field data to guide how long this might take.

Supplementary Table 12: Years to recovery of vulnerable carbon

Ecosystem	Average vulnerable biomass carbon (MgC ha-1)	Average time to recover biomass carbon (years)	Average vulnerable SOC (MgC ha-1)	Average time to recover SOC (years)
Boreal forest	71.5	**101**	0	NA
Temperate broadleaf forest	131.0	**78**	0	NA
Temperate conifer forest	134.3	**78**	0	NA
Tropical moist forest	160.1	**60**	19	29
Tropical dry forest	99.2	**77**	14	29
Temperate grassland	0.8	~1	30	**35**
Tropical grassland	1	~1	10	**19**
Montane grassland	0.6	~1	35	**205**
Mangroves	141.4	15	256	**153**
Seagrasses	2.6	5	78	**93**
Marshes	18.2	2	153	**64**
Boreal peatlands	NA	NA	135	**>100**
Temperate peatlands	NA	NA	135	**>100**
Tropical peatlands	NA	NA	450	**>200**
Note: Values in bold are the longer time to recovery and thus the number of years used in Table 2.				

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