Risks to carbon storage from land-use change revealed by peat thickness maps of Peru

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Tropical peatlands are among the most carbon-dense ecosystems but land-use change has led to the loss of large peatland areas, associated with substantial greenhouse gas emissions. To design effective conservation and restoration policies, maps of the location and carbon storage of tropical peatlands are vital. This is especially so in countries such as Peru where the distribution of its large, hydrologically intact peatlands is poorly known. Here field and remote sensing data support the model development of peatland extent and thickness for lowland Peruvian Amazonia. We estimate a peatland area of 62,714 km² (5th and 95th confidence interval percentiles of 58,325 and 67,102 km², respectively) and carbon stock of 5.4 (2.6–10.6) PgC, a value approaching the entire above-ground carbon stock of Peru but contained within just 5% of its land area. Combining the map of peatland extent with national land-cover data we reveal small but growing areas of deforestation and associated CO₂ emissions from peat decomposition due to conversion to mining, urban areas and agriculture. The emissions from peatland areas classified as forest in 2000 represent 1–4% of Peruvian CO₂ forest emissions between 2000 and 2016. We suggest that bespoke monitoring, protection and sustainable management of tropical peatlands are required to avoid further degradation and CO₂ emissions.

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Although tropical peatlands are known to be among the most carbon-dense ecosystems in the tropics 1,2, their absolute contributions to the global carbon cycle remains highly uncertain, with recent estimates placing their total below-ground carbon storage between 105 (70–130) and 215 (152–288) PgC (refs. 3,4). They face various threats, which include land-use and climate change 5,6. The deforestation and/or drainage of peatlands inhibit the accumulation of organic matter and promote the rapid decomposition of peat, which releases large quantities of the greenhouse gases (GHGs) CO₂ and N₂O into the atmosphere 7,8. Moreover, drained peatlands are prone to fires, which lead to large pulses of emissions 9. The experience of Indonesia provides a cautionary tale: in 1997 alone, it was estimated that between 0.81 and 2.57 PgC were released as a result of peat and vegetation fires, which at the time equated to 13–40% of global fossil fuel emissions 10. Indeed, the peatlands of Southeast Asia have already been severely damaged with almost 80% cleared and drained 11. In contrast, the largest known peatland areas in tropical Africa and South America are thought to remain largely intact 12,13. As such, commitments to avoid further deforestation and degradation by (1) promoting conservation and sustainable management of intact peatlands and (2) restoring degraded peatlands are essential to reduce CO₂ emissions and avoid global warming of 1.5 °C or more 14,15. A funding mechanism for this is potentially offered by United Nations Framework Convention on Climate Change initiatives, including REDD+ (reduce emissions from deforestation and forest degradation in developing countries) and wider nationally determined contributions 16 to the Paris Agreement, but a necessary first step towards conservation and restoration is reliable mapping of the spatial distribution of peatlands and their carbon stocks at scales relevant to the development of national policies. Peru has substantial known regions of hydrologically intact peatland. Previous research identified a large area in the Pastaza-Marañón Foreland Basin (PMFB) in northern Peru (Supplementary Fig. 1), and estimated its carbon stock to be 3.14 (0.44–8.15) PgC, which included above- and below-ground carbon 17, and a smaller area in the Madre de Dios (MDD) region of southern Peru, which holds an estimated 0.03 PgC (ref. 18). However, published wetland maps 19,20 and visual examination of remote sensing imagery suggest that there are probably other substantial peatlands in Peru whose carbon stocks remain unquantified. Even in the best-known region, the...
PMFB, previous mapping was based on relatively small numbers of peat thickness measurements and did not attempt to model and map the spatial variation in peat thickness\(^2\), one of the major sources of uncertainty in the below-ground carbon stock\(^1\). Rather, the total below-ground carbon stock for the PMFB was estimated by determining the area of different peat-forming vegetation classes (that is, peatland pole forest, palm swamp and open peatland) and multiplying those areas by a mean below-ground carbon stock for each vegetation class. This approach makes several simplifying assumptions\(^2\): that these three vegetation classes are always underlain by peat, that peat thickness varies more between than within classes and that other land-cover classes (including some wetland ecosystems, such as seasonally flooded forest) do not overlie peat\(^2\). In fact, field observations indicate that these assumptions are no longer valid; in particular, peat thickness varies substantially in space, which includes within single vegetation classes\(^3\). Data-driven maps that equate to an area of 1,951 km\(^2\) and a PC stock of 0.11 PgC (Supplementary Table 2).

We estimate that 2% of the seasonally flooded forest overlies peat\(^2\),22. In fact, field observations indicate that these three vegetation classes are always underlain by peat, that peat thickness varies more between than within classes and that other land-cover classes (including some wetland ecosystems, such as seasonally flooded forest) do not overlie peat\(^2\). In fact, field observations indicate that these assumptions are no longer valid; in particular, peat thickness varies substantially in space, which includes within single vegetation classes\(^3\). Data-driven maps that more accurately capture the spatial variation in peat thickness and carbon storage, and that cover not just selected study areas but the whole of Peruvian Amazonia, are required to support national and regional peatland conservation planning.

Although Peruvian peatlands are believed to remain largely intact, thus far there has been no quantitative assessment of the GHG emissions that result from land-cover change. Moreover, they face varied and increasing threats, which include agriculture expansion, illegal mining, oil exploration, infrastructure development and the selective felling of the female *Mauritia flexuosa* palm for commercial purposes\(^1\). In recognition of these threats, legislation was recently enacted that, for the first time, mandates the explicit protection of peatlands in Peru for climate-change mitigation\(^2\). To enforce this legislation effectively will depend on robust mapping of peatland distribution, and a knowledge of the scale and distribution of recent peatland disturbance, none of which is presently available.

Here we present extensive new field observations (Fig. 1) to test whether previous evidence of a relationship between distance to peatland edge and peat thickness found in other tropical peatlands\(^2\) also applies in Peru. These data are used along with remote sensing imagery to develop the first data-driven models of peatland extent and peat thickness distribution across the whole of lowland Peruvian Amazonia (LPA). We quantified the spatial variation and total peat carbon (PC) stock of these peatlands, and associated uncertainties. Finally, we used these models, along with national data on land-cover change (Geosubes), to map peatland disturbance and estimate the associated CO\(_2\) emissions for the period 2000–2016.

**Peat thickness distribution reveals a large carbon store**

We estimated a total peatland extent of 62,714 (58,325–67,102) km\(^2\) (Supplementary Fig. 2), a mean peat thickness of 203 (179–224) cm (Fig. 2 and Supplementary Fig. 3) and a total PC stock of 5.38 (2.55–10.58) PgC (Supplementary Fig. 4) across LPA. In addition to the well-known peatlands of the PMFB and MDD basin, we identified substantial areas of peatland in the Ucayali (11,110 km\(^2\); 2,258 km\(^2\) in the Tapiche sub-basin), Napo (3,670 km\(^2\)) and Putumayo (2,319 km\(^2\)) basins (Fig. 2, Supplementary Fig. 1 and Supplementary Table 1). Palm swamp is the most extensive peat-forming ecosystem (46,423 km\(^2\)) and therefore contains the greatest stock (3.83 PgC), even though pole forest and open peatland have higher PC densities (1,054 and 1,061 MgCha\(^{-1}\), respectively; Supplementary Table 2). We estimate that 2% of the seasonally flooded forest overlies peat, which equates to an area of 1,951 km\(^2\) and a PC stock of 0.11 PgC (Supplementary Table 2).

The distribution of peat thickness across LPA is highly variable, with the greatest mean peat thicknesses predicted in the Tigre (232 cm), Marañón (230 cm), Tapiche (234 cm) and Napo (223 cm) basins (Fig. 2 and Supplementary Table 1). Our models of peatland area and peat thickness distribution performed well against observations (Supplementary Table 3 and Supplementary Fig. 5), which gives confidence in our results. We ran two separate peat thickness models: one for the MDD basin and another for the rest of the study area (which contains 97% of the total peatland area). The model that excluded the MDD basin performed better \((P < 0.0001, R^2 = 0.66, \text{ root mean square error (r.m.s.e.)} = 66\%); \text{Supplementary Fig. 5a}) than the MDD model \((P < 0.0001, R^2 = 0.38, \text{ r.m.s.e.} = 70\%); \text{Supplementary Fig. 5b})\). We found a significant linear relationship between peat thickness and distance to peatland edge \((P < 0.0001, R^2 = 0.13); \text{Supplementary Fig. 6a})\). This relationship was more significant when the data from the MDD basin were excluded (which gave \(R^2 = 0.39, P < 0.0001); \text{Supplementary Fig. 6b})\) and there was no significant relationship between peat thickness and distance to peatland edge within the MDD data \((P > 0.1, R^2 = 0.005); \text{Supplementary Fig. 6c})\).

**CO\(_2\) emissions from land-use change are small but growing**

Our analysis of land-use change data shows that a total peatland area of 1,052 km\(^2\) was drained and/or cleared during 2000–2005, which increased to 1,667 km\(^2\) by 2013–2016 (Table 1). Annual emissions from peat decomposition also increased from 3.26 million MgCO\(_2\)yr\(^{-1}\) in 2000–2005 to 5.11 million MgCO\(_2\)yr\(^{-1}\) in 2013–2016, and the total estimated emissions accounted for 63.83 million MgCO\(_2\) during the period 2000–2016 mainly due to deforestation (Fig. 3b). Our analysis suggests rapid increases in CO\(_2\) emissions from the conversion to mining, urban areas and agriculture, which increased from 2000 to 2016 by 11 times (from 2,426 to 27,634 MgCO\(_2\) yr\(^{-1}\)) in 2013–2016, and the total estimated emissions accounted for 63.83 million MgCO\(_2\) during the period 2000–2016 mainly due to deforestation (Fig. 3b). Our analysis suggests rapid increases in CO\(_2\) emissions from the conversion to mining, urban areas and agriculture, which increased from 2000 to 2016 by 11 times (from 2,426 to 27,634 MgCO\(_2\)yr\(^{-1}\)), 9 times (from 2,848 to 26,881 MgCO\(_2\)yr\(^{-1}\)) and 5 times (from 77,807 to...
411,528 MgCO$_2$ yr$^{-1}$), respectively (see Supplementary Tables 4 and 5 for further details). These estimates exclude emissions from areas in which natural peatland vegetation may have been misclassified in 2000 as secondary forest in the land-cover dataset Geobosques (which amounts to 1,353 km$^2$; Supplementary Table 5). These misclassified areas were revealed by visual inspection of a Google map image of the department of Loreto by someone with local expert knowledge (Fig. 3a).

For those areas classified as forest in 2000, as accounted for in Peru’s 2016 Forest Reference Emission Level report, emissions from peat decomposition represent 0.99–3.72% of the total national CO$_2$ emissions from LPA forests (that is, from peat decomposition and biomass loss due to gross deforestation; Table 1).

**Synthesis and future directions**

Our estimate of the total PC stock of 5.38 (2.55–10.58) PgC across LPA is 75% of a recent estimate of the entire above-ground C stock of Peru$^{29}$, and approximately doubles previous estimates of the Peruvian tropical peat stock calculated for the PMFB and the MDD regions only.$^{19,22}$ Our maps are driven by intensive field sampling which has, for the first time, generated peat thickness data widely across LPA, and which confirms that substantial peatlands extend far beyond the relatively well-studied PMFB. Across the main peat-forming land-cover classes of pole forest, open peatland and palm swamp, above-ground carbon densities (Supplementary Table 2) are an order of magnitude lower than the respective PC densities, and total 0.45 PgC (Supplementary Table 2). Summing the above- and below-ground carbon stocks gives a central estimate of 5.83 PgC stored in LPA peatlands.

The quantitative uncertainties around the peatland carbon stock are reduced compared with those of previous studies, even though our study covers an area more than five times greater.$^{2,22}$ Future improvements may be gained by collecting field data where they are still lacking, notably the northwest PMFB and parts of the Ucayali (for example, around Pucallpa) and Morona basins. Unlike previous studies$^{2,22}$, our study placed no constraints on which land-cover classes peat can form under, and we predict that around 2% of seasonally flooded forest is underlain by peat. This suggests that the search for peat should not be solely limited to the well-known peat-forming vegetation types of palm swamp, pole forest and open peatland. In addition to land-cover classification maps, we recommend that future fieldwork is informed by examining maps and remote sensing imagery related to hydrology and inundation, such as height above nearest drainage$^{30}$, normalized difference water index$^{31}$ and ALOS-PALSAR$^{32}$ (where possible with multitemporal images).

Our approach is driven by remote sensing layers with a global coverage and can thus be readily adapted to other regions, provided sufficient field data are available for calibration and validation. Our results call for caution in treating all tropical peatlands as similar, and demonstrate the importance of field data. For example, the distance to peatland edge has been found to correlate with peat...
thickness in other regions, such as the Congo basin\textsuperscript{1}, and in most of the basins we studied in Peru. However, we found no significant linear relationship between peat thickness and distance to peatland edge for the data in the MDD basin (\(P > 0.1, R^2 = 0.005\); Supplementary Fig. 6c). Householder et al.\textsuperscript{19} suggest that this may be because of specific geological conditions in this region: many of the deepest peats in the MDD are often located adjacent to upland (terra firma) terraces, close to the peatland edge. This means that the relationship between peat thickness and distance to peatland edge is more complex in MDD than in other regions. Past research points to geomorphological differences between the northern and southern parts of Peruvian Amazonia\textsuperscript{33}; although floodplains in

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**Table 1 | Mean CO\textsubscript{2} emissions from peat decomposition (95% confidence interval) and biomass loss across LPA from 2000 to 2016**

| Period          | 2000–2005 | 2005–2011 | 2011–2013 | 2013–2016 |
|-----------------|-----------|-----------|-----------|-----------|
| Duration (years)| 5         | 6         | 2         | 3         |
| Total peatland area with disturbance (km\textsuperscript{2}) | 1,051.63 | 1,264.50 | 1,392.82 | 1,666.76 |
| Total emissions from peat decomposition due to disturbance (\(\times 10^6\) MgCO\textsubscript{2}) | 16.29 (6.94–29.16) | 23.27 (9.91–41.61) | 8.95 (3.73–16.03) | 15.33 (6.12–27.59) |
| Peatland area with disturbance for categories classified as forest in 2000 (km\textsuperscript{2}) | 158.46 | 404.38 | 536.48 | 808.92 |
| Emissions from peat decomposition due to disturbance for categories classified as forest in 2000 (\(\times 10^6\) MgCO\textsubscript{2}) | 1.25 (0.44–2.25) | 5.33 (1.94–9.55) | 2.98 (1.08–5.35) | 6.40 (2.21–11.59) |
| Gross deforestation throughout LPA areas classified as forest in 2000 (km\textsuperscript{2})\textsuperscript{a} | 2,483.38 | 3,945.33 | 1,915.72 | 3,303.01 |
| Emissions from biomass loss due to gross deforestation throughout LPA (\(\times 10^6\) MgCO\textsubscript{2})\textsuperscript{b} | 124.80 | 198.65 | 95.85 | 165.60 |
| Percentage due to peat decomposition for categories classified as forest in 2000 | 0.99 (0.35–1.77) | 2.61 (0.97–4.59) | 3.02 (1.12–5.29) | 3.72 (1.32–6.54) |

Calculated using the peatland model and the Geobosques dataset\textsuperscript{42}. Peat emissions are from this study and biomass emissions are national estimates. \textsuperscript{a}2016 Forest Reference Emission Level report of Peru\textsuperscript{28}. \textsuperscript{b}CO\textsubscript{2} emission from biomass includes both above- and below-ground biomass of living trees as calculated in the 2016 Forest Reference Emission Level report of Peru\textsuperscript{28}.

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**Fig. 3 | Distribution of peatlands classified as natural vegetation, secondary vegetation and deforestation based on the 2016 forest land and land-use categories within Geobosques\textsuperscript{42} in LPA.** Non-peatland areas are shown in grey, and the relevant departments of Peru are labelled within the study area. \textit{a,b}. Google map images show examples of natural peatland vegetation misclassified as secondary forest \textit{(a)} around the Puinahua channel and the Ucayali River in the department of Loreto, and peatland areas correctly classified as deforestation \textit{(b)} near Pucallpa in the department of Ucayali. Panels \textit{a} (left) and \textit{b} (left) reproduced with permission from TerraMetrics. Panels \textit{a} (right) and \textit{b} (right) adapted with permission from TerraMetrics.
northern Amazonia are often wide, rivers in southern Amazonia more often have narrow floodplains confined by terraces. We recommend that new transects should aim to target a range of landscape types (for example, based on elevation maps) and, where possible, should cover the full cross-section of each individual peatland. In spite of this limitation, our random forest regression model for the MDD region performs reasonably well.

This study assessed CO₂ emissions that result from peat decomposition due to land-cover change in Peru. Our results suggest that land-cover change in the peatlands of LPA has thus far been restricted to a few hotspot areas, with the largest area of deforestation identified near Pucallpa in the department of Ucayali, an area in which recent ground observations confirm the presence of deforested peatlands (E.N.H.). Access to these peatlands has been facilitated by the development of roads and the increasing demand for land for commercial plantations (for example, oil palm and rice),[14,15] and, D. García-Soria, personal communication. Overall, the estimated emissions from peat decomposition remain low in Peru, but our analysis suggests that the annual emissions are increasing. These findings have two implications for the conservation of these ecosystems. First, the low current emissions support the view that the extensive peatland complex of LPA is an emblematic example of hydrologically intact moist tropical forest with a high structural integrity and therefore should be a high conservation priority.[14,15,16,17] Second, the increasing threats and rising emissions from specific land-use transitions in some peatlands mean that it is important to improve the detection of deforestation and secondary vegetation across the full range of peatland forest types, and to make more extensive measurements of GHG emissions associated with specific land-use transitions across the different forest types.

Taken together, our results indicate a carbon stock within the peatlands of LPA that is three-quarters as large as the entire above-ground carbon stock of Peru but contained within just 5% of its land area. The peatlands also contribute substantial ecosystems and floristic diversity to the Amazon[14,15]. Although our study indicates that these peatlands remain largely intact, they face varied and growing threats.[15,16] Our mapping and carbon stock estimates may be used to support the implementation and enforcement of recent legislation that aims to reduce emissions[17] and should act now. Nature 593, 191–194 (2021).

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Methods

Fieldwork. Between 2019 and 2021, we collected 445 new GRPs within LPA (Fig. 1: 294 of these were presented by Honorio Coronado et al.), which included data on the substrate (that is, peat thickness, where peat is present) and vegetation type (for example, palm swamp). We focused data collection on regions with no existing GRPs and in which peat was believed to be present based on remote sensing imagery (for example, various Landsat 8 (Supplementary Fig. 7) and Sentinel-2 bands), and included the Napo, Putumayo, Tapiche and Tigre river basins (Fig. 1 and Supplementary Fig. 1), using the only available means of access, that is, via rivers and streams. We also collected new data on peat thickness and carbon concentration from under-sampled peatland ecosystems (for example, peatland pole forest). We made the sampling as spatially representative as possible within the constraints of logistical feasibility, personal safety and accessibility, which are substantial in these remote regions of Peru. The previously published datasets that we incorporated here were also subject to the same constraints.

Within the present study, depth was measured using an auger or Russian type peat corer, either along transects perpendicular to the river at intervals of 200–500 m, or at the four corners and centre of the vegetation plots (see below) in which case the value for peat thickness used is the mean of five point measurements. Working along transects that led away from the river and into the peatlands allowed us to sample across wide hydrological and topographic gradients, which included both minerotrophic and ombrotrophic ecosystems. At 91 of these GRPs, we collected 1,050 or 0.1 ha vegetation plot surveys (collecting floristic data) for the quantitative classification of ecosystem type (Supplementary Methods). Additionally, we used 218 previously published GRPs (24 with floristic data) collected using a similar transect sampling strategy in northern Peru and 465 GRPs (with floristic data) collected in southern Peru, which amounted to a total of 1,128 GRPs (Fig. 1). Of these, 887 GRPs (Supplementary Fig. 8) indicated the presence of peat (defined as an organic layer ≥30 cm thick). Two examples of transects of peat thickness measurements in the Napo basin are shown in Supplementary Fig. 7.

The majority of peat thickness observations do not have corresponding carbon concentration measurements and thus we cannot enforce a precise cutoff in terms of carbon content. However, we visually identified peat and underlying sediments in the field on the basis of their physical properties (for example, colour, structure and texture) and composition (for example, wood, roots and mineral components). At 35 vegetation plots identified by fieldworkers as being on peat, we took sediment samples in the near-basal peat, transition zone and underlying mineral sediment (typically silts or clays) and measured the loss on ignition (LOI) in each to test the visual assessments. The peat transition zone and mineral samples had mean LOI values of 70, 28 and 13%, respectively (Supplementary Table 6). This gives us confidence that fieldworkers in this region are able to visually identify peat (in this case, soil with an LOI of at least 50%), as there is typically a clear and distinct transition to mineral sediment in Peruvian peatlands.

Model of predicted peatland extent in LPA. We created a 50-m-resolution map (Supplementary Fig. 2) of predicted peatland extent in LPA (defined here as the area covered by two of the ecozones recognized by Peru’s Ministry of Environment: Ecoweb Selva Baja and Ecoweb Hidromórficas). First, we ran a supervised random forest algorithm (200 trees) in Google Earth Engine to predict the distribution of five classes: peat forest, peat below non-forest (that is, herbaceous vegetation and shrubland), non-peat forest, non-peat below non-forest and open water. The model was trained and validated (50/50 split of the data) with 80% of the data (randomly selected) and testing with the remaining 20% (Supplementary Fig. 5c,d).

To account for the uncertainty associated with our estimate of peat thickness distribution, we ran a k-fold analysis as in Rodriguez-Veiga et al., splitting the data into 1,000 folds and therefore generating 1,000 predictions of peat thickness per pixel. We took the median, 5th and 95th percentiles of the 1,000 predictions to represent our best estimate (Fig. 2a), minimum (Supplementary Fig. 3a) and maximum (Supplementary Fig. 3b) peat thickness distributions. We subsequently masked the maps of peat thickness distribution using the map of peatland extent (Supplementary Fig. 2) and thus restricted our model to only regions predicted to contain peat.

Below-ground carbon stock. A dataset of 68 stratigraphic profiles of carbon concentration (%) and dry bulk density (DBD (g cm⁻³)) was compiled using data from refs. 23,24,51 (Supplementary Table 9). This included ten new profiles collected as part of this study and described in Honorio Coronado et al. (Supplementary Table 4 of Honorio Coronado et al.). We calculated PC stock (MgC ha⁻¹) from the peat cores by multiplying peat thickness (cm) by DBD and carbon concentration evaluated at regular intervals down the peat profile to the base of the peat. Laboratory conditions varied depending on the study and can be found in the original papers, along with information on protocols. The studies used a variety of standard methodologies to determine the sample carbon concentrations. In line with our definition of peat, we only retained those profiles which the peat was ≥30 cm thick, with a mean LOI of ≥50% and those collected using a Russian corer to ensure that DBD measurements were based on a reliable volumetric sample.

We performed a sensitivity analysis to test which of the three components of PC (that is, peat thickness, DBD and carbon concentration) is the most important. Peat thickness was found to be the most important determinant of total PC (P < 0.0001, R² = 0.81; Supplementary Fig. 11). We thus used our model of peat thickness distribution to estimate the total PC for each 100-m grid cell and then summed across the entire LPA to produce a total value for the PC stock.

To produce uncertainty bounds for our estimate of the total PC stock, we ran a Monte Carlo analysis which accounted for the uncertainty in each stage of our methodology. We ran 1,000 simulations for PC, constrained using the standard error of the k-estimates from the regression equation (peat thickness versus PC; Supplementary Fig. 11). This was performed twice, once using the 5th and then the 95th percentile distribution of peat thickness calculated previously (Supplementary Fig. 5a). We used 1,000 PC simulations in turn multiplying by 100 simulations of peatland area per grid, constrained by the confidence intervals calculated previously. Finally, the maps of the 5th and 95th percentile of PC stock per grid were summed across LPA to derive the final minimum and maximum uncertainty bounds.

Activity data and emissions from peat decomposition. To estimate changes in forest cover, we used reports of activity data provided by Peru’s national monitoring platform, Geoobservaciones. These reports were generated using Landsat 8 and Sentinel-2 images from 2001 to 2016, with cumulative areas of different land uses for the year 2000. In these data, Peruvian Amazonia is classified into 11 land uses for the periods 2000–2005, 2005–2011, 2011–2013 and 2013–2016. Figure 3 shows our predicted peatland map (produced by re-running our model at a 50 m resolution to match activity dataset grid) plotted against natural vegetation (forest, forest on wetland, wet savannah, water body and non-forest on wetland), secondary vegetation and deforested areas (agriculture, pasture, urban areas, mining areas and bare ground).

Emission factors for organic soils were taken from Chapter 2 of the 2013 Supplement to the 2006 IPCC Guidelines for the National GHG Inventory of Wetlands (IPCC, Intergovernmental Panel on Climate Change). The values range from 7.5 MgCha⁻¹yr⁻¹ for secondary vegetation to 9.6 MgCha⁻¹yr⁻¹ for deforested peatlands (Supplementary Table 4). These IPCC values are intended to be used for drained peatlands, but peatland disturbance in Peru does not necessarily entail drainage. Nonetheless, undrained secondary forests on peat in Indonesia lose soil carbon at a similar rate to that of shallow-drained palm plantations (1.5 MgCha⁻¹yr⁻¹ (ref. 6)) and CO₂ emissions in highly degraded undrained peatlands in Peru (for example, degraded Mauritia-dominated palm swamps classified as secondary vegetation, 7.1 Mg Cha⁻¹yr⁻¹ (ref. 7)) fall within the range of the values of deforested drained peatlands in Indonesia.
Where PDE is total CO₂ emissions from peat decomposition (Mg CO₂); A is the area (ha) on peatlands of the original land-use category i that was converted into category j during the time period t (yr); EF is the mean annual emission factor of peat decomposition assigned to the conversion from category i to category j (MgCha⁻¹·yr⁻¹) and converted into CO₂ by multiplying by the atomic mass factor of 44/12 (refs. 44,45). For example, within peatlands (according to our map), forest on wetland (ecosystem saturated with water and assumed zero CO₂ emissions) that is converted into mining area (ecosystem assumed similar to that of drained grasslands with emissions of 9.6 MgCha⁻¹·yr⁻¹) will receive an EF value of 4.8 MgCha⁻¹·yr⁻¹ following ref. 46 method (Supplementary Table 5).

Data availability
An interactive map of modelled peatland extent (50 m resolution) can be viewed at https://code.earthengine.google.com/a07b25e62adb7ce71a6fa77e4a34e23b1b and the source map downloaded at https://datashare.ed.ac.uk/handle/10283/4364. An interactive map of the modelled land-cover class (50 m resolution) can be viewed at https://code.earthengine.google.com/3a6655b536db612be1d7lid09991530 and the source map downloaded from https://datashare.ed.ac.uk/handle/10283/4364. An interactive map of the modelled peat thickness distribution (100 m resolution) can be viewed at https://code.earthengine.google.com/8845760a7e086df8b1e66075985e705 and the source maps downloaded from https://datashare.ed.ac.uk/handle/10283/4364. An interactive map of the modelled peat thickness distribution (100 m resolution) can be viewed at https://code.earthengine.google.com/394ed1f119c1917f5cf086b909c8194 and the source maps downloaded from https://datashare.ed.ac.uk/handle/10283/4364. The MINAM Geobosques® raster file can be downloaded from https://geobosques.minam.gob.pe/geobosque/view descargas.php/122345gxx345w34gg.

Code availability
The Google Earth Engine links include code for some basic analysis of the maps. Code for other parts of the analysis will be made available upon reasonable request to the corresponding author.

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Author contributions
A.H., I.T.L., E.N.H.C., E.T.A.M., K.H.R., T.R.B., L.E.S.C. and C.E.W. all contributed to the conception, development and design of the study. A.H. and E.N.H.C. performed the analysis with input from E.T.A.M., K.H.R., I.T.L., C.M.A., T.R.B., G.D. and E.C.D.G.; Leverhulme Trust (grant ref. RPG-2018-306) to K.H.R., L.E.S.C. and C.E.W.; Gordon and Betty Moore Foundation (grant no. 5439, MundoPeru network) to T.R.B., E.N.H.C. and G.F.; Wildlife Conservation Society to E.N.H.C.; Conicyte/British Council/Embajada Británica Lima/Newton Fund (grant ref. 220–2018) to K.H.R. and J.D.; Conicyte/NERC/Embajada Británica Lima/Newton Fund (grant ref. 901–2019) to E.N.H.C. and N.D.; the governments of the United States (grant no. MTO-009018) and Norway (grant agreement no. QZA-12/0882) to K.H.; and NERC Knowledge Exchange Fellowship (grant ref. no. NE/V018760/1) to E.N.H.C. We thank SERNANP, SERFOR and GERFOR for providing research permits, and the different Indigenous and local communities, research stations and tourist companies for giving consent and allowing access to the forests. We acknowledge the invaluable support of technicians J. Iraurica, J. Sanchez, H. Vasquez and R. Flores, without whom much of the fieldwork would not have been possible.

Competing interests
The authors declare no competing interests.

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