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A new data-driven map predicts substantial undocumented peatland areas in Amazonia

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Abstract

Tropical peatlands are among the most carbon-dense terrestrial ecosystems yet recorded. Collectively, they comprise a large but highly uncertain reservoir of the global carbon cycle, with wide-ranging estimates of their global area (441 025–1700 000 km^2) and below-ground carbon storage (105–288 Pg C). Substantial gaps remain in our understanding of peatland distribution in some key regions, including most of tropical South America. Here we compile 2413 ground reference points in and around Amazonian peatlands and use them alongside a stack of remote sensing products in a random forest model to generate the first field-data-driven model of peatland distribution across the Amazon basin. Our model predicts a total Amazonian peatland extent of

251 015 km^2 (95th percentile confidence interval: 128 671–373 359), greater than that of the Congo basin, but around 30% smaller than a recent model-derived estimate of peatland area across Amazonia. The model performs relatively well against point observations but spatial gaps in the ground reference dataset mean that model uncertainty remains high, particularly in parts of Brazil and Bolivia. For example, we predict significant peatland areas in northern Peru with relatively high confidence, while peatland areas in the Rio Negro basin and adjacent south-western Orinoco basin which have previously been predicted to hold *Campinarana* or white sand forests, are predicted with greater uncertainty. Similarly, we predict large areas of peatlands in Bolivia, surprisingly given the strong climatic seasonality found over most of the country. Very little field data exists with which to quantitatively assess the accuracy of our map in these regions. Data gaps such as these should be a high priority for new field sampling. This new map can facilitate future research into the vulnerability of peatlands to climate change and anthropogenic impacts, which is likely to vary spatially across the Amazon basin.

1. Introduction

Tropical peatlands, which include some of the most carbon dense terrestrial ecosystems known to science (Dommain *et al* 2011, Draper *et al* 2014), are a substantial but highly uncertain component of the global carbon cycle. Estimates of their total area range from 441 025 (Page *et al* 2011) to 1700 000 km^2 (Gumbricht *et al* 2017), and of their total below-ground carbon from 105 (70–130) to 215 (152–288) Pg C (Dargie *et al* 2017, Ribeiro *et al* 2021). Tropical peatlands host invaluable biodiversity (Posa *et al* 2011, Draper *et al* 2018) and support the livelihoods of local populations throughout the tropics (Page and Baird 2016; Roucoux *et al* 2017, Girkin *et al* 2022). However, various pressures including climate and land use change threaten the integrity of tropical peatlands (Roucoux *et al* 2017, Baker *et al* 2019, Dargie *et al* 2019, Mishra *et al* 2021, Lawson *et al* 2022), with South-East Asia being a cautionary example. Approximately 80% of South-East Asian peatlands have been deforested and drained to make way for plantations and agriculture (Mishra *et al* 2021) and peat fires in Indonesia have caused huge pulses of CO_2 emissions to the atmosphere (Page *et al* 2002, Huijnen *et al* 2016). These events have also been linked to tens of thousands of premature human deaths (Johnston *et al* 2012), the loss of invaluable flora and fauna (Posa *et al* 2011), as well as huge economic costs (Kiely *et al* 2021). It is thus urgent that we develop reliable estimates of tropical peatland distribution and carbon stocks to inform and prioritise conservation and climate change mitigation actions.

Decades of research have resulted in relatively high confidence in peatland mapping in Southeast Asia (Jaenicke *et al* 2008, Warren *et al* 2017), yet substantial gaps remain in our understanding of the distribution of peatlands and their carbon stores in other key tropical regions (Xu *et al* 2018, Ribeiro *et al* 2021, Melton *et al* 2022). There have been recent intensive field efforts in regions such as the Congo basin (Crezee *et al* 2022) and Peruvian Amazonia (Hastie *et al* 2022), which have driven the development of more accurate regional peatland and below-ground carbon maps. Despite research on peatlands in the Tepuis region of Venezuela (Zinck and Huber 2011), recent progress in Peru (Honorio Coronado *et al* 2021, Hastie *et al* 2022), and ongoing efforts in Colombia (Santofimio-Tamayo and Benavides 2019, Winton *et al* 2021), the Amazon basin arguably remains the greatest remaining knowledge gap in tropical peatland research. Central, eastern, and southern Amazonia are particularly understudied. A 2013 study (Lähteenoja *et al* 2013) confirmed the presence of peat at a handful of sites within the Rio Negro River basin, but otherwise the distribution of peat across Brazil remains poorly understood. Pantropical peat distribution modelling by Gumbricht *et al* (2017) estimated that Brazil could hold the single greatest peatland area in the tropics, more than twice that of Indonesia.

Maps of peatlands across the Amazon basin have primarily relied on modelling approaches due to the limited availability of field data. Gumbricht *et al*'s study was driven by a distributed hydrological model, as well as remote-sensing products, and required a positive interannual water balance for peatland presence. This approach is justified in regions with sparse field data, but the results remain extremely uncertain: Gumbricht *et al* (2017) used a total of only 275 field data points for ground-truthing (validation) of their maps across the entire tropics (and no data for model training). Melton *et al* (2022) developed a global peat distribution model, driven by various remote-sensing predictors and trained and tested using previously derived (i.e. secondary) peatland mapping products. The Melton map therefore inherits the limitations of its input maps and like the Gumbricht product is only indirectly guided by field data. Peatland mapping, particularly in the tropics, requires closer integration with expanded in situ databases to reach higher levels of accuracy and reliability for regional/national-scale applications.

Here we combine new and published field data to establish a database of 2413 ground reference points (GRPs) in and around the peatlands of the Amazon basin, including 548 new GRPs in Brazil. We use these GRPs along with radar and optical remote sensing imagery and topographical data, in a random forest model to produce the first high-resolution (90 m resolution) field-data-driven map of peatland extent across the entire basin. We then use this map and an assessment of its uncertainties to identify and discuss the remaining gaps in our understanding of peatland distribution in the Amazon basin.

2. Methods

2.1. GRPs

The dataset used here represents more than a decade of fieldwork in and around the peatlands of the Amazon basin by several teams (table S1). The data include 1702 published (including grey literature-i.e. theses and governmental reports) GRPs from Peru (Lähteenoja *et al* 2009, 2012, Householder *et al* 2012, Draper *et al* 2014, de Jong 2019, Diaz Cardenas 2019, Honorio Coronado *et al* 2021, Hastie *et al* 2022, IIAP-PROFONANPE 2023, Lawson *et al* 2023); 548 unpublished GRPs from Brazil, plus nine published by Lähteenoja *et al* (2013); 147 GRPs from Colombia (comprising 87 GRPs digitized by Paukku (2021) from Duivenvoorden and Lips (1991a, 1991b), 56 unpublished GRPs by Winton *et al* (2021), and four GRPs from Santofimio-Tamayo 2019); five GRPs from Ecuador (Montoya, E., unpublished); and two from Bolivia (Escobar-Torrez *et al* 2020, Smith *et al* 2021) (table S1). At each GRP, substrate type was recorded, along with an assessment of overlying vegetation cover (in this study simply forest or non-forest). Peat thickness (where present) was measured using a gouge auger or a Russian-type corer, typically along transects at 100–500 m intervals.

Of the total 2413 GRPs, 1590 were defined as peat, meaning an organic layer of at least 30 cm, with the remaining 823 defined as non-peat (figure 1). At the majority of GRPs, no corresponding soil carbon concentration or organic matter measurements were taken. Thus, we could not impose a minimum carbon concentration or organic matter threshold for our definition of peat. However, we visually identified peat based on composition (e.g. roots, wood) and physical properties (e.g. structure, colour, texture) (Troels-Smith 1955, Kershaw 1997). Previous studies have shown that Amazonian peatlands typically show a clear transition from an organic layer to underlying mineral sediment. For example, Hastie *et al* (2022) found that material visually defined as peat had a mean loss on ignition (LOI) of 70%, whilst material defined as mineral had a mean LOI of only 13% (table S2). We are thus confident that our peat GRPs represent an LOI of at least 50%, a common definition of peat (Burton & Hodgson., 1987, Gumbricht *et al* 2017). Dargie *et al* (2017) also demonstrated that a similar visual method was effective at identifying peat in the Congo basin.

2.2. Model of peatland extent

We used our 2413 GRPs to train a supervised random forest algorithm (250 trees, three variables per split, at 90 m resolution) in Google Earth Engine. We used a minimum 20 m diameter buffer to create polygons around our sample points to sample gridded predictors. We merged adjacent polygons of the same class wherever possible; for example, in situations where they were sufficiently close together (i.e. within a 90 m grid cell) or where we were confident (based on field/local knowledge) that the soil did not substantially change between sites. We supplemented our GRPs with additional data points within or close to predicted peatlands, from the RADAMBRASIL soil profile database (figure S1, Negreiros *et al* 2009 e.g. in locations where preliminary maps predicted isolated peat patches), as well as with points which could be assumed to lack peat such as urban settlements and rivers (based on visual examination of satellite images).

The model was driven using a remote sensing stack (table 1, 11 bands in total) containing selected Landsat 7 bands and indices (Hansen *et al* 2013) including normalized difference water index (NDWI) and normalized difference vegetation index (NDVI), ALOS PALSAR HH polarisation & HH/HV (Shimada *et al* 2014), height above nearest drainage (HAND Donchyts *et al* 2016), upstream drainage area (UPA, Yamazaki *et al* 2019), slope (derived from SRTM 30 m DEM, Farr *et al* 2007), and topographic landforms (Theobald *et al* 2015). The Landsat bands and indices are important for inferring overlying ecosystem type and vegetation density. HAND, UPA, slope and topographic landforms provide information on the relative topographical and hydrological position of each grid cell, and in turn an approximation of wetness. Variation in PALSAR L-band backscatter is indicative of variation in soil/vegetation moisture as well as forest structure. We started the model with more variables but removed several bands to avoid overfitting. Namely, we removed Landsat 7 Band 3 (red), Band 7 and ALOS PALSAR-HV polarisation as they exhibited particularly high collinearity (Pearson correlation of >0.85, $p < 0.001$) with other driver variables (table S3). Their removal only marginally reduced model performance.

We used the algorithm to map the following five categories: peat below forest (PF), peat below non-forest (PN), non-peat below forest (NF), non-peat below non-forest (NN), and open water (WA). The forested versus non-forested categories were chosen largely for remote sensing reasons, i.e. they are easy for satellite derived data to delineate and because we

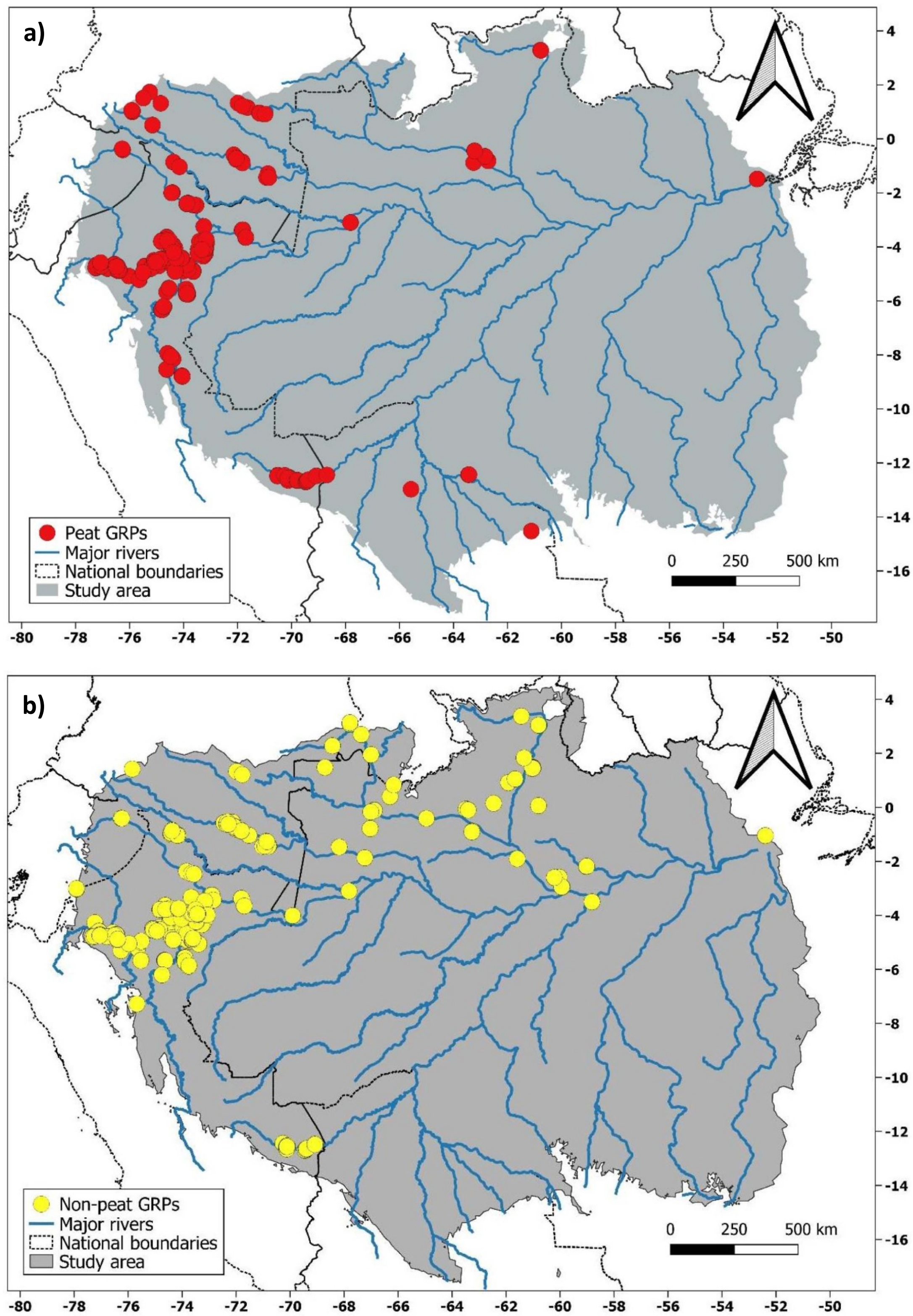

Figure 1. Distribution of (a), the peat ground reference points (GRPs) and (b), non-peat GRPs sampled for peat presence/absence, peat thickness (where present) and vegetation cover used in this study.

believe that the distribution of forested versus open peatlands could be of interest to the research community (figure S2).

We evaluated model accuracy using a spatial leave one out cross validation (e.g. Meyer *et al* 2019, Garcia 2021) tailored to our dataset. Our data was collected in four main areas which were used to inform the selection of four clusters for the spatial cross validation: (1) Northern Peru (centred around the Pastaza-Marañón foreland basin, PMFB), (2) Colombian Amazonia, (3) Southern Amazonia, (4) Brazilian Amazonia (figure S3). These clusters of

Table 1. Data used as predictors in the peatland classification random forest model.

Dataset	Resolution (m)	Acquisition date	Polarisation/Bands/ Indices	Source
PALSAR-2/PALSAR annual mosaics	25	2014–2023 (period median)	HH, HH/HV	Shimada *et al* (2014)
Landsat 7 mosaic	30	2021 (growing season median)	Band 4(NIR), Band 5 (SWIR), NDVI, NDWI	Hansen *et al* (2013)
Slope (SRTM)	30	2000	NA	Farr *et al* (2007)
Upstream drainage area (flow accumulation grids, MERIT)	50	1987–2017	NA	Yamazaki *et al* (2019)
Height above nearest drainage (HAND)	90	2016	NA	Donchyts *et al* (2016)
Landforms (SRTM)	90	2006–2011	NA	Theobald *et al* (2015)
Landforms (ALOS)	90	2006–2011	NA	Theobald *et al* (2015)

data were collected independently on separate field campaigns with different team members (albeit with some crossover between Southern Peru and Brazilian Amazonia). Moreover, none of these regions share a substantial contiguous peatland area. Thus, we consider these clusters as sufficiently independent and therefore suitable for cross validation purposes. In turn, we estimated the 95% confidence intervals of peatland area using the mean confusion matrix (mean of the four cross validations, tables S4 to S7, Goldblatt *et al* 2016), applying the method described in Olofsson *et al* (2013) (equations (9)–(13)). See supplementary materials for further discussion.

Note that for the final classification (figure 2), we used all polygons to train the model to produce the best map possible, following Honorio-Coronado *et al* (2021). For comparison, results of predicted peatland area per country are also given for the model trained using only 50% (random) of the data (table S8). While the accuracy assessment (based on the spatial leave one out cross validation, table 2) helped to inform our final model choice, we also undertook rigorous local-scale assessment of the map iterations. In line with the recommendations of Meyer and Pebesma (2022) we compared predicted peatland distributions to local data-driven products such as Householder *et al* (2012) and Hastie *et al* (2022), as well as examining areas where the authors have expert knowledge, e.g. the main stem of the Amazon.

To avoid extrapolating into regions which are climatologically unlikely to support the formation of peat, we masked out areas of the Amazon basin where annual precipitation is estimated at <1390 mm on average over the last decade in the CHIRPS database (Funk *et al* 2015). The cutoff of 1390 mm is based on the lowest mean annual precipitation at which peat has been observed in our GRPs (1393 mm in eastern Bolivia: Smith *et al* 2021), the next lowest peatland precipitation mean being 1455 mm at a GRP in northern Brazil. We further masked out areas above 500 m elevation, as our model was trained using only lowland data.

3. Results

Across the study region (Amazon basin below 500 m and mean annual precipitation >1390 mm) we estimate a total peatland area of 251 015 km^2 (128 671–373 359; 95th percentile confidence interval) (figure 2) at 90 m resolution, with the majority (66%) being overlain by forest (figure S2). The map broadly represents conditions over the period 2000–2021 when GRPs and remote sensing imagery were collected. Brazil contains the greatest estimated peatland area of 132 759 km^2 (68 024–197 493) followed by Peru with 55 890 km^2 (28 748–83 032) (table 2). Overlaying our peatland estimate with the 30 m-resolution deforestation map of Hansen *et al* (2013), we estimate that approximately 8743 km^2 or 3.5% of our predicted peatland area has been deforested from 2000 to 2023, with the greatest deforested areas found in Brazil and Bolivia.

Our peatland land cover classification algorithm has an overall accuracy of 89% based on the spatial leave one out cross validation (table 3). While accuracy per class is highly variable the model still performs relatively well with the lowest producer's and user's accuracy being 67% and 75% respectively (for the PN category). There is little confusion between the forested and non-forested categories, but greater confusion between the peat and non-peat forming classes. This is not surprising given that only the synthetic aperture radar bands (i.e. the L-band PALSAR) are capable of penetrating the canopy to any substantial degree. NDVI is the most important model variable, corresponding to the greatest mean decrease in the Gini coefficient, followed closely by NDWI and then PALSAR HH (figure 3). Please see supplementary materials for further information on model parameterization and accuracy assessment.

4. Discussion

Our map of peat distribution across Amazonia, the first high-resolution field-data-driven estimate

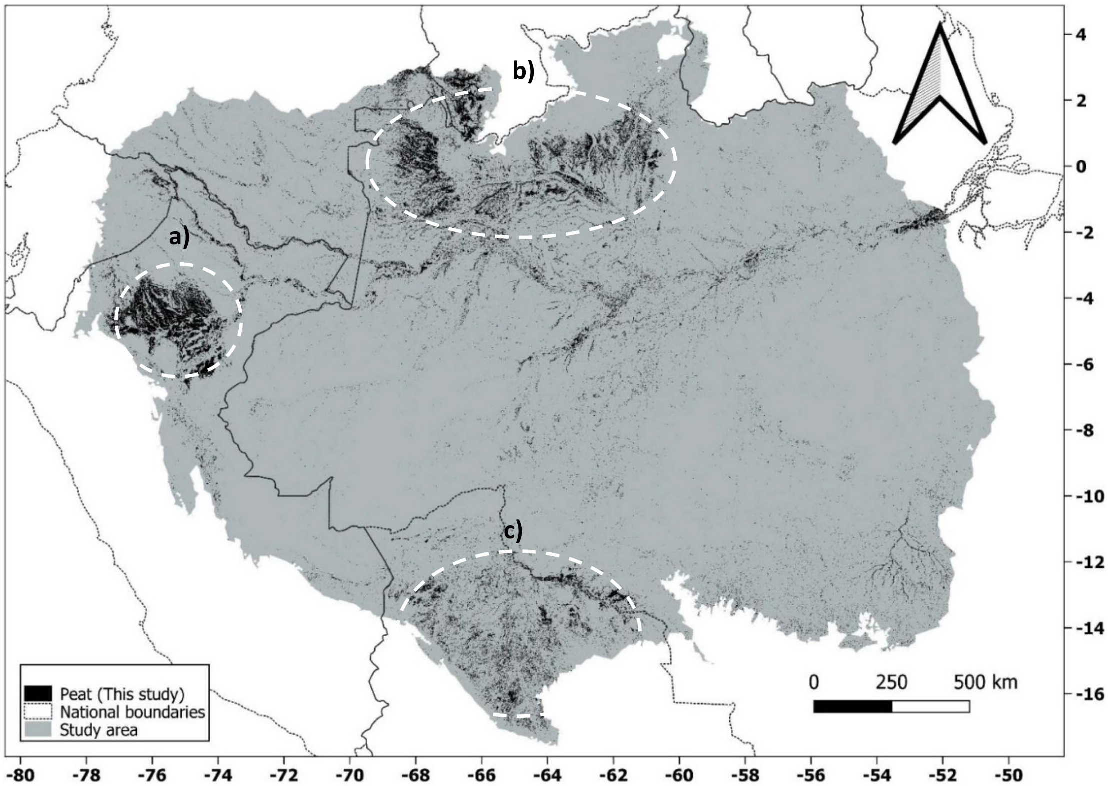

Figure 2. Predicted extent of peatlands (organic soil of ⩾30 cm thickness) across the study area (Amazon basin below 500 m and mean annual precipitation >1390 mm) at 90 m resolution. (A), The Pastaza-Marañón foreland basin (PMFB) in Peru. (B), the Rio Negro basin (Brazil) and south-western Orinoco basin (Venezuela). (C), the Llanos de Moxos region of Bolivia. In this map, we merged the two peat-forming categories. See figure S2 for a map displaying all five mapped classes (aggregated to 10 km for ease of interpretation).

Table 2. Predicted area of peat below forest (PF), peat below non-forest (PN) and total peatland area by country within the study region.

Country	PF area (km^2)	PN area (km^2)	Total peatland area (95% confidence intervals) (km^2)
Brazil	83 450	49 309	**132 759** (68 024–197 493)
Peru	49 649	6241	**55 890** (28 748–83 032)
Bolivia	13 403	25 010	**38 413** (19 600–57 226)
Colombia	7275	2538	**9813** (5037–14 589)
Venezuela	8493	2919	**11 412** (5857–16 967)
Ecuador	2237	154	**2391** (1231–3551)
Guyana	91	171	**262** (134–390)

across the basin, predicts substantial peatland areas that are currently unconfirmed by field research. To place these results, their associated uncertainties, and remaining knowledge gaps into context, we compared our map to previous model-based estimates and discuss the field evidence for peat formation across the region.

Our total estimated peatland area of 251 015 km^2 is substantially less than the 359 711 km^2 estimated by Gumbricht *et al* (2017) over the same study area, who mapped peatlands at a resolution of 232 m. This is at least in part because the Gumbricht map predicts greater peatland areas along rivers, including the Amazon main stem (figure 4). We are doubtful that peatlands along the Amazon main stem could be so extensive given the highly seasonal nature of the flooding in várzea forests (Junk 1983), and the associated influx of nutrients and mineral material (Wittman *et al* 2004). Indeed, our map has a relatively high degree of uncertainty in this region (figure S4) and may therefore also be overpredicting peatland extent along the main stem.

Table 3. Random Forest (250 trees) classification accuracy matrix for the peatland map, based on a spatial leave one out cross validation (mean of four iterations). Units are pixels. Includes producer's (PA) and user's accuracy (UA) for five classes: non-peat below forest (NF), peat below forest (PF), peat below non-forest (i.e. herbaceous vegetation and shrubland, PN), non-peat below non-forest (NN) and open water (WA).

Class	NF	PF	PN	NN	WA	Total	PA (%)
NF	522	39	10	2	0	573	0.91
PF	66	234	23	0	0	323	0.72
PN	7	30	136	29	0	202	0.67
NN	4	2	13	714	5	738	0.97
WA	2	2	0	8	1669	1681	0.99
Total	601	307	182	753	1674	3507	
UA (%)	0.87	0.76	0.75	0.95	1.00		

Overall accuracy (%): 89.

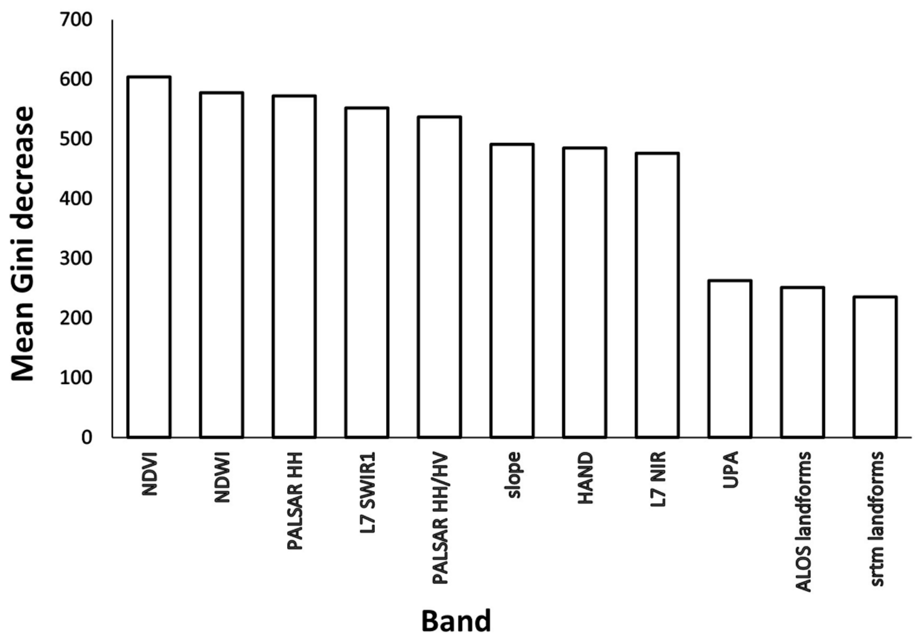

Figure 3. Relative importance (greatest mean decrease in Gini) of predictor variables in the random forest model.

The Melton *et al* (2022) global map of percentage peat cover (figure 4, multiplying each 10 km grid cell by surface area per cell) yields an estimated total peatland area of 183 263 km^2. Our distribution of peat across Peru, Venezuela, Ecuador, and some areas of Colombia broadly resembles the estimated distribution in both previous studies (figure 4), while greater divergence is apparent across some regions of Brazil and Bolivia, particularly compared to the Melton map. These different regions are discussed later in more detail.

4.1. Country level comparisons

Our predicted distribution of peat in Peru closely aligns with the data-driven distribution predicted by Hastie *et al* (2022) (figure 5). The largest area of peatland is forested and located in the PMFB (figure 2(a)), a major geological depression with very flat topography situated in one of the climatically wettest parts of Amazonia. Smaller areas of peatland are concentrated on the floodplains of the Napo, Putumayo, and upper Amazon rivers in northern Peru, Ucayali River in central Peru and Madre de Dios River in southern Peru. However, our total area of 55 890 (28 748–83 032) km^2 is somewhat less than the 62 714 km^2 predicted by Hastie *et al* (2022) despite sharing some GRPs over Peru, for two reasons: firstly, the present model was run at a lower resolution (90 m) than Hastie *et al* (50 m), and thus may exclude some smaller peatlands; secondly, the Hastie *et al* (2022) model had the benefit of additional high-resolution driver variables which only cover Peru (e.g. MINAM *et al* 2019).

Our distribution along the Madre de Dios River is very similar to that mapped by Householder *et al* (2012) (figure 5), and our predicted peatland area of

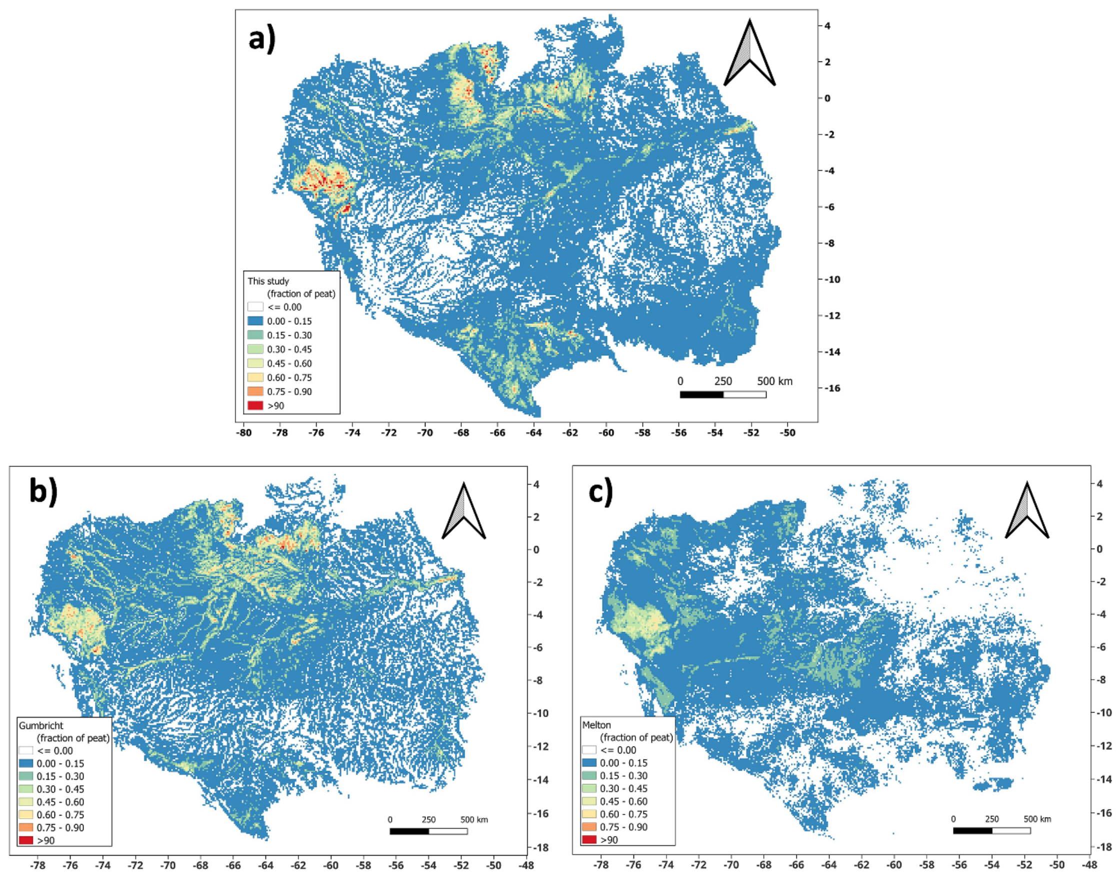

Figure 4. Predicted fraction of peatlands per 10 km grid from (a), this study, (b) Gumbricht *et al* (2017) and (c), Melton *et al* (2022), across the study area (Amazon basin below 500 m and mean annual precipitation >1390 mm). Reproduced from Gumbricht *et al* (2017). CC BY 4.0. Reproduced from Melton *et al* (2022). CC BY 4.0.

408 km^2 across this region is also relatively close to their value of 294 km^2. As a comparison, Gumbricht *et al* (2017) mapped 908 km^2 of peatlands along the same section of the Madre de Dios, more than three times the estimate of Householder *et al* (2012). Peruvian peatlands are dominated by palm swamps and to a lesser extent by pole forest and open peatlands (Honorio Coronado *et al* 2021, Hastie *et al* 2022).

In common with Gumbricht *et al* (2017), we predict that Brazil holds the greatest peatland area in the Amazon, covered mostly by forest (63%, figure S2), albeit distributed across several different regions, unlike the dense concentration of peatlands in the PMFB in Peru (Hastie *et al* 2022, figure 2(a)). One of the most substantial peatland areas in Brazil is predicted to occur in the Rio Negro basin; adjacent to another large peatland predicted in the south-western Orinoco basin in Venezuela (figure 2(b)).

There has been very little fieldwork undertaken in the wetlands of the Rio Negro, but a few previous studies have confirmed the presence of peat. Fieldwork has documented several wetland sites forming peat ~1 m thick in the lower Rio Negro (Lähteenoja *et al* 2013 and unpublished data, included in our analysis), and the presence of peat at two sites in the upper Rio Negro (Dubroeucq and Volkoff 1998), albeit without high-precision coordinates. The predicted peatlands in this region are distinctive, apparently overlapping with what have previously been mapped as 'white sand' forests (Adeney *et al* 2016), which typically have a thin-stemmed and/or dwarfed forest structure known as Campinarana or Campinarana florestada in Brazil (IBGE 2004, 2009) and as Caatinga Amazonica in Venezuela (Coomes and Grubb 1996). Previous field studies have certainly indicated that white sand forests occur on 'white sands'—heavily leached podzols or hydromorphic podzols—not only in Brazil, but also in Peru, Colombia, Venezuela, Guyana and Suriname (Coomes and Grubb 1996, Quesada *et al* 2011, Adeney *et al* 2016). These forests are structurally similar to ombrotrophic 'peatland pole forest' (varillal hidromorfico) which are nutrient-poor habitats occurring on generally thick peats in Peru (Draper *et al* 2014, 2018, Honorio Coronado *et al* 2021). However, Dubroeucq and Volkoff (1998) also described 'histosols [i.e. soils with high organic material] scattered among giant spodozols [i.e.

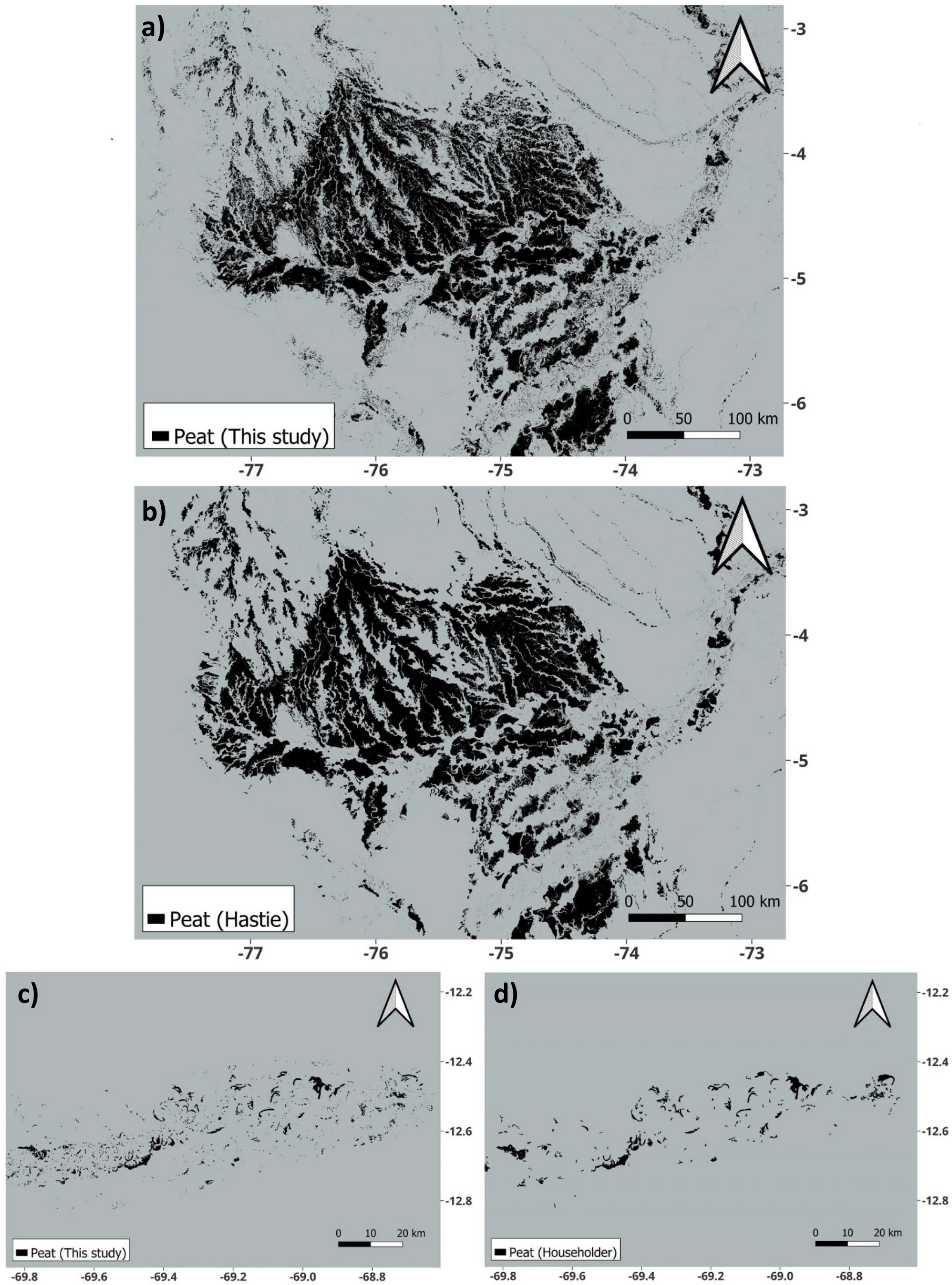

Figure 5. Predicted peat extent (a), across northern Peruvian Amazonia in this study, (b) across northern Peruvian Amazonia in Hastie *et al* (2022), (c), across the eastern Madre De Dios basin in this study, (d), across the eastern Madre De Dios basin in Householder *et al* (2012). Adapted from Hastie *et al* (2022), with permission from Springer Nature. Adapted from Householder *et al* (2012), with permission from Springer Nature.

podzols]' at one of their sites in the upper Rio Negro. Similar intermingling of peats and white sands has been observed by the authors (S.W., I.L., K.R.) in white-sand forests in Colombia and Peru (García-Villacorta *et al* 2003). While we were unable to access any high-resolution peat GRPs located in the upper Rio Negro, we were able to use four published GRPs for non-peat-forming podzol sites (Doupoux *et al* 2017) in our training/testing data. Furthermore, comparison of our results with less precisely geo-located reports of white sand forests (Herrera 1977, 1979, Montes *et al* 2011, Lucas *et al* 2012) suggests that our model correctly identifies these sites as non-peat-forming (i.e. while they do not provide precise enough coordinates to test quantitatively, they lie outside of our larger peatland areas).

We also note that our study is not the first to predict high soil carbon stocks in the Rio Negro/Orinoco region (Bernoux *et al* 2002, Gomes *et al* 2019). Interestingly, Melton *et al* (2022) also predicted peat in the Rio Negro Campinarana ecoregion but removed it during post-processing on the conservative grounds that the ecoregion was associated with white sands, not peat. In conclusion, while previous mapping studies have largely classified these Rio Negro ecosystems as white sand forests underlain by podzols, there are multiple lines of evidence, including firm field observations, which suggest that peatlands are present in the Rio Negro basin (and similar habitats in adjacent countries; ITL & SRW, pers. comm). Nevertheless, our prediction in this area is associated with a high degree of uncertainty (figure S4). The true extent of peat (including in what are presently mapped as 'white sand' forests), and crucially the variation in peat thickness (existing evidence suggests that mean thickness may be lower in Brazil than in Peru), remains to be determined through targeted fieldwork. Although the largest areas of predicted peat in our map are remote, further fieldwork in the Rio Negro and Orinoco basins (figure 2(b)) is important to test for the presence of large soil carbon stocks, and to help to refine our understanding of the relationship between white sand forests and peat.

Peatlands have also been directly sampled in Venezuela (Rull 1992, Vegas-Vilarrúbia *et al* 2010, Montoya and Rull 2011), and French Guiana (Cubizolle *et al* 2013), and observed in Guyana (Guyana Lands & Surveys Commission 2013) and Suriname (Sevenhuijsen 1977), but the points lie outside of our study area. While we were only able to include two unpublished peat GRPs (of five total GRPs) in Ecuador in our study, all three pan-Amazon maps (this study, Gumbricht *et al* 2017 and Melton *et al* 2022) predict a substantial concentration of peat in the same region where our GRPs are located (within the Yasuni and Cuyabeno National Parks).

Over Bolivia, our map estimates 38 413(19 600–57 226) km^2 of peatland, a substantial area given the strong climatic seasonality found in the majority of Bolivian Amazonia. Much of this large peat-forming area is predicted to occur along rivers and lakes and between the large grasslands of the Llanos de Moxos (figure 2(c)), where the topography may promote water retention even during the dry season. Only two peatland GRPs were available for inclusion in our study (Escobar-Torrez *et al* 2020, Smith *et al* 2021), but Brugger *et al* (2016) also described peatlands north and south of Lake Rogaguado in the Llanos de Moxos, in agreement with our map (figure 2(c)). Consistent across the descriptions of the ecosystems described in the Bolivian studies is the presence of *Mauritia flexuosa* and/or *Mauritiella* sp. palm communities, which is potentially significant as they are common in peat-forming swamps elsewhere in Amazonia (Householder *et al* 2012, Honorio Coronado *et al* 2021).

Winton *et al* (2021) and Montoya and Rull (2011) describe the presence of peat in the climatically similar Llanos of Colombia and Venezuela, despite strong seasonal and El Niño–Southern Oscillation-driven drought cycles. Melton *et al* (2022) also predicted peat deposits in the Llanos de Moxos, but removed these peatlands from their final model on the assumption that peats were unlikely to occur under strongly seasonal climates. The combination of consistent model predictions and field evidence of peat presence in areas of strongly seasonal climate suggests that this assumption should be tested. Our map has relatively low confidence in Bolivian Amazonia (figure S4). Further fieldwork would help to refine our understanding of soil carbon storage in seasonally dry parts of the Amazon basin.

5. Conclusion

As the first high-resolution field-data-driven map of peatland extent across the Amazon basin, our map represents a significant step forward in our understanding of the distribution of tropical peatlands and can inform future research priorities. Our analysis confirms the presence of peat underlying a diverse set of Amazonian ecosystems including the typical palm swamps in extensive depressions and along rivers and streams, as well as the less-known peat-forming 'white sand' forests. Nonetheless, comparisons of our map to a regional field-data-driven study (Hastie *et al* 2022), along with a relatively conservative precipitation mask, indicate that our map may be underestimating total peatland area in some regions.

Most sites which have so far been sampled in these regions are restricted to peatland edges, the sampling of more remote areas being limited by cost, time and logistical considerations. Substantial uncertainties thus remain. Most notably, the central Amazon basin urgently requires further investigation, particularly the Upper Rio Negro, the adjacent south-western Orinoco basin, and Bolivian Amazonia (figure S4). Data needs include not only sampling of peat depth and carbon density, but data on substrate, nutrient status, hydrological regime, and floristic diversity/composition, all of which would help us to better understand the mechanistic drivers explaining peat distribution and help to inform the choice of data products for future mapping studies. The extent and carbon storage of peat soils associated with 'white sand' forests, a relatively understudied topic, could be a key focus. Even in relatively densely sampled regions such as northern Peru, research is still in an exploratory phase and is regularly uncovering new insights into Amazonian peatlands. Recent fieldwork (IIAP-PROFONANPE 2023) discovered peats up to 8 m thick (included in this study) in the Datem del Marañón region, some of the deepest Amazonian peats ever recorded. Much more fieldwork will be needed before we can claim to have a solid understanding of the distribution of peat carbon in Amazonia.

We also know little about the palaeoecological history of Amazonian peatlands and their vulnerability to land-use and climate change (Cole *et al* 2022, Girkin *et al* 2022). Their past response to climate and land-use change, particularly in terms of carbon accumulation, requires investigation given that the central and eastern Amazon is projected to undergo more significant climatic change than the western basin (Duffy *et al* 2015). Even in the NW of the basin where climate change is likely to be less pronounced, there has been an intensification of the hydrological cycle (Barichivich *et al* 2018, Gloor *et al* 2013) which could have a significant impact on the floristic composition and formation of fluvial peatlands (Flores Llampazo *et al* 2022). Moreover, recent research in the middle Rio Negro suggests that repeated fires can induce ecosystem shifts from floodplain forest to white sand savannah over relatively short timescales, namely within 40 years (Flores and Holmgren 2021). With these points in mind, it is crucial to understand the climatological, ecological, and hydrological tipping points at which peat carbon storage will cease and even reverse, and whether these tipping points vary across the basin. The Hansen forest-change maps (2013) suggest that deforestation on the forested peatlands has been modest thus far but threats to peatlands, as well as carbon losses associated with degradation, may be increasing (Hastie *et al* 2022, Lawson *et al* 2022, Hergoualc'h *et al* 2023).

Many of these predicted peatlands are found on indigenous land (Adeney *et al* 2016) and appear to be used sustainably (Hidalgo Pizango *et al* 2022), so it is vital that indigenous and local communities' perspectives are included in future research efforts. These research priorities must be urgently pursued before further land-use-change threatens the integrity of the peatlands of the Amazon basin.

Data availability statement

The data that support the findings of this study are available upon request from the authors. A subset of data from Peru is available to freely download at the following link- https://catalogue.ceh.ac.uk/documents/ab13a06f-392f-4bc6-b1bf-06dd8b020307.

The map of predicted peat distribution (90 m) can be dowloaded here- https://zenodo.org/records/13142590.

The map of predicted landcover/ecosystem distribution (90 m) can be dowloaded here- https://zenodo.org/uploads/13142855.

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Conflict of interest

The authors declare no competing interests.

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