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Monitoring, reporting and verification of peatland water table and greenhouse gas balance using Sentinel 1 radar

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ABSTRACT

Recognition of the global significance of peatland GHG emissions has led to growing investment in peatland restoration. However, a lack of robust, affordable measurement, reporting and verification (MRV) methods for reporting outcomes at scale acts as a barrier to wider investment. Here, we demonstrate a novel MRV solution based on Sentinel 1 radar backscatter data, which provides a detailed estimate of water table depth. The approach correctly identifies areas of periodic inundation and estimates the water table depth within the 0–20 cm range across a 400-ha raised bog complex. Combining satellite-derived water table predictions with published relationships between water table and CO₂, and CH₄ fluxes showed modelled uptake of 2.9–3.2 t CO₂ ha⁻¹ yr⁻¹ compared to measured uptake of 1.8–3.5 t CO₂ ha⁻¹ yr⁻¹. With further development, such an approach has the potential to facilitate a more detailed approach to restoration, MRV and GHG emissions reporting.

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KEYWORDS

Remote sensing; net zero; peatlands; water table; GHG; synthetic aperture radar

Introduction

Peatlands are among the largest carbon stores and strongest long-term carbon sinks in the terrestrial biosphere, but human activity means that many are now carbon and greenhouse gas (GHG) sources (e.g. Joosten et al., 2016). This is primarily the result of accelerated aerobic decomposition following drainage, and water table depth is therefore a strong predictor of whether a peatland is a carbon source or sink (Evans et al., 2021). The importance of peatlands for carbon storage and sequestration has led to increasing funding available for restoration in the hope of safeguarding existing carbon stocks within the peat (e.g. NPAP, 2025) and initiating further carbon sequestration as natural peat-forming vegetation recolonises, thus contributing to the long-term attainment of net-zero greenhouse gas (GHG) emissions. To date, restoration effectiveness in the UK has been primarily reported through the completion of restoration actions (for example, the length of ditches blocked, or the area of scrub vegetation removed), with comparatively little long-term monitoring of changes in conditions, such as vegetation cover and water table depth, or direct monitoring of GHG fluxes (e.g. NPAP, 2025). The Intergovernmental Panel on Climate Change's (IPCC) Tier 1 emissions reporting methodology for peatlands, set out in the 2013 Wetlands Supplement (Hiraishi et al., 2014), applies a relatively simple, categorical approach based on broad land-use classes. While appropriate for baseline national reporting, these categorical approaches cannot capture emission changes associated with management interventions within categories, such as reducing drainage depths in agricultural peatlands or restoring the hydrological function of degraded semi-natural areas. This limits the utility of the approach at smaller scales, such as for individual ecological restoration projects or carbon offsetting schemes. Part of the reason for this is the relative lack of low-cost, spatially comprehensive data that can be used to regularly record peatland condition variables at temporal scales of interest for restoration. Reliable, low-cost measurement, reporting, and verification (MRV) solutions that can operate at scale are required to quantify projected carbon benefits following restoration and thus drive investment (West et al., 2023).

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While the water table depth (WTD) relationship with peatland carbon and GHG balance is well established (e.g. Couwenberg et al., 2011; Evans et al., 2021), reliable and low-cost MRV solutions have not been resolved at a regional to national scale. Directly measuring carbon stock changes in peatlands is effectively impossible, because of the size and intrinsic heterogeneity of existing peat carbon pools (Hiraishi et al., 2014), and direct measurement of GHG fluxes between the land and the atmosphere is limited to relatively few locations due to cost and accessibility. As a result, most MRV methods use the categorical approach developed by the IPCC (Hiraishi et al., 2014), which is based on indirect proxies for peat conditions, such as land-use and land use change, the vegetation community within semi-natural peat areas, and other condition metrics such as bare peat extent. These categorical approaches form the basis for the UK Peatland Code (IUCN Peatland Programme, 2022) and for similar schemes applied in other countries, such as the greenhouse gas emission site types (GEST) approach in Germany (Couwenberg et al., 2011). No large-scale approach has been developed to date that uses direct or indirect measurements of water table depth as a predictor of emissions.

One area of research that makes large-scale, long-term MRV of peatland restoration possible is satellite-based remote sensing. The increasing deployment of high-resolution spectral, hyperspectral and synthetic aperture radar (SAR) satellites, and platforms that allow rapid extraction and analysis of large volumes of data covering areas of interest, means that large-scale remote sensing of peatland restoration is now achievable. Optical remote sensing data have been used to classify peatland vegetation (e.g. Ball et al., 2023; Williamson and Morton, 2018) and to infer water table depth, for example, using the normalized difference water index (NDWI) metric (Kalacska et al., 2018) or the Optical Trapezoid Model (OPTRAM) (e.g. Burdun et al., 2023). The use of optical data is typically limited by high levels of cloud cover over most peatlands, as well as issues such as phenological variations in the optical properties of vegetation and seasonally varying light levels and angles.

Unlike optical data, satellite synthetic aperture radar (SAR) is less affected by cloud cover, although corrections may be needed in the event of heavy precipitation at the time of image acquisition (Carrasco et al., 2019). Increasing numbers of studies have demonstrated a relationship between Sentinel-1 SAR backscatter data and soil wetness (e.g. Hrysiewicz et al., 2023), and several global SAR-based soil moisture products exist (e.g. Beale et al., 2021; Das et al., 2019) and have been used to infer peat wetness (e.g. FAO, 2021). However, these products tend to saturate at high moisture levels characteristic of natural or even modified peatlands, limiting their utility for this purpose. SAR-based approaches specifically for estimating peatland WTD have been developed for a range of management contexts, including near-natural and restored blanket bogs (Lees et al. 2021; Toca et al., 2023), lowland raised bogs (Reddin et al., 2025), and lowland grazing meadows and pastures (Asmuss et al. 2019). Other studies report stronger WTD–signal relationships using optical data (Räsänen et al. 2022) or optical and radar datasets (Isoaho et al., 2024; Reddin et al., 2025).

In this study, we describe a simple, empirically based approach to site-scale WTD monitoring in peatlands, based on a single satellite data source (Sentinel 1 SAR) and readily available ground-data metrics, following the approach outlined in Williamson et al. (2025). We demonstrate the effectiveness of the approach based on detailed spatial and temporal WTD data from a large, heterogenous and historically modified raised bog complex that is now under restoration management. We combine the approach with empirical functions linking WTD with GHG emissions to produce detailed maps and an overall annual balance of GHG emissions for the study area.

Methods

Site characteristics

Cors Caron National Nature Reserve (52° 15' 12" N, 3° 55' 59" W) is the largest remaining raised bog complex in Wales, UK, with approximately 400 ha of raised bog within the wider 800 ha reserve. The site consists of three peat domes (hereafter called the west bog (236 ha), north-east bog (71 ha), and south-east bog (102 ha)) that are each hydrologically isolated from each other, with the River Teifi separating the west bog from the two eastern bog domes (Figure 1). The peat depths at the site reach up to 10 m in the center of the bog domes (Godwin & Mitchell, 1938). Although the three bog domes at Cors Caron have retained their semi-natural bog vegetation, human activities, including historic domestic peat cutting, have modified large parts of the site, removing most of the margins of each dome (nutrient-rich 'lagg' fen), and encroaching onto the bog

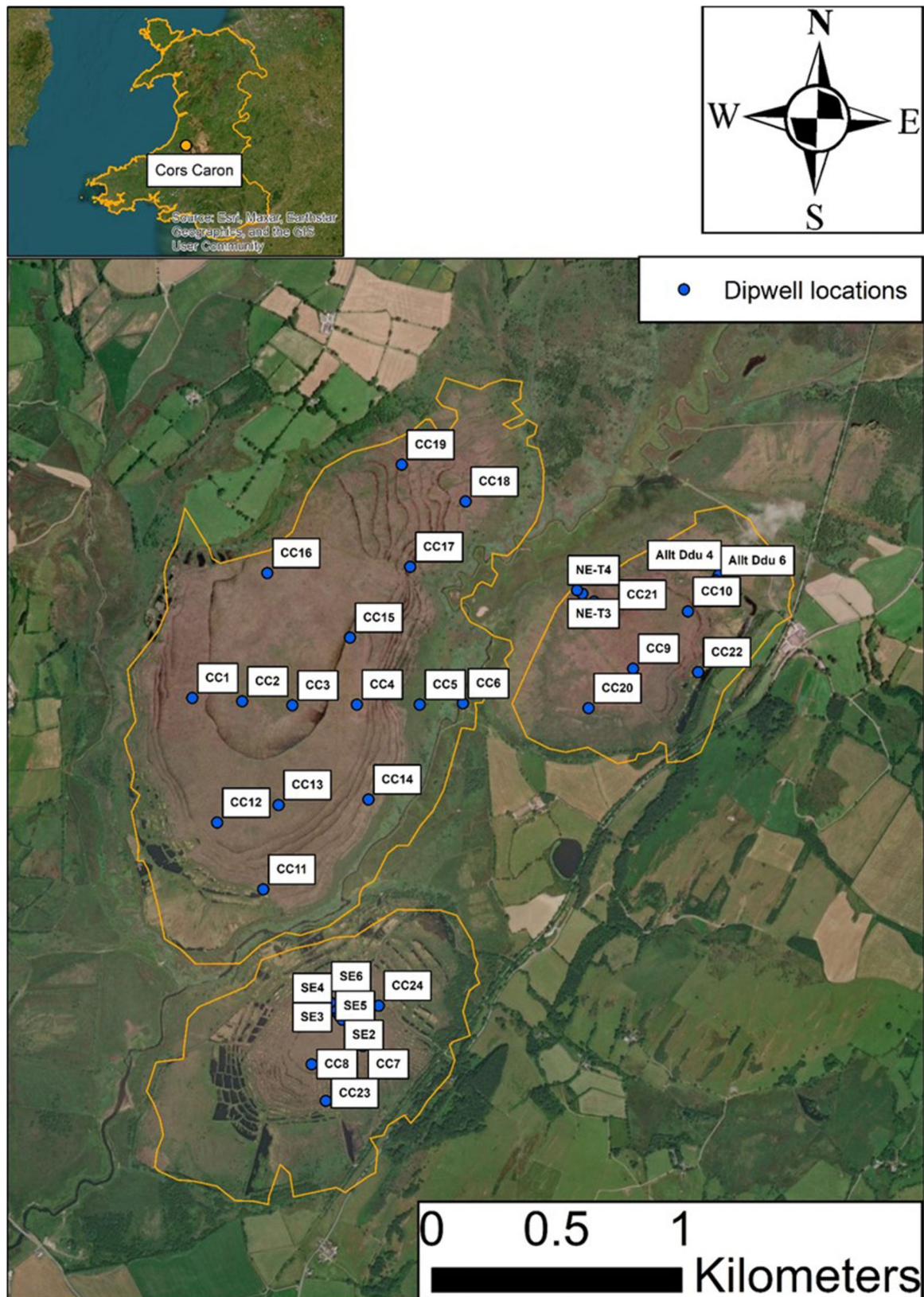


Figure 1. Cors Caron and the dipwell locations across the site. Bund lines, installed as part of the restoration work, are visible on the aerial imagery, as well as deeper pools at the edge of the SE bog dome in the former peat-cutting area.

domes in some areas. Much of the area has been affected by drainage and grazing. These pressures have resulted in large areas of the site becoming dominated by *Molinia caerulea* with encroachment of scrub species such as *Betula pendula* (Lindsay & Reed, 2024).

Since 2018, an EU LIFE-funded restoration project has aimed to return the sites to a condition enabling the development of active raised bog habitat. Restoration actions at the site have included low contour bunding (visible in Figure 1), mowing of *Molinia caerulea*, drain blocking, and clearance of encroaching scrub vegetation.

Datasets used

- SAR data

Annual Sentinel-1 high-resolution Level-1 ground range detected (GRD) imagery for Cors Caron between 2018 and 2022 at a 10 m resolution was downloaded through the Google Earth Engine (GEE). The imagery was pre-processed, radiometrically calibrated, and corrected for terrain (GEE, 2023). These data were multi-looked and projected to the ground range using an Earth ellipsoid model (ESA, 2023). Once downloaded, median monthly VV and VH polarisation (the method of pulses being emitted and received from the sensor, VV = vertical transmit, vertical receive; VH = vertical transmit, horizontal receive) backscatter values for each month of the year were calculated for both ascending and descending orbits and were analysed further using ArcMap v10.7.1 and R (v4.2.1). The median monthly values were used because of the limited number of available acquisitions per month and to avoid the influence of extremes due to a single anomalous image (Carrasco et al., 2019; Marston et al., 2023).

- Water table data

Twenty-eight continuously logging dipwells were installed across Cors Caron between 2019 and 2021, with the aim of capturing the range of hydrological and vegetation conditions seen on site (Figure 1). Principal component analysis demonstrated that the locations of the dipwells occupied the central portion of the predictor space, broadly capturing the principal environmental gradients. Unvented Solinst level loggers (stated accuracy 0.05%) provide hourly pressure data from January 2019 onwards, which are converted to water table depths by correcting for atmospheric pressure using barometric logger data collected adjacent to the bog, and the height of the dipwell tube above the bog surface. The mean water table depth for each month was calculated from the hourly water table depth data for comparison with the SAR data.

- Height and slope

The NextMap UK 5 m pixel digital elevation model (DEM) provided elevation data for each of the dipwell locations across the three bog domes. The elevation at each point location (vertical RMSE 1 m) was extracted in ArcMap v10.7.1. The DEM was used to calculate the mean slope for each pixel using the 'slope' function in ArcMap v10.7.1. Datasets were resampled to 10 m to align with Sentinel-1 data.

- Peat location

The unified peat map of Wales (Evans et al., 2020) was used to estimate the distance from the edge of the peat dome for all the water table monitoring locations. Distance from peatland edge was calculated from points in a 10 m x 10 m grid to the nearest boundary of the dataset and converted to a 10 m raster.

Random forest modelling

To determine whether Sentinel-1 backscatter data can be used to provide an MRV solution to allow remote monitoring of peatland restoration, the relationship between water table depth as the response variable and VV and VH polarisation backscatter data (ascending and descending orbits assessed separately), elevation, slope, and distance from peatland edge as explanatory variables was assessed using a random forest (RF) machine learning approach.

Random forest regression is a machine learning technique that establishes multi-variate regression relationships. RF is an ensemble machine learning technique training multiple decision trees, outputting the

mean response across all the trees as the result (Kuhn & Johnson, 2013; Meinshausen & Ridgeway, 2006). These have been used in classification and regression analyses across a range of habitats, urban environments, and soil classification mapping (Belgiu & Drăguț, 2016; Veronesi & Schillaci, 2019). RF models have produced the most consistent results out of several for upscaling bare peat coverage (Trippier et al., 2020; Williamson and Morton, 2018).

The dataset was a-priori split into calibration (70%) and validation (30%) subsets by site and month of year. To account as best as possible for the spatial and temporal autocorrelation, while accounting for the limited replication of site conditions, the water table data were split into blocks by location within each peat dome and time of year, with 6 months of the year in each block. Random blocks of data were selected for calibration and validation. All the statistical modelling was conducted in R v4.2.1 (R Core Team, 2022) using the RandomForest package (Breiman, 2001) and input variables are listed in Table 1. The model was restricted to 500 decision trees, and the number of variables to sample at each split was calculated as per model defaults. RF regression runs on one component at a time but needs training areas that represent the component in question with a representative mix of the other components, i.e. the training areas need to represent the areas that the method is being applied to, so that the model is not being used to extrapolate beyond the bounds of the training data. Model performance was evaluated using out-of-bag testing, whereby (30%) of the dataset was withheld while training the model and then used to test the model performance by comparing the measured values with the predicted output. The model feature importance was also calculated using the 'feature_importance' attribute in the RandomForest package.

Upscaling

The outputs of the RF regression modelling were applied across the whole site using 10 m gridded input data. Each raster input dataset was tabulated in R, and the RF regression equation was applied across the tabulated dataset. Outputs were converted to a 10 m raster using ArcMap v 10.7.1. Carbon dioxide (as net ecosystem production (NEP)) and methane fluxes were modelled from the whole-site water table model using the empirical relationships between annual mean water table depth and measured GHG fluxes developed by Evans et al. (2021) across all UK peatland condition categories with measured GHG flux data, as shown in Equations (1) and (2). Modelled emission outputs were limited by the range of water table data used in Evans et al. (2021) in order to minimise assumptions of the relationships continuing outside of the published data. The uncertainty in the upscaled annual water table depth model was derived from the 25th and 75th centiles reported from the Random Forest modelling, while the uncertainty in the modelled GHG fluxes is based on the water table depth uncertainty multiplied by the uncertainty ranges in the water table depth responses described in Evans et al. (2021). The modelled annual CO₂ flux was compared to the site-wide measured CO₂ flux, as derived from data in D'Acunha et al. (2024) and previous personal communication from the author.

$$\text{NEP} = 0.1341 * \text{WTD} - 1.73 \quad (1)$$

$$\text{CH}_4 = 0.334 * 0.5^{((\text{WTD}+5)/6.31)} \quad (2)$$

Results

Time series:

An initial assessment of the performance of the relationship between SAR backscatter and water table data using linear regression showed a closer relationship between descending orbits and water table; hence, from

Table 1. Increase in MSE and variable importance for the random forest regression.

Variable	% Increase in MSE	Variable importance
B1 (VV)	22.3	0.776
B2 (VH)	18.2	0.623
Month	12.7	0.400
Distance from peat edge	35.8	0.611
Elevation	37.2	0.667
Slope	37.9	0.579

here on, the analysis used the VV and VH polarisation from the descending orbits only. The random forest model described 56% of the variance in the spatio-temporal water table dataset. The explanatory variables were VV and VH descending backscatter data, distance from the edge of the peat, elevation, slope, and month. The highest percentage RMSE was seen for slope, distance from the peat edge, and elevation, followed by the VV and VH polarisation datasets (Table 1), indicating that the environmental variables were influential components of the regression analysis. However, band 1 (VV polarisation) was the variable with the highest feature importance, as measured by the residual sum of squares (Table 1), followed by band 2 (VH polarisation), distance from the edge of the peat dome, elevation, and slope. Using the out-of-the-bag (OOB) cross-validation estimates the RMSE was 0.067, and the comparison between observed and OOB estimates is shown in Figure 2a. Meanwhile, using the validation subset, the model also showed a positive relationship between measured and modelled water table depth, also with an R^2 of 0.52 (Figure 2b). Note that this similarity in variance explained suggests that there is an element of spatial and temporal autocorrelation in the datasets. When the model was converted to a comparison of the mean monthly water table depths for each location, the model was able to accurately predict water table fluctuations until the water table depth dropped to more than 20 cm below the peat surface. (Figures 3–5).

The measured dipwell locations show a range of water table depths and differing temporal variations across the three bog domes. The water table depth model reproduced the temporal trends across all the sites, including those where the water table depths rose above the surface, those where it was at the surface, and those where the water table dropped to approximately 20 cm below the surface. None of the locations used in this work showed prolonged water table drawdowns below 40 cm below the surface at any time, and the deepest annual mean WTD was 28 cm, on the edge of the NE bog dome. When looking at dome-wide water table depth metrics, comparing modelled and measured water table depths at the measured locations, the modelled mean water table depth closely reproduced the mean depth over the whole measurement period, though the standard deviation of the modelled data was smaller in all the cases. This is reflected by the comparison of the data extremes (Table 2). The model also successfully reproduced the temporal variability within and between locations, for sites with both large and small water table variations (Figures 3–5).

Predicting spatial variations in the mean annual water table and GHG fluxes.

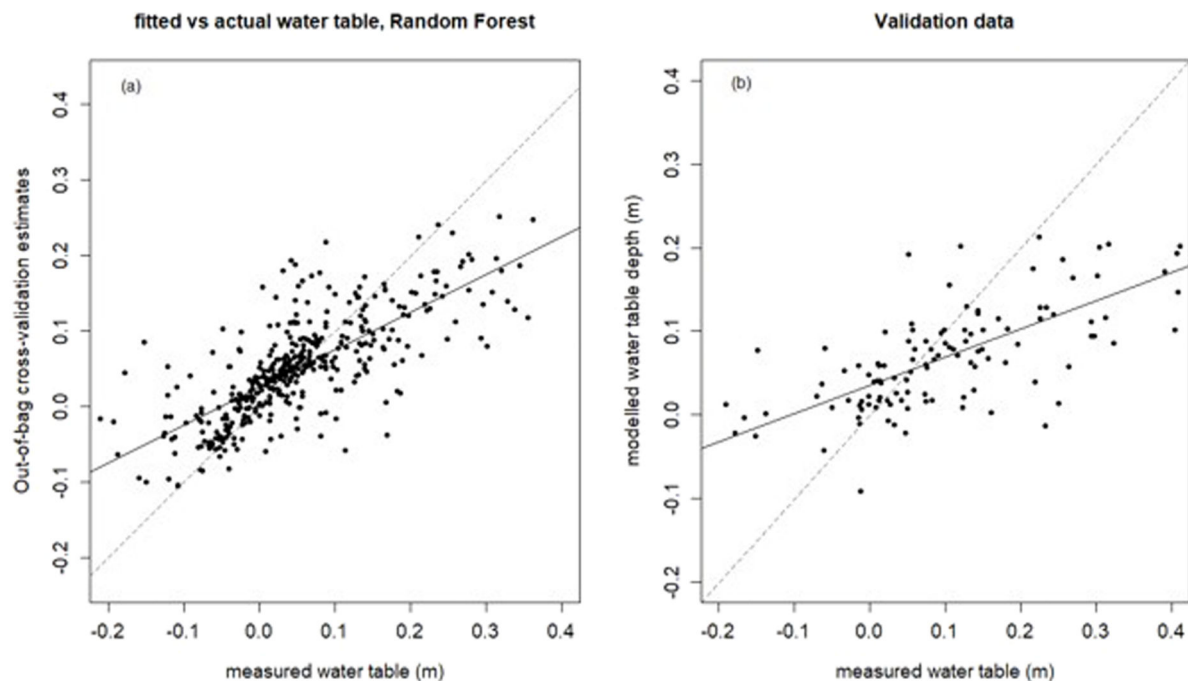


Figure 2. Comparison of measured and modelled water table depths for the out-of-bag validation ((a), $R^2 = 0.56$) and independent validation data only ((b), $R^2 = 0.52$). The 1:1 relationship between measured and modelled data is shown by the dashed line on the graphs.

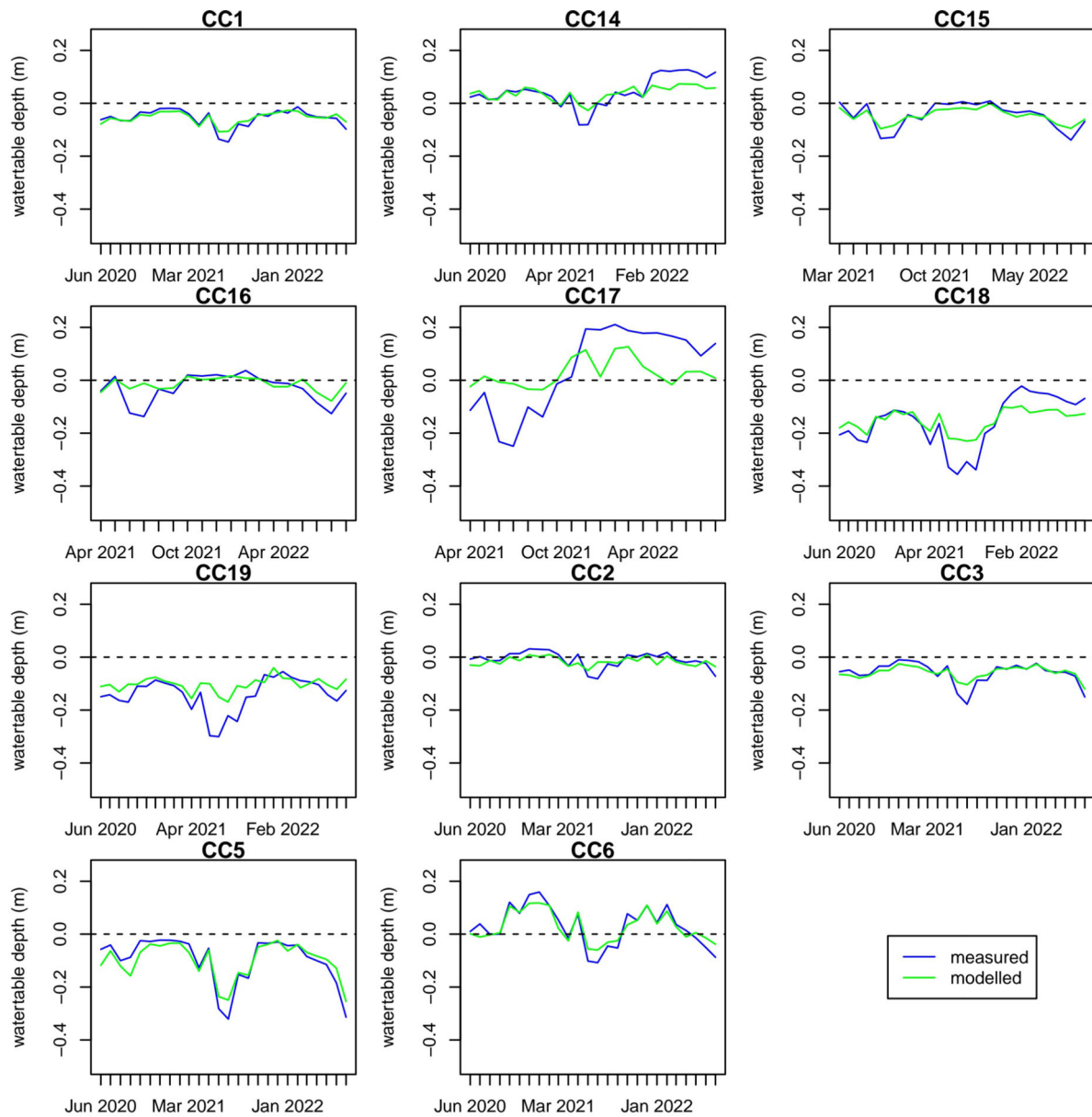


Figure 3. West bog time series plots. The measured monthly water table depth is in blue, while the modelled is in green. See Figure 1 for dipwell locations.

The 2021 modelled water table depth shows that the water tables across the three peat domes at Cors Caron were deepest in a ring around the shoulder of each dome (Figure 6), which approximately corresponds to the steepest areas of the domes caused by the inward extent of domestic peat cutting during the 19th and early 20th century. Within these areas, where the peat is relatively undamaged by human activity, water tables are nearer the surface. The largest remaining dome, the west bog, is generally wetter than the north-east and south-east bog domes. The areas of peat where the surface level has been lowered, either by peat cutting or through erosion and subsequent flooding by the River Teifi, are the wettest parts of the site, with annual mean water levels at or above the peat surface.

When GHG fluxes for the site were modelled based on water tables, the majority of the site was predicted to be sequestering CO_2 , but the driest areas were predicted to be net CO_2 sources (Figure 7). Modelled CO_2 sequestration was higher in the wetter west bog dome compared to the others. The predicted rate of CO_2 uptake for this area, between 2.9 and $3.2 \text{ t CO}_2 \text{ ha}^{-1} \text{ yr}^{-1}$ (Table 3), is consistent with the rate of CO_2 uptake measured by eddy covariance at the same location of 1.8 – $3.5 \text{ t CO}_2 \text{ ha}^{-1} \text{ yr}^{-1}$ (D’Acunha et al., 2024). Little CH_4 emission was modelled from the steeper, drier areas of the peat, and modelled emissions were

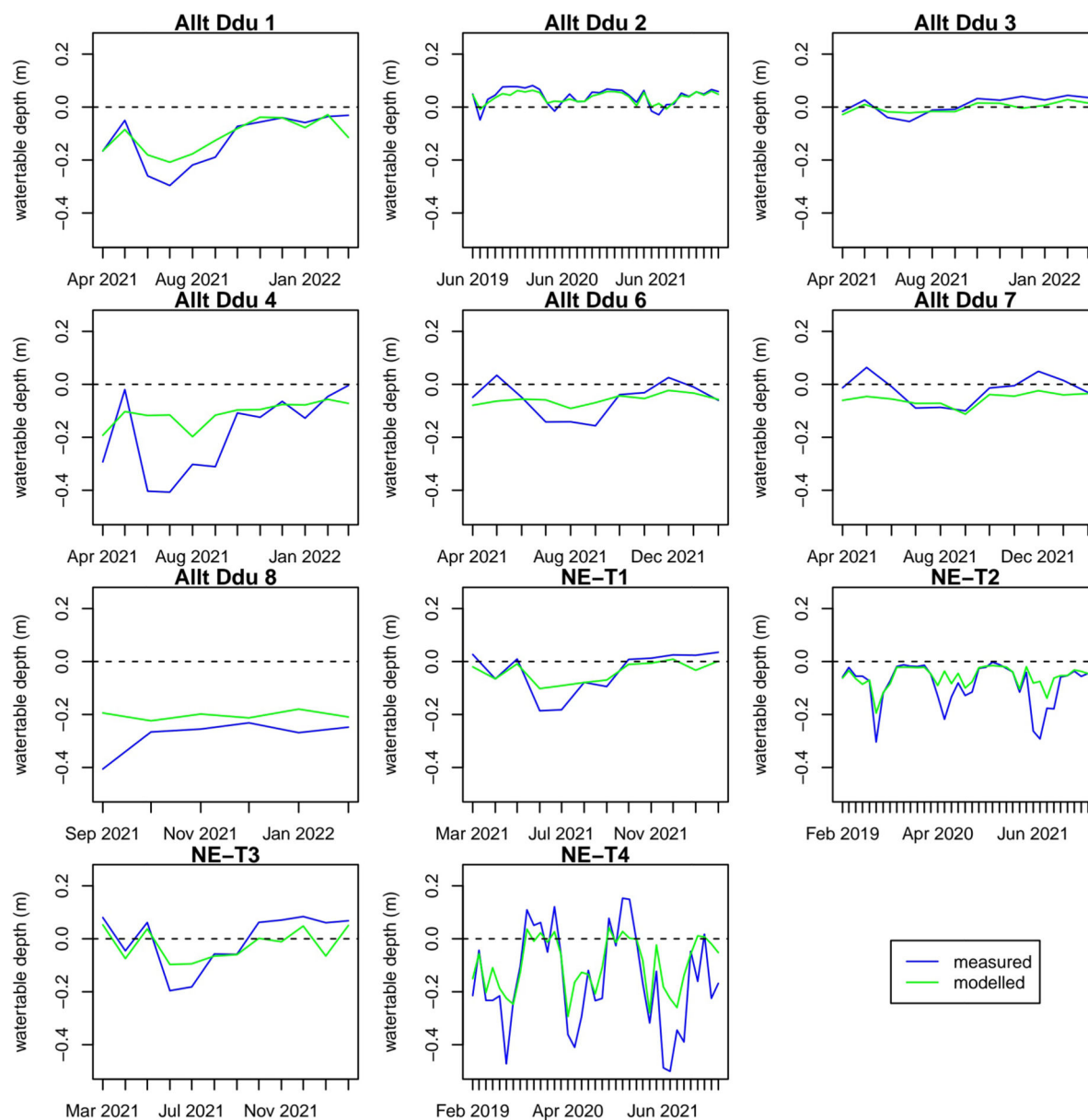


Figure 4. NE bog time series plots. The measured monthly water table depth is in blue, while the modelled is in green. See Figure 1 for dipwell locations.

modest for the relatively intact areas at the centre of each peat dome. However, the inundated areas around the fringes of the peatland showed high predicted CH_4 emissions, of up to $0.3 \text{ t C ha}^{-1} \text{ yr}^{-1}$ (Figure 8). Across the whole of the Cors Caron peat domes, the EO-based model suggested that in 2021, there was net sequestration of just over 1200 t CO_2 . However, the high water levels in areas affected by historic peat cutting meant that (based on Equation (2)) the site was predicted to be a substantial net source of methane emissions, in the region of 1450 t CO_2 equivalents over the year (Table 3), when calculated using the 100-year GWP for methane of 28.

Discussion

Our analysis demonstrated that Sentinel-1 backscatter data, alongside simple and readily available topographic data, can be used to model temporal and spatial water table dynamics, on a monthly timestep, in raised bog systems, with 53% of the variance in the dataset being described by the model. The results suggest that at these sites, the use of SAR data offers a site-wide MRV option to estimate annual water table depths

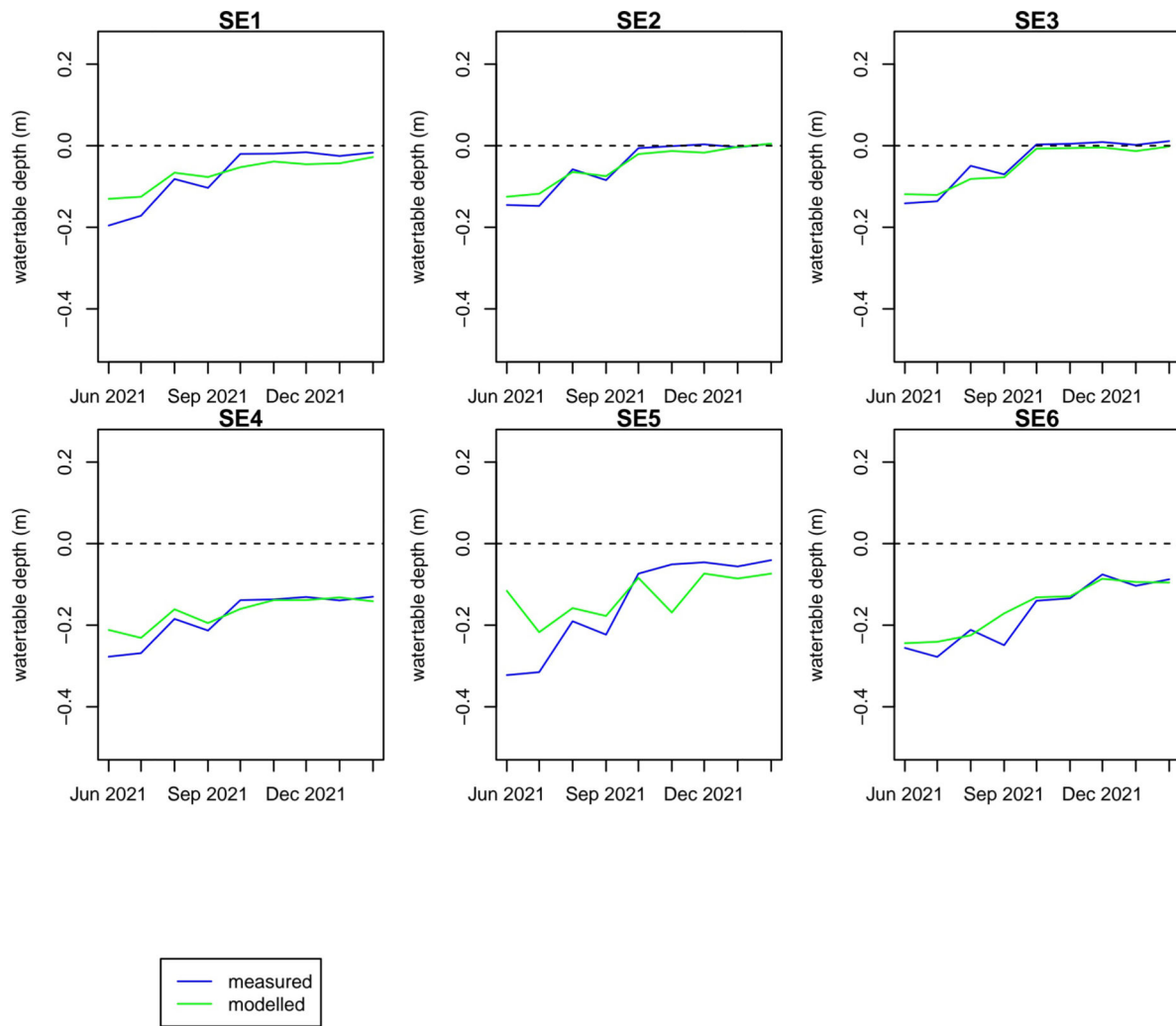


Figure 5. SE bog time series plots. The measured monthly water table depth is in blue, while the modelled is in green. See Figure 1 for dipwell locations. Note the shorter duration of observations from this area compared to those shown above.

Table 2. Measured and modelled water table depth metrics for the measurement locations at Cors Caron. Note these cover the whole measured period and are not mean annual values.

metric	North-east bog	South-east bog	West bog
Mean measured WTD (m) $\pm$ standard deviation	0.07 ± 0.13	0.11 ± 0.09	0.05 ± 0.10
Mean modelled WTD (m) $\pm$ standard deviation	0.07 ± 0.10	0.12 ± 0.07	0.05 ± 0.07
Maximum and minimum measured WTD (m)	0.50, -0.15	0.32, -0.01	0.36, -0.21
Maximum and minimum modelled WTD (m)	0.38, -0.07	0.28, 0.01	0.26, -0.12

and hence estimates of GHG emissions. Further work remains to understand the extent to which the methodology could be upscaled to provide annual national mapping of water table depths in semi-natural peatlands, including the extent to which structural peat properties affect the SAR signal and what approach could be used for more deeply drained peatlands.

Sentinel 1 backscatter data can be used alongside simple location metrics to detect water table depth relationships in both restored and near natural bogs (Isoaho et al., 2024; Reddin et al., 2025; Toca et al., 2023). Among the additional environmental predictors, distance to the peat-dome edge, slope, and elevation were the most influential. Slope has been found to be important in peatland condition monitoring (Trippier et al., 2020), as shallower slopes will hold water better than steeper slopes, meaning that the water table will be closer to the surface (Daniels et al., 2008). The approach described in this work aims to reproduce the broad monthly trends in water table dynamics, enabling both annual means and seasonal amplitudes to be calculated. This approach offers a remote MRV solution to the unresolved challenge of quantifying GHG fluxes from peatland

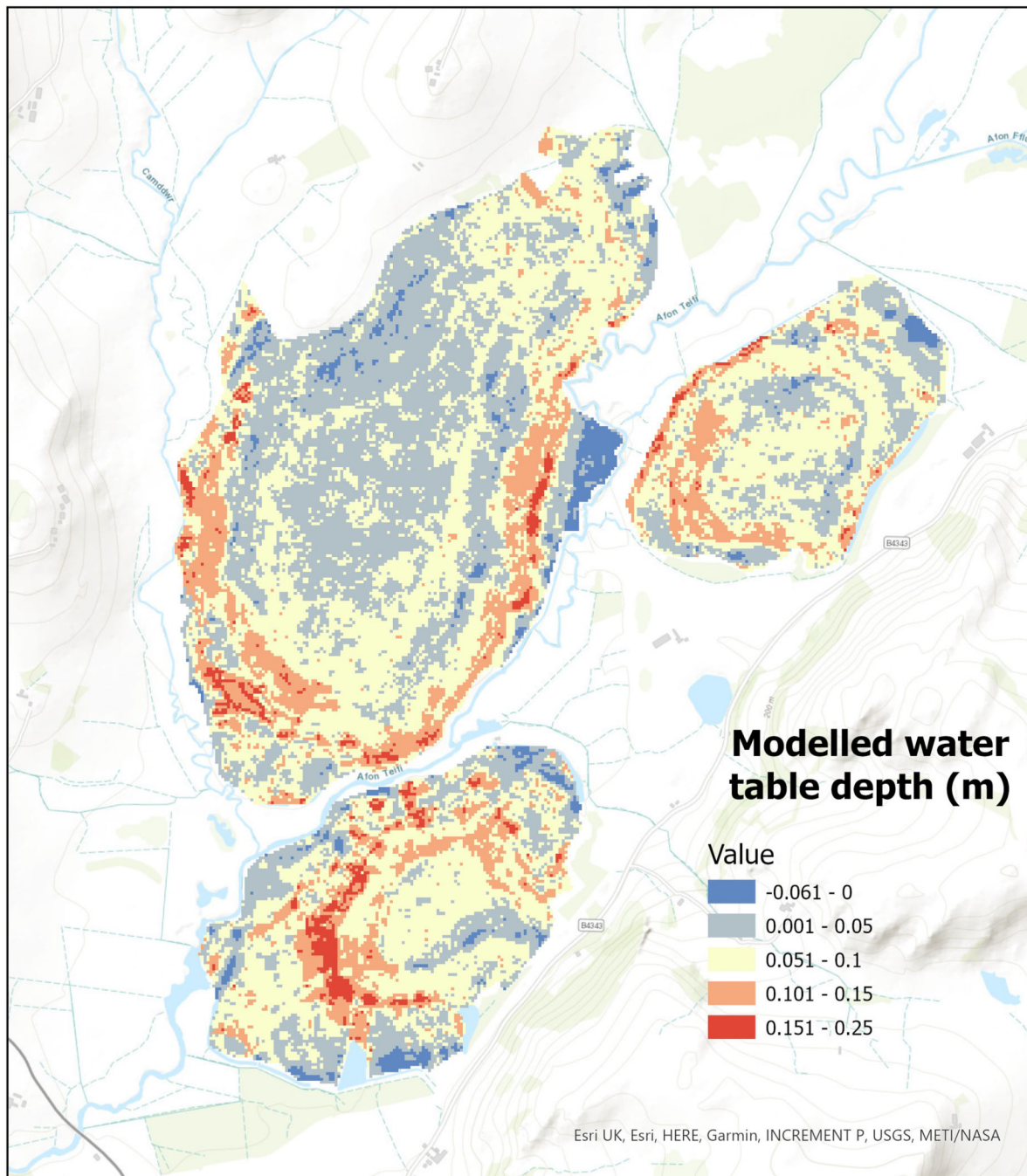


Figure 6. Mean annual modelled water table depth for 2021.

systems at scale. Previous methods have focused on replicating individual measurements at the six-day return frequency of the Sentinel 1 satellites (Toca et al., 2023), whereas adopting a monthly timestep reduces some of the effects of short-term variability in water table depths, and provides a means of upscaling reporting of site-wide effects. A limitation of methodologies linking both radar and optical data is the need to acquire cloud-free data (Reddin et al., 2025), which inevitably means that wet day data is removed from the modelling, potentially biasing the outputs.

For raised bogs (as well as other peat types such as tropical peat swamps), the elevation and distance from the edge of the dome are linked, particularly in undisturbed systems where the centre of the bog dome will typically be the highest point (Cobb et al., 2024). In modified systems, this may not always be the case, however, depending on the location and impacts of past land use (Cobb et al., 2024). Another potentially relevant predictor variable would be proximity to a ditch or canal, which (although not present at our site) would be

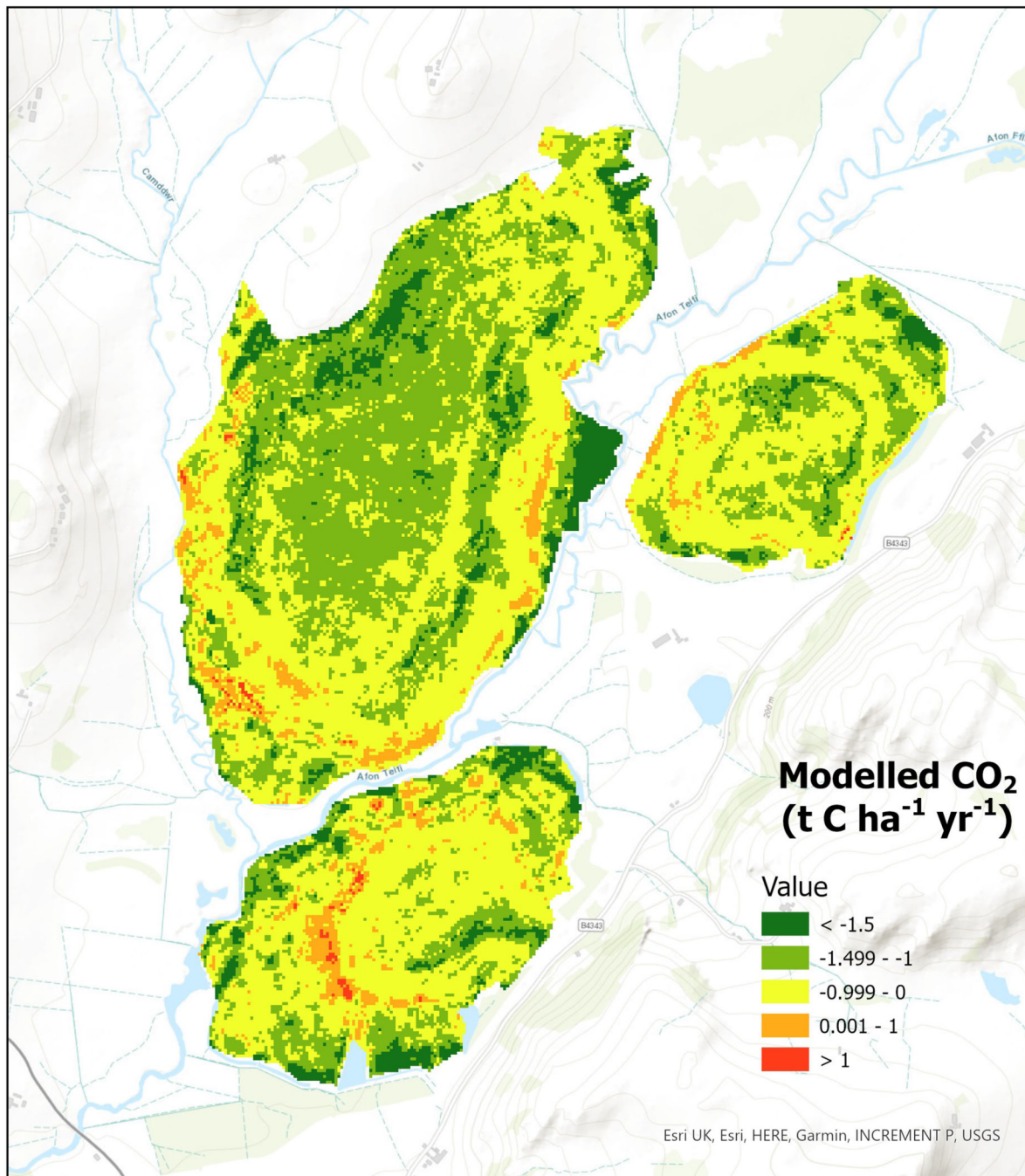


Figure 7. Mean annual modelled CO₂ balance for 2021.

Table 3. Mean modelled water table, total CO₂ flux and total CH₄ flux for 2021.

Bog dome	Area (ha)	Mean annual water table (modelled)	Total CO ₂ flux (t CO ₂ -e/yr)	Total CH ₄ flux (t CO ₂ -e/yr)
West	236	0.06 (0.03–0.09)	–764 (–601––2200)	927 (333–1930)
North East	71	0.07 (0.04–0.10)	–204 (–205––634)	256 (92–530)
South East	102	0.07 (0.04–0.10)	–300 (–315––891)	362 (130–751)

expected to exert an impact on local WTD (Evans et al. 2019). A number of recent studies have shown promise in mapping peat ditches from remote sensing data (e.g. Connolly & Holden, 2017, Robb et al., 2023), although this is typically a data-intensive process. As with all empirically based models, adding additional variables increases complexity and may limit model transferability to other areas, for which equivalent data (such as

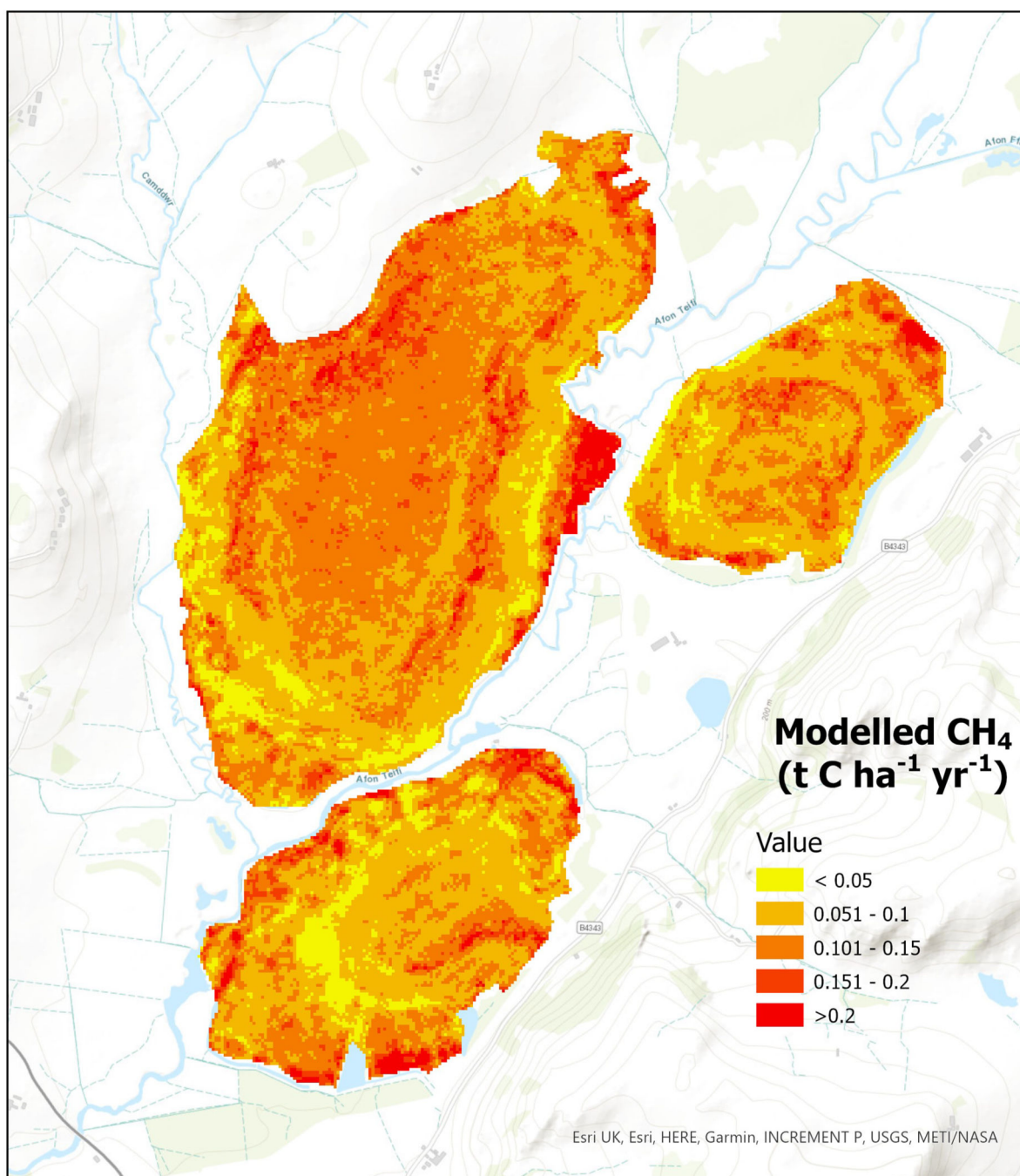


Figure 8. Mean annual modelled methane emissions for 2021.

high-resolution landcover or ditch maps) may not be available, or where (particularly across country borders) the resolution or classification of land-cover may differ. Reliable maps of peat extent may also not be available in all areas, restricting the application of our method, although a number of promising approaches to remote mapping of peat presence/absence are now being developed (Minasny et al., 2023; O’Leary, 2021).

The relationship between modelled and observed water table depth became increasingly non-linear once the water table fell beyond ~20 cm below the surface. A key question is which component of the system is detected by Sentinel-1 backscatter. Although previous studies have proposed that SAR data can be used to directly model peatland water table depth (Bechtold et al. 2018; Asmuss et al. 2019; Toca et al., 2023), evidence indicates that the signal is primarily driven by surface and near-surface soil moisture (Millard and Richardson 2018; Hrysiewicz et al., 2023), rather than the water table position itself, given that C-band SAR penetrates only a few centimetres into the soil (Hrysiewicz et al., 2023). During drier periods, the backscatter intensity declines

as both the water table depth and surface moisture decrease (Hrysiewicz et al., 2023). Bechtold et al. (2018) reported an approximately linear relationship between water table depth and SAR backscatter down to 1 m, but because the water tables at our sites did not approach such depths, we cannot assess whether similarly robust relationships would hold in more deeply drained peatlands. This uncertainty is particularly relevant if the method is to be applied to predict WTD and associated GHG emissions in peatlands under drainage, such as cropland or grassland agriculture.

The spatial modelling of mean annual water table depths across Cors Caron shows a similar pattern across the three bog domes, with relatively wet centres of the bogs, drier areas that correspond to past limits of peat extraction (peat ‘banks’) and very wet areas on the bog periphery. The modelled spatial variation in WTD shows clear consistency with the land-use history of the area, although it is noteworthy that it shows evidence of both large-scale drying in areas such as steep slopes around the central domes, and artificially wet conditions in other areas where the peat cutting took place. Both these human modifications to the natural hydrological function of the peatland appear to have had detrimental impacts on GHG emissions, based on the implementation of the equations given in Evans et al. (2021). While the less impacted central domes appear to remain strong CO₂ sinks, and only modest CH₄ sources, the dry dome-edge areas are thought to be CO₂ sources, while the waterlogged areas affected by peat cutting are suggested to be artificially large CH₄ sources. Although ground validation for the GHG data is limited to CO₂, our results thus suggest that from a GHG perspective, it might be appropriate to include measures to reduce the extent of waterlogging in former peat cut areas, as well as to re-wet the dry areas.

Our approach has so far been evaluated in semi-natural raised bogs, where the water table remains near the surface, and vegetation is dominated by low-stature, slow-growing perennial species. Extending the methodology to other peatland types, and particularly to highly modified agricultural peatlands characterised by deep drainage and annual cropping, will require further investigation. For raised bogs, our results demonstrate that median monthly Sentinel-1 backscatter, combined with simple spatial metrics, can reproduce both the spatial and temporal variability of monthly water table depth. These spatially explicit water table estimates can then be translated into site-level annual GHG fluxes. Collectively, this provides evidence that such methods could underpin an MRV framework capable of supporting long-term, landscape-scale monitoring of peatland restoration and mapping GHG emissions for reporting purposes.

Conclusion

Our analysis demonstrates that Sentinel 1 SAR backscatter data can provide a spatially explicit monthly record of water table depth in semi-natural raised bogs. This allows the calculation of annual mean water table depth across a site, from which GHG fluxes can be estimated. We believe that the approach outlined in this work could have the potential to transform the MRV of peatland restoration and management by providing a relatively simple and cost-effective tool to determine peatland restoration outcomes. With further research to develop a model across the range of peatland habitats in the UK, this approach could facilitate a more robust approach to national emissions inventory reporting and provide the clarity needed to drive private investment in peatland-based carbon credits.

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Author contributions

CRedit: **Jennifer Williamson:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Writing – original draft; **Aneurin O’Neil:** Funding acquisition,

Investigation, Methodology, Writing – review & editing; **Alice Fitch:** Funding acquisition, Methodology, Project administration, Software, Validation, Writing – review & editing; **Jake White:** Data curation, Funding acquisition, Investigation, Writing – review & editing; **Christopher D. Evans:** Conceptualization, Funding acquisition, Methodology, Writing – review & editing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data that support the findings of this study are available from Natural Resources Wales. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the Welsh National Peatland Action Program with the permission of Natural Resources Wales.

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