Delivering robust measurement pathways for a Scottish carbon land tax: an evidence review and feasibility study

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1 Executive summary

Implementing a carbon land tax faces key measurement and administrative challenges. Accurate quantification of emissions from peat, requires reliable methods that reflect real fluxes while managing uncertainty transparently. Spatial and temporal resolution must be sufficient to attribute emissions fairly to individual landholdings and capture changes arising from management and climate. The system must incentivize emission-reducing practices equitably across diverse land tenures, ensuring accessibility for smaller or resource-limited landowners. Transparency, clear compliance procedures, and robust dispute resolution are essential to maintain credibility, fairness, and public trust.

Current national emission-factor approaches used in the UK Greenhouse Gas (GHG) Inventory do not provide sufficient precision and spatial accuracy for taxation at the level of individual holdings. This report therefore evaluates whether a peat-based carbon tax could be made scientifically robust and administratively credible, balancing environmental ambition with fairness and feasibility based on current methods and research evidence. Differences in peat condition, management and access can produce unequal emission outcomes, and if measurement systems fail to reflect this variation they risk appearing arbitrary. Complex or opaque monitoring requirements could impose excessive costs and erode legitimacy, especially for smaller or less technically equipped landholders.

Alternative configurations of existing measurement methods highlight clear trade-offs between accuracy, cost, spatial resolution and administrative burden in a land emissions carbon tax. Although potentially most cost-effective to run (total annual operating cost £42,000 for a 250,000 ha), model development costs for purely remote-sensing approaches would be costly (as much as £3M). Moreover, these methods are not yet reliable enough because water-table depth, a key control on CO_2 and CH_4 emissions, cannot be inferred remotely with sufficient confidence at parcel scale, creating a risk of misestimated liabilities. Introducing ground-based water-table measurements (dipwells) materially improves accuracy and responsiveness to management and restoration, but installation, maintenance and quality control become costly (estimated upfront costs of £11.3m and annual operating costs of £513k for 250K ha). However, costs are sensitive to dipwell density, servicing frequency and sensor costs. New sensor-development work by CEH could materially reduce capital costs without weakening the evidential standard, by lowering per-unit sensor costs while retaining the higher-specification performance needed for audit and appeals; under the report’s assumptions, reducing unit cost from £518 to £100 would lower installation costs by around £4.2m for a 250,000 ha rollout, all else equal. Additional measures (for example, soil testing for N_2O or hyperspectral data for photosynthetic uptake) provide marginal gains in terms of completeness, with associated additional costs and complexity. A further source of uncertainty is the national peat extent and condition baseline, which contains omission and commission errors at the scale of individual holdings.

The report concludes that current methods do not yet provide the accuracy, fairness or transparency required for a nationally applied, emissions-based peatland land tax without significant cost, and that any move towards implementation should therefore be accompanied by further evidence-gathering and testing. In light of these risks and uncertainties, three steps are proposed (Table 1), starting with additional research and progressing through phased pilot approaches targeting the highest-emitting peat types, followed by the piloting of water-table based measures, exploring approaches to reduce costs and improve the scalability of these types of measurement, alongside piloting of administrative procedures. We conclude that (Table 1):

- The lowest immediate-risk approach is to prioritise the commissioning of targeted research and improving national screening layers before any live liabilities are applied, given the current constraints on accuracy and the potential for dispute.
- Limited piloting could still be proportionate if designed to manage risk and cost through sequencing, beginning with a narrow pilot focused on bare, actively eroding peat where verification is comparatively straightforward and lower-cost.
- After evaluation of the research and initial pilot findings, piloting could progress to a WTD-based approach for drained or modified peat, recognising that this phase carries materially higher operational complexity, dispute exposure and monitoring costs (driven largely by dipwell/logging requirements).

This sequencing would limit initial cost and risk, target the highest emitting and most visible class first, and allow the WTD-based system to be piloted and refined before wider application. In parallel, integration with wider carbon-pricing instruments such as the UK Emissions Trading Scheme could be explored as an alternative route to a land emissions carbon tax. Actioning the steps outlined in this report needs to balance messaging to the land management community (given evidence that proposals to introduce a similar tax in Denmark are already influencing decisions to sell peatlands to avoid future liabilities) with the risks of piloting a tax using methods that are known to have significant limitations, potentially undermining the legitimacy of a future tax.

Table 1: Proposed three-step sequencing for assessing and piloting a peatland emissions carbon tax

Step	Description	Pros	Cons	Risk profile	Cost implications
1: Further research	A programme of research to close key technical evidence gaps, including: • Calibrating water-table–flux response functions for Scotland's main peat types using long-term chamber and eddy-covariance data; • Determining parcel-scale minimums for dipwell/piezometer spacing, logger frequency and QA procedures relative to site features such as slope breaks and drainage features; • Building national screening layers of peat extent and condition with pixel-level uncertainty suitable for setting default liabilities; and • Investigating options for improving remote inference of water-table depth, for example, by integrating ground-penetrating radar (GPR), InSAR and SAR, LiDAR and optical indices, supported by targeted ground-truthing using low-cost in situ measurements (including redox potential (eH)) to provide contextual information on oxygen availability and persistent saturation, and, where appropriate, citizen-science approaches to increase spatial coverage.	Directly targets key feasibility constraints (accuracy, fairness, transparency at holding scale) before liabilities are set; strengthens the technical basis for any later rollout by improving calibration, mapping baselines and uncertainty handling.	Delays any behavioural signal from taxation while evidence gaps are closed; does not test operational issues (verification, audit, appeals) under live conditions.	Lowest immediate implementation risk (no live liabilities based on weak methods), but continued exposure to risks identified in the report if later steps proceed without resolving identified uncertainties.	Research and data-development costs could be commissioned or integrated into Scottish Government's next Strategic Research Programme and reduce later compliance and dispute costs by improving baselines and response functions.
2: Initial pilot	An initialpilot could apply only to bare and actively eroding peat, by publishing an eroding-peat layer with pixel-level uncertainty to set default liabilities, using low-cost visual verification to confirm status and change.	Targets the highest emitting and most visible class first, with comparatively straightforward evidence	Covers only a subset of peat emissions; does not address emissions from drained/modified peat until later; selective	Key risks are misclassification and contestation at holding scale due to map omission/commission	Lower monitoring costs than WTD-based approaches (desk-based screening and

Step	Description	Pros	Cons	Risk profile	Cost implications
	Challenges would rely on, for example, recent orthophotos or UAV imagery, repeat UAV/LiDAR surface models showing reduced roughness and infilled haggs/gullies, and dated, georeferenced records of stabilisation works. A focus on surface roughness and erosion is supported by sub-surface structural evidence showing bare peat is associated with hydrophobic surface layers and loss of fine-scale pore structure and microtopography (Brennand, 2025), conditions likely linked to enhanced runoff, drainage efficiency, and elevated carbon loss.	and change detection; avoids upfront dependence on WTD measurement networks, while allowing verification/audit/appeals processes to be tested in a bounded scope.	scope raises equity and fairness questions within wider taxation principles.	errors and boundary effects.	imagery-based verification), but still requires versioned screening layers with uncertainty and a functioning challenge route; dispute-handling costs are difficult to predict depending on mapping accuracy.
3: Expand pilot to drained or modified peat	Subject to evaluation of accuracy (discussed in this report) and dispute rates and administrative cost (a subject of future research), the pilot could expand to drained or modified peat using water table depth (WTD) measurements for verification. Defaults could be set from national screening layers and adjusted using rolling multi-year WTD evidence collected to a published minimum standard; uncertainty could be treated explicitly through confidence thresholds for desk screening, targeted review or field checks, published intervals for parcel estimates, and predefined discounts where uncertainty is material, alongside clear appeal routes.	More responsive to management and restoration than class-based approaches because WTD is identified as the most informative driver; supports a structured uncertainty framework (thresholds, intervals, predefined discounts) that can improve transparency and adjudication.	High complexity and technical burden relative to most taxes; depends on reliable WTD measurement at sufficient spatial resolution and on robust baselines; remote WTD remains the limiting factor and dipwells are currently the only viable high-accuracy route.	Elevated risk of dispute and administrative load if uncertainty is high, evidence routes are unclear, or compliance capacity varies across land tenures; the report flags risks of misestimated liabilities and significant transaction costs when assessments are contested.	Highest cost profile: installation, maintenance and QA of dipwells/loggers are identified as the dominant cost driver in higher-accuracy measurement scenarios; costs may fall if lower-cost sensors mature, but this remains developmental.

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2 Introduction

Reducing greenhouse gas (GHG) emissions from peatlands represents one of the most direct routes to meeting national climate targets (Kopansky *et al.*, 2022). Degraded peat is estimated to emit more than six million tonnes of carbon dioxide equivalent each year; roughly fifteen per cent of Scotland's total GHG emissions (Brown *et al.*, 2024). Current annual rates of re-wetting degraded peatland are insufficient to achieve area targets by 2030 (NatureScot, 2025). This challenge is particularly acute in on severely degraded or bare peat surfaces, which will not recover passively, and contributes disproportionately to peatland GHG emissions. Peatland re-wetting[1] would need to proceed at roughly three times the current rate to meet the 250,000-hectare target by 2030 (Climate Change Committee, 2022). A carbon land tax could complement restoration grants from Peatland ACTION and incentives to restore via carbon markets through the Peatland Code, encouraging landowners and land managers to restore damaged peatlands whilst creating a sustained economic signal to maintain peat in good condition without further damage (e.g., from drainage or inappropriate burning). If carefully designed, theoretically, such a tax could internalise many of the environmental costs of degraded peatlands that are currently borne by society, whilst generating revenue to support further public funding for restoration (Kotchen, 2022).

However, any new land-based tax must balance environmental ambition with fairness, administrative efficiency and technical credibility (Heine et al., 2012). Land managers would be expected to pay liabilities proportional to the emissions associated with their peat holdings, but heterogeneity in land quality, vegetation, management, tenure and accessibility means that identical actions may yield widely different emission outcomes. If measurement or modelling methods cannot resolve these differences, the tax could be perceived as arbitrary, undermining its legitimacy. Justice frameworks suggest that fairness is not just about distribution of burden, but about recognition of difference, procedure, transparency, and the capacity to contest (Ghafouri, 2023). As such, depending on the accessibility of the landholding and the capacity of landowners to use measurement methodologies, those with less capacity may be unfairly disadvantaged. Highly technical monitoring requirements have the potential to increase transaction costs, while the use of "black-box" models may simplify measurement needs but reduce trust, leading to increased contestation of liabilities. These concerns make it essential that any measurement method is transparent, accounts explicitly for

[1] Restoration and rewetting are used interchangeably in this report. In doing so, we do not imply that it is likely that peatlands will be restored to their historic undisturbed state, but emphasise the aim of restoring the functioning of the area as a wetland. This is done through raising water tables, i.e. rewetting.

measurement error, and allows for audit or appeal, and calibrates liability to avoid excessive penalisation of variance that cannot be controlled. The Scottish Government's tax framework offers guiding principles for assessing these challenges. Proportionality requires that the burden reflects both ability to pay and the scale of emissions (Scottish Government, 2021). For efficiency, the system should deliver environmental outcomes without imposing excessive compliance or enforcement costs and should also account for the carbon costs of restoration interventions, to ensure liability reductions reflect net GHG benefit (Brennand *et al.*, 2025). Certainty and convenience principles require clear rules for liability and simple processes for both taxpayers and tax administrators.

Reducing LULUCF emissions through a tax on directly or indirectly measured peat GHG fluxes will require sufficient temporal resolution so that tax rates can be updated regularly (for example, every one to five years) to encourage restoration management. This implies resolving fundamental measurement and administrative challenges so emissions can be quantified accurately, attributed fairly at holding level, and managed efficiently. Current inventory and Peatland Code approaches are scientifically credible for national reporting and restoration verification, but rely on fixed emission factors for broad condition classes and cannot distinguish liabilities at the level of individual holdings, so a tax would need to move beyond these methods. Proxy-based systems linking emissions to measurable drivers, especially water-table depth, offer a practical route but require calibration against direct flux data, transparent error reporting, and spatially balanced sampling to connect fine-scale process understanding to landscape-scale assessment. Functional indicators of peat condition (including surface and sub-surface proxies) can help interpret hydrological change, but do not remove the need for validation at the GHG flux level. For credibility and fairness, the evidence route must also be accessible across diverse owners and tenures, support independent verification and appeal, and avoid penalising those with limited technical capacity. This requirement means that any tax scheme tied to measured emissions must diverge from the principle of GHG reporting following Intergovernmental Panel on Climate Change (IPCC) methods, where yearly reported emissions should be independent of short-term yearly changes in weather. To achieve the temporal responsiveness required for taxation, emission estimates will inevitably capture inter-annual weather effects, meaning that if a tax is tied directly to net emissions, liabilities could fluctuate annually with weather conditions. Mechanisms would therefore need to be incorporated into the tax design to smooth volatility, such as setting a fixed total annual tax yield, with each landowner's contribution proportional to their relative emissions, so that no one pays excessively in dry years or disproportionately little in wet years.

For clarity, this report distinguishes between three general approaches to quantifying GHG emissions from peat. These are not mutually exclusive but differ in their purpose and resolution:

- National inventory, emissions factor, or discrete approach: defines discrete condition classes and assigns each a specific emissions factor derived from available scientific evidence. Each parcel of peat is allocated to a class based on land-use, peat depth, and satellite data. The UK tier 2 example will be given.
- Direct measurements: physical measurements of GHG concentrations and fluxes, typically using chamber or eddy-covariance techniques.
- Indirect or proxy measurements: estimation of emissions using variables statistically or physically strongly associated with GHG fluxes, including hydrological, chemical, and indicators of functional condition (e.g., water-table depth, eH, pH, and surface vegetation structure).

In practice, these approaches are interdependent. Both the national inventory and proxy methods rely on direct measurements to establish emissions factors and model relationships, while the inventory approach itself can be viewed as a composite of indirect methods.

Set against the measurement and administrative challenges outlined above, this report has four aims:

- to provide a desk-based review of existing research on methods for measuring peat-related greenhouse gas emissions;
- to summarise the key strengths and limitations of each method;
- to assess feasibility and applicability for use in a Scottish tax context where liabilities must be attributable to individual landholdings and contestable on an evidential basis; and
- to identify priority further research needs to support Scottish Government policy development.

The remainder of the report is structured as follows. Section 3 sets out the evidence synthesis methodology, followed by Section 4 summarising the evidence base in a form intended to support policy use. Section 5 then draws together the implications to describe pathways towards a future carbon emissions land tax, including where the current evidence base is sufficient for limited piloting and where it is not. Supporting detail is provided in the appendices: Appendix 1 elaborates design options for a land emissions carbon tax based on current methods and evidence; Appendix 2 summarises implementation challenges (including issues with existing inventory and Peatland Code approaches and comparators); Appendix 3 documents the review methodology in full; and Appendix 4 provides the detailed review findings, including comparison of measurement strategies and costing assumptions.

3 Evidence Synthesis Methodology

The evidence synthesis identified and evaluated methods for measuring GHG emissions from peatlands that could underpin a fair and technically credible carbon land tax. The synthesis was divided into two distinct stages.

The first and major stage of the project was a targeted literature review designed to collect evidence demonstrating whether measurements of proxy variables (remote or ground-based) provided robust and quantifiable relationships to direct emission measurements. Only studies that included a clear comparison between proxy-based estimates and direct flux measurements of GHGs were considered valid evidence. This strict condition on literature inclusion produced highly relevant studies but certainly excluded relevant evidence on measurements of peat erosion, where emissions occur off site are not measured and typically assumed to have a fixed emissions factor.

The second stage evaluated the proxy measurements of emissions in the context of a carbon land tax. The context, as set out by the call document, was interpreted in terms of quantifiable features of the measurement methods, which were expected to:

1. Have high enough temporal frequency (<5yrs) so that it can detect changes in management practices and restoration activities to adjust carbon tax rates regularly;
2. Have sufficient spatial resolution so that emissions from an area of peat can be allocated to a landowner;
3. Have the prospect of being low cost, both economically and in terms of intervention-related carbon costs;
4. Land-owners can significantly affect the proxy variable/measurement via land management changes and interventions so tax can encourage/discourage good/bad practices; and
5. Transparency in approach for ease of tax-dispute resolution and credibility.

The synthesis focused on studies conducted in peatland environments (defined Table), examining how various measurement approaches, such as remote sensing proxies (e.g. InSAR-derived surface height changes) and other geo-biophysical indicators (e.g. water table depth, supported by eH), related to direct measurements of peat emissions obtained through methods such as chamber or eddy covariance (EC) techniques. Chamber methods trap gas in small chambers and are representative of the small measured-areas while EC measurement use windspeed and gas concentrations to determine the transfer of gases to and from the atmosphere over larger spatial scales. Literature from other countries and climates was also included to capture the most up-to-date methodologies. The targeted review concentrated on studies that used statistical measures such as R-squared values and root mean square error to quantify the performance of proxy measurements compared to direct measurements.

The assessment identified and summarised direct measurement techniques for peat emissions, outlining their strengths and limitations in the context of a potential peat emissions tax. It then provided background on the proxy variables and measurements, along with the search terms used in the targeted review. This was followed by the main findings of the targeted review, which were discussed to derive recommendations for the Scottish Government.

4 Summary of Evidence Synthesis findings

This review focused on methods for measuring CO_2 and CH_4 fluxes as the major contributors to peat GHG emissions, while noting that nitrous oxide flux in nitrogen rich environments (grass/crops/livestock on peat), and the downstream carbon loss in actively eroding conditions, can be significant contributors in some circumstances. Direct measurements of GHG emissions via EC or peat chambers were deemed too costly at relevant spatial resolution to be viable. Direct measurements via peat chambers are labour intensive while EC is expensive and sampling of emissions would require careful coordination with ownership boundaries and both require expert knowledge to interpret the results. Therefore, the review focused on indirect measurements of proxy variables or "drivers" of emissions, including water-table depth, supported by chemical indicators of saturation and oxygen availability (e.g. eH and pH) and surface ecological indicators of hydrological function (Brennand, 2025), which could then be used to predict yearly emissions.

The targeted literature review (methodology detailed in Appendix 3 and results in Appendix 4) found that specific components of the GHG balance of peatlands are best approximated by using different measurement methods. Since separate components dominate the GHG balance of peat in different conditions, no singular measurement method can be accurate across all of Scotland. However, there are common control variables across components, and combinations of measurements and modelling can be used to target several GHG components together. Water-table depth (WTD), soil temperature and measurements of "greenness" (i.e. proxies of photosynthetic activity) were found to be important variables for predicting peat GHG emissions. How each of these drivers can be measured and the qualitative accuracy of the measurement method can be seen in Table 1.

A full summary of the results of the evidence synthesis are in Appendix 4, detailing: primary drivers/proxies of each component in the full peat GHG; how the drivers can be measured by either remote or ground-based measurements and gives an assessment of how well they measure the proxy in the context of yearly peat emissions; and how suites of measurement methods which target the full peat GHG balance and meet the criteria of sufficient spatial and temporal resolution are likely to perform in terms of accuracy, cost and scalability. Key findings and implications from the evidence synthesis include:

- Direct flux measurement methods (eddy covariance and chambers) were judged not viable for taxation at holding scale because they are too costly and labour intensive, require specialist interpretation, and are difficult to align with ownership boundaries.
- No single measurement method is accurate across all Scottish peat conditions; different components dominate in different settings, but water-table depth, soil temperature and “greenness” are common control variables that can be combined to improve prediction.
- GHG emissions from actively eroding peat can be significant, but erosion-related emissions are rarely directly measurable and would require proxy monitoring and conservative assumptions in any tax design.
- Spectral Earth Observation is the most established and cost-effective approach for tracking vegetation and surface processes, and can help estimate photosynthetic activity. It is not a reliable predictor of CH_4 or heterotrophic respiration (R_h) across the range of Scottish peatlands, however interpretation is strengthened where the most up-to-date, high-quality spatial and temporal datasets are used.
- Further research is required on the combined and individual use of SAR and InSAR for peatland applications, including rigorous, transparent testing and validation of existing (sometimes proprietary) algorithms that infer WTD and related variables, and joint assessment of how SAR/InSAR outputs relate to ground-measured WTD, NEE and CH_4. Although elevation change and InSAR-derived surface motion (including “bog breathing”) could in principle indicate peat loss and emissions, no quantitative studies were found that directly compare topographic measurements (InSAR, LiDAR, photogrammetry) with measured peatland GHG emissions or annual emissions estimates; in the literature, topographic variables are mainly used to interpret spatial differences in flux measurements or for eddy-covariance quality control rather than to estimate emissions, while greater surface microtopographic complexity (hummock–hollow development) is associated with improved hydrological and biogeochemical function supporting water retention and carbon accumulation.
- The development of reliable remote methods for measuring WTD at scale provides the greatest potential for cost-effective estimation of site-level GHG emissions, but WTD remains difficult to measure remotely at parcel scale and, on current evidence, a dipwell network is the only approach capable of delivering sufficient accuracy for an emissions-tax basis (with potential for future cost reductions via emerging low-cost WTD sensor development).

*Table 2: Drivers of peat emissions and how they can be measured. Drivers (columns) are Soil Temperature (Temp); Water Table Depth (WTD); soil nutrient status, particularly nitrogen Nutrients/pH); Ebullition refers to the sudden release of gas from peat. N_2O was not examined in this review and drivers are inferred from understanding of the mineral-soil nitrogen cycle. Scores between, Low, Medium, High and Very High are qualitative and represent the accuracy at which the method can approximate the driver in the context of GHG emissions. Measurement methods with a * are ground-based measurements, otherwise they are remotely sensed.*

Measurement method/Proxy	Description of method	Light & Leaf Area	Temp	WTD	Nutrients/pH	Ebullition
Vegetation Indices (Vis)	Satellite derived measurement of 'greenness' from surface reflectance. Indicates vegetation coverage.	High	-		-	-
Solar Induced Fluorescence (SIF)	Plants emit radiation during photosynthesis, the strength of this signal indicates the degree of photosynthetic activity.	Very High			-	-
Quantum Sensor*	Quantum-level light detection to precisely measure photosynthetically active radiation (PAR)	Very High	-	-	-	-
Inforeometric Synthetic Apperature Radiation (InSAR)	Comparison of radar data through time to measure movement			Low		Low
Land Surface Temperature (LST)	Satellite derived estimate of land temperature from surface reflectance	-	High	-	-	-
Meteorological data	Temperature data, interpolated from readings taken at weather stations	-	High	-	-	-
Temperature probes*	In situ measurement of temperature taken by sensor	-	Very High	-	-	-
Dip wells*	In situ measurement of water table using monitoring well	-	-	Very High	-	-

Land Surface Water Index (LSWI)/ Modified Water Index (MWI)	Satellite derived measure of soil moisture conditions from surface reflectance	-	-	Medium	-	-
Soil tests	Sampling and lab analysis	-	-	-	High	-
Fertilisation data	Survey data on quantities of fertiliser applied to fields.	-	-	-	Very High	-

- Proxy-based approaches are strengthened when WTD evidence is interpreted alongside indicators of persistent saturation and oxygen availability (eH and pH) and surface ecological indicators of hydrological function, including as lower-cost contextual checks on hydrological conditions, subject to appropriate quality control.
- Any emissions approach using calibrated proxy-driver models would need field calibration and validation (with performance reported using standard metrics) plus explicit, published rules for quantifying and managing uncertainty, including confidence thresholds for screening/review, parcel-level intervals, and predefined uncertainty discounts where evidence remains material, to support audit and dispute resolution.

5 Pathways to a future carbon emissions land tax

The brief for this project recognised that calculating emissions from peatlands is difficult and requires specialised measurement techniques. Approaches to emission measurement which are applied elsewhere within the nascent carbon market, UK GHG inventory and the Peatland code, are based on emission factors connected to a range of condition categories. However, they are designed to operate across the UK, and uncertainty is high at site level, so these approaches do not produce a sufficiently robust dataset to enable an emissions-based tax system which could:

- Determine liability at individual taxpayer level;
- Be sufficiently responsive to emission changes to enable reliefs which would encourage land management practices to achieve emission reductions; and
- Be sufficiently robust and transparent to enable appeal and adjudication of tax disputes.

Our research has shown that no single measurement can adequately meet the above challenges. Direct measurement techniques would provide the necessary level of accuracy and resolution to inform the design and implementation of an emissions-based tax instrument. However, they are not scalable for routine assessment across holdings, given the expertise and costs involved in doing so. Proxy variables (measured by a combination of ground sensors and remote platforms) may provide repeatable, auditable signals at costs compatible with tax administration.

Table 3: Comparison matrix of measurement strategies for estimating peatland greenhouse gas (GHG) emissions. Each scenario outlines a suite of methods used to measure light and leaf-area characteristics, surface temperature, and water-table depth (WTD), with optional soil sampling for nutrient and pH data. Costs are presented for two monitoring extents (ScotGov Target: 250,000 ha and all degraded peat: 1,952,000 ha) and include annual operational and initial capital expenditures. Scenarios progress from low-cost, low-accuracy remote sensing (Scenario 1) to increasingly detailed hybrid ground/remote approaches incorporating on-site dipwells, soil analysis, and hyperspectral data (Scenarios 2–4). Reported GHG coverage (CO_2, CH_4, N_2O) and indicative accuracy reflect each method's capacity to resolve drivers of emissions.

Scenario	Assumed measurement protocol	Item	Annual operational cost		Initial capital cost		GHG Coverage	Accuracy
			250,000ha	1,952,000ha	250,000ha	1,952,000ha		
Scenario 1: Remote Sensing **Light and Leaf area**: Satellite derived VIs – Utilising open source MODIS, Landsat, Sentinel data **Temperature**: LST/ Meteorological data **WTD**: LSWI/MWI	Open source satellite and meteorological data obtained, inspected and processed annually. Initial model development and calibration using existing UK and Ireland site measurements drawn from literature.	Initial model development Annual data acquisition cost Data integration and processing	- Nil £42,000 Total: **£42,000**	- Nil £84,000 Total: **£84,000**	£3,000,000 - - Total **£3,000,000**	£3,000,000 - - Total **£3,000,000**	CO_2, CH_4 (Missing N_2O)	**Poor** LSWI provides an inconsistent approximation for water table over longer time periods, and modelling of respiration and CH_4 requires information on WTD.
Scenario 2: Remote Sensing with on-site water table measurement **Light and Leaf area**: Satellite derived VIs – Utilising open source MODIS, Landsat, Sentinel data **Temperature**: LST/ Meteorological data	Open source satellite and meteorological data obtained, inspected and processed annually. Initial model development and calibration using existing UK and Ireland site measurements drawn from literature.	Initial model development Dipwell construction cost Annual data acquisition cost Data integration and processing	- - Nil £63,000	- - Nil £126,000	£3,000,000 £8,305,000 - -	£3,000,000 £64,845,000 - -		

WTD: Dipwells installed at site. Remote monitoring of water table by pressure transducer.	Average annual water table depth determined from 3-5 dipwells per 100ha. installed at site and remote sensing by pressure transducer.	Annualised cost of 5 yearly dipwell servicing by ecological surveyor.	£450,000 Total: **£513,000**	£3,500,000 Total: **£3,626,000**	- Total: **£11,305,000**	- Total: **£67,845,000**	CO_2, CH_4 (Missing N_2O)	**Good and costly**
Scenario 3: Remote Sensing with on-site water table measurement and soil testing to target N_2O **Light and Leaf area**: Satellite derived VIs – Utilising open source MODIS, Landsat, Sentinel data **Temperature**: LST/ Meteorological data **WTD**: Dipwells installed at site. Remote monitoring of water table by pressure transducer. Annual calibration. **Nutrients and Ph:** Annual soil testing.	Open source satellite and meteorological data obtained, inspected and processed annually. Initial model development and calibration using existing UK and Ireland site measurements drawn from literature. Average annual water table depth determined from 3-5 dipwells per 100ha. installed at site and remote sensing by pressure transducer. Annual soil testing of 9,000ha cropped peatland area.	Initial model development Dipwell construction cost Annual data acquisition cost Data integration and processing Annualised cost of 5 yearly dipwell servicing by ecological surveyor. Annual soil testing	- - Nil £63,000 £450,000 £8,000 Total: **£521,000**	- - Nil £126,000 £3,500,000 £56,000 Total: **£3,682,000**	£3,000,000 £8,305,000 - - - - Total: **£11,305,000**	£3,000,000 £64,845,000 - - - - Total: **£67,845,000**	CO_2, CH_4, N_2O	**Good and costly** Improves applicability of Scenario 2 to better reflect N_2O emissions

Scenario 4: Hyperspectral data with on-site water table and soil testing **Light and Leaf area**: Hyperspectral data **Temperature**: LST/ Meteorological data **WTD**: Dipwells installed at site. Remote monitoring of water table by pressure transducer. Annual calibration. **Nutrients and Ph:** Annual Soil testing.	Hyperspectral data obtained, inspected and processed annually. Initial model development and calibration using existing UK and Ireland site measurements drawn from literature. Average annual water table depth determined from 3-5 dipwells per 100ha. installed at site and remote sensing of pressure transducers. Annual soil testing of 9,000 ha cropped peatland area	Initial model development Dipwell construction cost hyperspectral data acquisition cost Data integration and processing Annualised cost of 5 yearly dipwell servicing by ecological surveyor. Annual soil testing	- - £110,000 £63,000 £450,000 £8,000 Total: **£631,000**	- - £860,000 £126,000 £3,500,000 £56,000 Total: **£4,542,000**	£3,000,000 £8,305,000 - - - Total: **£11,305,000**	£3,000,000 £64,845,000 - - - Total: **£67,845,000**	CO_2, CH_4, N_2O	**Good and costly** Improves accuracy at predicting GPP compared to scenario 3 but may lose spatial resolution.

Water-table depth is the most salient proxy, as there is strong site-level evidence that it responds to restoration, it is easy to interpret, supports independent verification and underpins the interpretation of remote indicators. Unfortunately, water-table depth was found to be the most difficult proxy to measure remotely. We found that a network of dipwells is currently the only viable approach to measure water-table depth at a sufficient accuracy to be the basis of an emissions tax. Although costly using current methods, more efficient, lower-cost approaches are currently being developed via Environment Agency funded research by the Centre for Ecology and Hydrology, with additional scope to explore supplementary citizen science approaches and low-cost eH probing to support interpretation of hydrological conditions (Brennand, 2025), subject to appropriate quality control.

To support consideration of feasible pathways, alternative measurement configurations were grouped into a small number of illustrative scenarios in Table 3. Each scenario combines remote and ground-based methods to differing degrees and reflects trade-offs between accuracy, cost, spatial resolution and administrative burden. The scenarios are not proposals for implementation but structured comparisons intended to clarify the implications of different design choices for a land emissions carbon tax. The table shows that purely remote sensing approaches are not currently sufficient to estimate peatland greenhouse gas emissions with the accuracy required for taxation. Scenarios relying only on satellite-derived proxies fail primarily because water-table depth, the dominant control on CO_2 and CH_4 emissions, cannot yet be measured remotely with adequate reliability at parcel scale. As a result, these approaches risk systematic misestimation of liabilities.

Introducing ground-based water-table measurements produces a step change in accuracy, but this improvement comes with a substantial increase in cost and operational complexity. Scenarios that incorporate dipwells enable emissions estimates that are responsive to management and restoration, but installation, maintenance and quality control represent the dominant cost driver across all higher-accuracy options. Although not yet commercially available, ongoing research by CEH into the development of low-cost WTD sensors that could substantially reduce these costs is significant.

Adding further measurements, such as soil testing to capture N_2O emissions, marginally improves completeness but does not fundamentally alter the cost–accuracy balance. These additions are relevant only for limited areas of cropped peat and do not resolve the core constraint imposed by water-table measurement requirements. Use of hyperspectral data improves estimation of photosynthetic uptake, but this gain is incremental relative to the costs incurred and may reduce spatial resolution, which is problematic for attribution to individual landholdings. Across all scenarios, Table 3 shows that accuracy gains are non-linear relative to cost. The largest improvement occurs when water-table depth is measured directly, after which additional expenditure yields diminishing returns. This suggests that a fully accurate, nationally applied emissions-based land tax is not currently feasible without disproportionate cost, but that narrower, phased or pilot approaches targeting the highest-emitting peat types are technically plausible, with further research focussed on reducing the cost and improving the scalability of water-table measurement.

A tax linked to emission estimates derived from calibrated water-table–flux response functions would complement, not replace, the UK inventory and the Peatland Code's class-based factors for bogs (note the Peatland Code already uses this approach in fens). Estimating emissions using models which use several proxy measurements as inputs would need to be calibrated, validated in the field and accompanied by clear rules to calculate and manage uncertainty.

However, proxies are indirect and rely on empirically fitted response functions (and their parameterisation), model calibration to local conditions and periodic ground truthing, which would benefit from spatially balanced sampling approaches to ensure field measurements are representative and capture meaningful hydrological and ecological variability (see Appendix 1). As they can be sensitive to weather, sensor limits and site heterogeneity, it is important to quantify uncertainty and factor this into decisions based on proxy data. As such, there are significant risks associated with the design and implementation of a carbon emissions land tax, based on current methods and evidence, including:

- The investment, skills and resources required to capture water table depth at sufficient spatial resolution;
- The confidence levels around the accuracy of data on which the tax will be based, particularly when compared to the authenticity and robustness of data on which other taxes are assessed;
- The complexity of measurement involved and the associated costs for tax authorities, taxpayers and adjudicators in making and assessing appeals; and
- The responsiveness of such a measurement regime to changes in emissions and its ability to accommodate reliefs to incentivise improved land management techniques

These challenges risk misestimating liabilities and imposing significant transaction costs on the tax authority and landowners when assessments are contested. As such, there are two broad pathways towards the design of a tax with sufficient accuracy, transparency, responsiveness and cost-effectiveness.

First, based on the evidence in this report, research may be commissioned to fill critical evidence gaps prior to a re-evaluation of the technical feasibility of administering a carbon emissions land tax. This could also usefully include the piloting of protocols and assessment of likely implementation costs, as outlined at the end of this section. Research gaps that could be addressed include:

- Calibrate functions which estimate emissions based on remotely-measured-water-table-depth (and possibly other proxy variables) for Scotland's main peat types and management states using multi-year chamber and eddy-covariance measurements, if possible based on the SCOT2FLUX network of research-grade reference sites (Artz *et al.*, 2023) with analogous flux sites elsewhere in the UK and Ireland (of which there are now many);
- Determine parcel- or holding-scale minimums for dipwell existing evidence[2], relative to site features such as slope breaks and drainage features etc; Build and validate national screening layers of peat extent and condition with pixel-level uncertainty suitable for setting default liabilities, published as dated, numbered releases with documented changes;
- Investigate options for improving remote inference of water-table depth, for example, by integrating radar, LiDAR and optical indices, with additional ground truthing data;
- Establish whether low-cost functional indicators of peat structure and chemistry can be used alongside water-table depth to verify recovery trajectories and time-lagged emissions reductions. Evidence indicates that peatland recovery following restoration is governed by changes in pore networks that control water storage and gaseous exchange (Rezanezhad et al., 2016), with hydrological, structural and carbon recovery progressing over years to decades and lagging behind surface vegetation change (Spencer et al., 2017; Brennand, 2025). µCT studies show that restoration increases vertically connected pore structures that support sustained saturation and restrict oxygen diffusion, while laterally connected drainage-related pores decline over 5–10 years, coinciding with improved bulk density, surface moisture, pH and redox potential (eH) profiles (Brennand, 2025). These functional changes are consistent with declining CO_2 emissions over decadal timescales and determine when restoration transitions from net carbon loss to net carbon benefit once intervention carbon costs are accounted for (Brennand et al., 2025). Research is needed to test whether depth-resolved pH and eH profiles can act as robust, auditable proxies of functional recovery and net emissions reduction, and whether such indicators could be used as eligibility triggers or scaling factors for tax relief within a water-

[2] For example, Artz et al. (2023) show that around seven loggers can estimate mean annual water-table depth within ~50 mm at 95% confidence on a rewetted raised bog with diminishing returns beyond ~15 and that daily readings are sufficient for annual means.

table-depth–linked tax model, rather than relying on fixed assumptions about recovery and payback.

Second, a tax could be designed with a narrowed scope, that could be introduced via pilots or in phases, to reduce risks and learn lessons for further refinement and wider roll-out. Appendix 1 suggests how, based on the strengths and weaknesses of the methods reviewed in this report, such a phased approach or pilot might be designed, starting with a narrow scope pilot targeting only the highest emitting eroding peats, verified using lower cost visual methods (e.g., including recent orthophotography, UAV imagery, repeat LiDAR or photogrammetric surface models to detect erosion features and stabilisation, and dated georeferenced photographs of restoration works). Next, pilots could be extended to drained or modified peatlands using proxy-based approaches centred on water-table depth, with default liabilities set from national screening layers and adjusted using rolling multi-year WTD evidence collected to a published minimum standard. Proxy estimates would be supplemented by sampled direct measurements for calibration and verification, with the intensity of measurement and review prioritised according to quantified uncertainty, dispute risk and the magnitude of claimed liability adjustments.

In addition to filling the evidence gaps identified above, it would therefore also be important to:

- Trial verification, audit and appeals protocols (including the proposals in Appendix 4 for desk screening, targeted analyst review, evidence requirements and triggers for field checks);
- Run place-based pilots of the narrow scope simple evidence rule proposed in Appendix 4, to quantify accuracy, costs, likely dispute rates and operational feasibility.
- Use pilot data to model likely administrative and transaction costs under authority-determined, self-assessment and hybrid designs to inform resourcing and case-handling capacity.

It is notable that the level of complexity and uncertainty involved in the proposals for a tax based on current methods and evidence is an outlier compared to most other taxes on land or property, even in the context of land value based taxes which rely on considerable technical assessment and are routinely challenged by taxpayers with disproportionate collection costs (e.g., land taxes applied in Australia and some US jurisdictions, and property taxes based on assessed value, such as the Ireland Local Property Tax). Whilst it may be technically possible to develop the broad structure articulated in Appendix 1 to pilot a tax with a narrow scope, doing so without further research may expose any regime to considerable challenge involving significant costs contrary to Scottish Government's tax principles of economic efficiency, certainty and convenience, and risking undermining the viability of the tax going forward.

Evidence on likely objections is outside scope, but it has implications for feasibility because compliance and appeals are likely to be shaped by administrative burden and by contested attribution of liabilities. Practical issues such as access constraints, shared tenure and crofting contexts, and coordination across boundaries could increase dispute rates and collection costs unless measurement protocols and evidence standards are transparent and workable in low-capacity settings. There is also a feasibility risk that expectations of future liabilities could incentivise baseline gaming (for example, pre-emptive drainage), reinforcing the need for robust baselines and clear rules on evidence and change over time.

Notwithstanding these wider issues around the design of any future tax, further research is required to refine measurement approaches to a level of robustness that could enable an equitable, practical and potentially cost-effective regime. This is an area of rapid development, not least in remote sensing, which may introduce additional measurement options, likely still proxy-reliant, capable of delivering datasets of sufficient resolution, reliability and transparency for administrative use. In the meantime, research should focus on the key challenges set out above, including improving parcel-scale inference of water-table depth, strengthening calibration and validation across Scotland's main peat types and management states, and developing published baselines and uncertainty rules suitable for verification, audit and appeals.

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Appendix 1: Design options for a land emissions carbon tax, based on current methods and evidence

7.1 Evidence base for WTD as a primary driver of emissions

The evidence reviewed in this report has shown that water-table depth (WTD) is the most consistent driver of GHG emissions across managed peatlands in temperate climates. In a UK and Ireland dataset, mean annual effective WTD alone explained most variation in annual CO_2 balance and much of the variation in CH_4, with linear and exponential responses respectively, which held true when other non- UK sites were included (Evans et al., 2021). Comparable patterns are reported in large chamber datasets from central Europe, which have been used to develop WTD-based response functions for drained organic soils (Tiemeyer et al., 2020). Some global analyses that pooled peatlands with other wetland types across multiple climate zones have ranked temperature more highly as a driver for methane and shown weaker or biome-specific WTD–CO_2 effects (Knox et al., 2019; Turetsky et al., 2014). However, Zou et al.'s (2022) global synthesis concluded that CO_2-equivalent emissions from wetland sites were kept to a minimum when the water table was close the surface (-30 to -5cm). This suggests that in Scotland, where blanket bogs and heaths dominate, WTD is a highly relevant proxy for the annual net greenhouse gas exchange of these habitats. Low-cost redox potential (eH) measurements at and below the surface can provide complementary information on oxygen availability and persistent saturation, helping distinguish between hydrologically dynamic surface layers and more stable, anoxic sub-surface zones associated with long-term carbon storage. Such indicators do not replace WTD-flux relationships, but can strengthen interpretation of snapshot WTD measurements and support identification of conditions conducive to sustained carbon retention and potential accumulation.

7.2 Measurement options and proxy indicators for WTD and function

There is case study evidence that it responds to many types of restoration and other forms of management and can be measured directly with dip wells or potentially inferred from variables such as InSAR-derived surface motion, Sentinel-1 backscatter–based surface-reflectance-based moisture indices, LiDAR-derived topographic wetness and ditch density, and simple water-balance modelling. UaV deployed thermal, RGB and ground-penetrating radar also offers considerable potential to map WTD at site level over short to long temporal frames. Surface indicators of functional condition - including *Sphagnum* presence and microtopographic development, bare peat extent, and graminoid or vascular dominance - are systematically linked to sub-surface hydrological structure, oxygen availability, and carbon retention, and offer proxy indicators of functionality that could be integrated with remote sensing to support interpretation of WTD-based approaches (Brennand, 2025). However, more evidence is needed to confirm WTD responses to restoration across different peatland contexts, and there are currently significant limitations affecting the accuracy of remotely sensed proxies. Although a tax anchored to WTD-responsive estimates may be more likely to ensure that liabilities correspond reliably to restoration actions than one tied to changes in condition categories linked to emissions factors, significant attention would need to given to the management of risk and uncertainty arising from these methodological limitations.

7.3 Administrative feasibility and costs

The case for WTD as the primary organising variable is further strengthened by administrative considerations. A parcel-or holding-level tax that changes with restoration must rely on data that owners can influence through practical actions, that are observable by the authority, and that can be verified independently. Dipwells with loggers are robust and increasingly used in restoration monitoring, but depending on the density and accuracy needed (e.g. to avoid drift and inter-operator errors), may be too expensive to be feasible within the context of a tax. Costing assumptions suggest mean annual WTD would typically be derived from around 3–5 dipwells per 100 ha (average 4), with costs driven by both installation labour and the unit cost of materials and pressure sensors/data loggers. On that basis, indicative installation costs scale rapidly, as outlined in Appendix 4, Section 10.4.

However, where continuous logging isn't feasible, a minimum programme of installed dipwells with periodic readings, plus documented drain blocking/rewetting works and mapped drainage density, may still support auditable WTD-based estimates. Moreover, lower-cost approaches are currently being developed via Environment Agency funded research by the Centre for Ecology and Hydrology. It is estimated that current sensor costs of around £200 may be reduced to as little as £100 per unit via this work, compared to current sensor costs of over £500 (Chris Evans, pers. comm., 18 December 2025). Where current commercial sensors cost £518, it is hoped that the outcome of this research will reduce the unit cost of sensors to £100- £200. Assuming that other costs remain the same, a £418 saving per sensor would equate to more than £4 milllion saving on the cost of installing and equipping 250,000ha or more than £32 million saving over the full peatland area of 1,952,000ha (compared to costings in section 10.4). Nevertheless, the cost of compliance of this approach, modest though it may be compared with other monitoring options, would represent a relatively high taxpayer burden compared with other UK and Scottish taxes. The worthwhileness of this expenditure to a taxpayer would depend on the amount of tax at stake. In addition, there are material central (non-landholder) costs implied by a WTD-linked system, including initial model development and calibration (costed elsewhere in the report as a multi-year research effort) and ongoing data integration/processing capacity, which would need to be resourced alongside field monitoring if the system is to remain auditable and consistent over time.

7.4 Uncertainty management and verification pathways

The evidence reviewed in this report shows that a number of important uncertainties would need to be quantified and accounted for, as WTD–flux functions vary among peat types and land uses, methane responses can be sensitive to vegetation, temperature and ebullition events, and short-term weather variations can mask or amplify management effects (e.g., Turetsky et al., 2014; Knox et al., 2019; Evans et al., 2021). There may be several options for managing these uncertainties. For example, liabilities could be based on rolling averages, so that weather noise is damped but lasting management effects still alter the average. This mirrors how bathing waters are classified, where SEPA uses four seasons of monitoring data to set the annual status for each site, updating the series each year (SEPA, n.d.; Marine Scotland, n.d.). Estimates of uncertainty would need to be reflected in any tax decision, for example by publishing confidence intervals, applying conservative adjustments where uncertainty is high, and setting clear appeal routes, with associated evidence requirements. This is consistent with the UK Emissions Trading Scheme, which requires formal uncertainty assessments and conservative substitute data where measurement uncertainty or gaps occur (UK ETS Authority, 2025; DESNZ, 2025). Where evidence supports action but retains material uncertainty (for example, the lower 95% bound of the rolling-mean emission estimate still exceeds a minimum threshold, or the mapped class probability is above the acceptance threshold), an uncertainty discount could be applied, so only the substantiated share is charged, with the same rule applied to claimed reductions (c.f. Heine et al., 2012).

The evidence that has been reviewed suggests that remote sensing may be able to play a useful role in mapping peatland extent and broad changes in condition, based on vegetation and surface proxies, to prioritise the deployment of more expensive methods for detecting WTD change. Optical reflectance and solar-induced fluorescence track Gross Primary Productivity well, so they are informative for CO_2 uptake, especially in open bogs, fens and cutover sites (Kross et al., 2013; Dubois et al., 2018). Yet heterotrophic respiration and methane emissions are rarely approximated well by optical signals, particularly over seasons when WTD dynamics decouple plant stress from microbial processes (Junttila et al., 2021). InSAR provides measurements of peat surface motion which can indicate hydrological change and identify re-wetted areas, but published links to annual carbon balance remain indirect. Moreover, InSAR signals are sensitive to sensor geometry, soil moisture and season, which complicates direct translation to annual carbon balance (Alshammari et al., 2020). In addition, the algorithms that are used to process InSAR data have not been independently tested in the UK, partly because many of them are proprietary.

Logistical and cost constraints limit the number of sites, samples, and deployment of monitoring equipment within peatlands, reducing confidence in the representativeness of peatland condition. A spatially balanced sampling framework (Kermorvant *et al.*, 2019; Mastrantonis *et al.*, 2024), developed for peatland restoration assessment (Brennand, 2025), provides a practical method for targeting WTD measurements and designing calibration studies for WTD-flux response functions. Rather than deploying equipment randomly or opportunistically, the approach combines mapped peat extent, peat depth, slope and aspect, accessibility, surface condition indicators (e.g., JNCC vegetation functional groups and physical degradation indicators including bare peat), drainage and restoration intensity, bog pool proximity, and microtopography to identify representative plots across gradients of degradation, restoration state, and hydrological setting.

Applied within a WTD-based tax or monitoring framework, this enables optimisation of WTD instrumentation in locations most likely to capture hydrologically and biogeochemically meaningful change, including areas influenced by drainage features, slope breaks, and restoration interventions. This could reduce the number of dipwells required while increasing confidence that measured WTD dynamics are relevant to emissions processes.

The same framework supports calibration of Scottish WTD-flux response functions, enabling chamber or eddy-covariance measurements to be spatially representative of wider peatland units. Surface indicators already used in condition assessment (JNCC, 2009) can be used to stratify calibration datasets, accounting for variation in vegetation, degradation state, and hydrological setting.

Used alongside remote sensing, spatially balanced field sampling offers a transparent and auditable means of optimising the deployment of higher-cost measurements, supporting improved model calibration and more cost-effective verification within a WTD-linked land emissions tax.

These limitations suggest that significant (and possibly costly) verification will be needed for extensive areas. To reduce the costs of verification, thresholds could be set, so that high-confidence areas are cleared by desk screening (an administrative check using maps, recent orthophotos, lidar/SAR layers and works records), medium-confidence areas undergo review (a targeted analysis by technicians, comparing multiple sources, recent imagery and any local evidence, with follow-up queries as needed), and the low-confidence areas trigger water-table measurements for verification and further model improvement. For example, in these sites, landholders could install and maintain dipwells or piezometers to record water-table depth at a specified frequency, with quality assessment including sensor checks and georeferenced site photos. For holdings that contest default liabilities in high and medium confidence areas, landowners could opt-up to a higher-evidence route by documenting hydrological works (for example, drain blocking or bunding) and installing WTD sensors, enabling recalculation on a stronger evidential base.

7.5 Initial rollout options and sequencing

Given the potential cost of water-table-depth (WTD) measurements needed to verify remote-sensing outputs, an initial phase could focus only on bare and actively eroding peat. This would avoid upfront investment in WTD networks, target the largest source of peatland emissions, and rely on lower-cost visual verification (e.g., recent orthophotos or UAV surveys) to confirm status and change. Landowners seeking to challenge how their liabilities have been assessed could show mapped areas are not eroding or have been stabilised (e.g., using repeat UAV/LiDAR surveys showing reduced roughness and infilled haggs/gullies, and GNSS-mapped, dated works with photos). As method reliability improves, scope could be widened to drained or modified peat, using remotely sensed proxies with WTD measurements reserved for verification and appeals. Selective application of a tax does raise questions about the broad taxation principles of equity and fairness, which are central to the Scottish government's general approach to taxation.

If a WTD-based approach is preferred, a sequenced approach might start with a narrow scope, restricted to degraded blanket bog above agreed extent/depth thresholds and applying a two-part evidence rule based on: 1) a published national screen (peat extent/condition with confidence) to set a default liability; and 2) a minimal water-table dataset collected by the owner on included peat (installed dipwells or piezometers at a fixed density, periodic readings or low-cost logging, and basic quality assessment such as georeferenced photos and installation records). The default liability would then be charged unless the owner's rolling-average WTD meets a stated threshold for wetter conditions, and where it does meet this threshold, liability could be reduced according to the published WTD–flux function. Field visits would only be triggered for low-confidence map areas or where claimed adjustments are large. Richer evidence streams (dense WTD networks, detailed ditch mapping, InSAR or spectral modifiers), complex data fusion and routine site surveys would then be deferred to later phases of the tax roll-out. Again caution would be needed with an approach like this with regard to the wider tax principles of fairness and equity as between taxpayers and the type of peatland they own or occupy.

7.6 Baselines, definitions and implementation constraints

When considering the feasibility of piloting a tax, whether based on visual or WTD-based methods, a number of additional method limitations should be acknowledged. Current peat maps were developed for broad survey purposes rather than parcel-scale administration, which creates a non-trivial risk of omission and commission errors at holding scale. The 50 cm organic horizon threshold currently used to define peat in Scotland is high by global standards, and there are extensive areas where measured depths lie close to this cut-off. In such contexts, small errors in mapping or depth measurement could determine whether otherwise similar land parcels are taxed or not, with significant implications for perceived fairness and dispute risk. Any peat-based tax would therefore require a versioned national peat baseline with pixel-level uncertainty, clear and consistently applied peat definitions, and explicit rules for treating soils close to depth thresholds, including how uncertainty is reflected in liabilities and appeals.

A practical approach to the question of peat depth definitions would be to adopt a single, published definition for tax purposes (for example, specifying an organic horizon thickness threshold and minimum organic carbon content) aligned as far as possible with the UK Inventory/Peatland Code and international conventions, but this would still raise material issues, including misclassification where depths cluster near the cut-off, inconsistency between map products and field measurements, incentives to contest or re-measure borderline soils, and the need to specify standardised field methods and error tolerances so that liability and appeals do not hinge on small differences in sampling location or technique.

Mean water-table depth remains the most informative driver at policy scales, but accuracy at local scale depends on reliable in situ logging. Remote inference of water table appears strongest for wetter sites and is weaker on deeply drained ground. The use of InSAR to infer peat motion or hydrological status shows potential but currently requires site-level validation against independent ground observations before it can inform liability. These uncertainties imply material risks of over- and under-assessment where evidence quality is uneven, and they strengthen the case for conservative defaults, clear appeal routes, and phased adoption linked to validation results.

Equity and feasibility constraints would also need to be considered. There are large tracts of unrestored peat in the Highlands and Islands, with fragmented ownership in shared hydrological units and a significant area of crofting common grazings. Heavy machinery access is limited in many places, coordination across boundaries is often required for re-wetting, and herbivore pressure can slow vegetation recovery. These factors imply that even with accurate measurement, charging rules would have to reflect realistic restoration timelines and constraints outside owners' immediate control. For example, exemptions or deferrals could be made for access-constrained sites. In addition to this, full land registration coverage has not yet been achieved, complicating the administration of any tax.

7.7 Links to UK GHG inventory, Peatland Code and international comparators

A tax linked to emission estimates derived from calibrated water-table–flux response functions would complement, not contradict, the UK's GHG Inventory and the Peatland Code's category-based emission factors for bogs and would align strongly with the Peatland Code's approach to assessing emissions from fens. It would provide finer temporal and spatial resolution while remaining anchored in measured fluxes, the same empirical basis used for emissions factors used in the Inventory and Peatland Code. Making such data available through the tax system could, over time, help refine emissions factors used in the Inventory and Peatland Code. For Peatland Code projects, the same datasets (e.g., logger-based WTD time series, mapped drainage density with documented rewetting works, and remote indicators of condition change) could substantiate baseline survey work, show movement between condition categories (reducing the need for site visits by independent verification bodies), and strengthen risk and monitoring plans. As such, tax-derived evidence may lower transaction costs and further increase confidence in the additionality, permanence and quantification of units issued via the Peatland Code.

While this alignment offers potential efficiencies, it remains important to recognise that comparable WTD-based systems in Europe have been developed primarily for monitoring and inventory purposes, and their transferability to a holding-level tax context in Scotland is not straightforward. Experience elsewhere in Europe appears to support a WTD-based approach to a future tax, however these countries are dominated by degraded agricultural peats compared to the diversity of semi-natural peatland habitats found in Scotland. Moreover, these systems have been developed primarily for the purposes of national monitoring, rather than a tax (although Denmark is proposing the use of this data in their proposed tax system), and may still lack the necessary spatial and temporal resolution needed. Germany's grid-based Tier 3 methodology relates CO_2 and CH_4 to long-term mean annual WTD with response functions fitted to national chamber data (Tiemeyer et al., 2020). The Netherlands operates a parcel-scale Tier 3 methodology for coastal organic soils, with groundwater–decomposition modelling calibrated to an extensive flux network (although upland peat emissions are still calculated using emission factors) (Erkens et al., 2022). Denmark has developed national WTD mapping with Danish-data response functions and uses the framework to compare restoration scenarios (Koch et al., 2023). Although it remains to be seen how this data will be used in the context of Denmark's proposed tax on carbon rich soils, there is evidence from ongoing qualitative research from RESAS's JHI-D5.3 Galvanising Change via Natural Capital project, that the threat of the proposed tax is already motivating some landowners to sell their land to the state (which is then retiring the land from agriculture and restoring the peat).

7.8 Conclusion

Ultimately, selection between the options outlined in this appendix needs to balance messaging to the land management community (given evidence that proposals to introduce a similar tax in Denmark are already influencing decisions to sell peatlands to avoid future liabilities) with the risks of piloting a tax using methods that are known to have significant limitations, potentially undermining the legitimacy of a future tax. In addition to the research outlined in Section 5 to refine the methodological evidence base, future work could evaluate tax design options, to ensure equity across diverse tenure systems (e.g., including the specific liabilities of crofters and tenants, community and NGO landowners etc), while resolving practical and legal complexities related to administrative enforceability, dispute resolution, and the potential feasibility of integrating peatlands into the UK Emissions Trading Scheme instead of a standalone tax. While peatlands are not currently included within the UK ETS because restoration is treated under existing accounting rules as an emissions reduction rather than a greenhouse gas removal, there is ongoing discussion across the UK ETS Authority and devolved administrations the opportunity for peatland restoration as an active abatement of a large, ongoing emissions source, that could become a credible future ETS option as evidence, accounting approaches and governance frameworks mature.

Appendix 2: Overview of implementation challenges

8.1 Overview of implementation challenges

The practical implementation of a carbon land tax depends on resolving a set of measurement and administrative challenges that determine whether emissions can be quantified accurately, attributed fairly, and managed efficiently:

- Measurement accuracy and validity: Methods must reflect net emissions from peat relative to direct flux measurements, with accuracies proportional to the greenhouse gases of concern (CO_2 and CH_4 at typical magnitudes). Current inventory approaches provide averaged emission factors for broad peat categories, limiting precision and the ability to attribute emissions to individual holdings. Developing proxy-based methods that approximate true fluxes within defensible margins of error will therefore be central to the tax's credibility. Measurement uncertainty remains a primary constraint, and transparent reporting of error margins and model assumptions is essential.
- Spatial and temporal resolution: Sufficient spatial resolution is required to allocate emissions reliably to specific landholdings, accounting for the fine-scale variability in peat condition, hydrology, and vegetation. Emissions also vary through time with weather and management interventions; hence, measurements must be frequent enough, ideally at least every three years, to detect meaningful change. Capturing this variability at acceptable cost will depend on proxy variables measurable by both remote and ground-based means, ensuring that change in management practices and restoration outcomes can be reflected in updated tax assessments.
- Equity, access, and behavioural responsiveness: Landowners must be able to influence the proxy variables through management decisions so that the tax can encourage practices that reduce emissions and discourage damaging activity. However, the system must operate equitably across Scotland's diverse tenure systems, including crofts, common grazings, and large estates, without disadvantaging those lacking technical capacity or access to measurement tools, or in occupation of land which is naturally harder to access and monitor. Cost-effectiveness and implementability by land managers are essential design considerations to avoid excluding smaller or resource-constrained participants.
- Transparency, compliance, and dispute resolution: The tax mechanism must be transparent in its data sources, modelling assumptions, and procedures, allowing independent verification and audit. Taxpayers require a clear route to contest or appeal assessments based on reproducible evidence, and ultimately

such contest must be capable of accurate determination by a third party. These measures are vital for public legitimacy, administrative efficiency, and procedural fairness.

As such, the feasibility of the tax therefore rests on whether a scientifically robust, replicable and transparent means can be developed to estimate greenhouse-gas fluxes from peat at parcel scale, at a reasonable cost in relation to the revenue raised or other public objectives achieved. Direct flux measurements, such as chamber and eddy-covariance methods, provide reference-quality data but are costly and logistically demanding for large-scale use (Aubinet, Vesala and Papale, 2012; Baldocchi, 2020). For this reason, proxy variables are widely used to approximate emissions at larger spatial and temporal scales through empirical or physical inference. Hydrological state is particularly important: shallower water tables are consistently associated with lower net warming effects (Evans *et al.*, 2021). Proxy variables themselves can be measured in several ways, divided in this report into “remotely sensed” (e.g. satellites or Unmanned Aerial Vehicles UAVs) and “ground-based” (e.g. dipwells) measurements.

Due to their large scale, remote measurements lend themselves to tax systems where all tax liabilities are determined by the tax authority. Ground-based measurements lend themselves to “self-assessment” style tax systems, where landowners are responsible for measuring the proxy variables on their land, from which their emissions and tax liability can then be determined by the tax authority. The potential land tax is at an early stage and the tax system is not fixed; therefore, both remotely-sensed and ground-based measurements are assessed in this report, and recommendations on appropriate tax systems are given.

Many models exist to predict GHG emissions from proxy variables, but their accuracy depends on both the reliability of the measurement of input variables and the strength of their relationship to actual emissions. This rapid evidence synthesis therefore prioritises assessing how well the variables approximate GHG emissions compared to direct measurements, and how these variables can be measured, either remotely or on the ground. Systematically assessing models for determining peat emissions from the proxy variables may be prioritised in future research. For example, this report will examine how well water-table depth predicts GHG emissions compared with flux tower measurements, as well as how accurately water-table depth itself can be measured. It will not, however, assess which modelling approach best predicts GHG emissions from water table depth.

8.2 Issues with using Tier 2 methods from the UK's GHG inventory and Peatland Code as the basis for a tax

The UK's national GHG inventory currently provides the most comprehensive means of estimating emissions from peatlands at national scales. However, as a national reporting methodology, though scientifically robust for reporting purposes, it cannot resolve emissions with the spatial precision or temporal frequency required for taxation. IPCC reporting for the Paris Agreement is designed to represent long-term averages that are insensitive to year-to-year weather variation, ensuring reported anthropogenic emissions reflect management change rather than climatic fluctuation (Eggleston *et al.*, 2006). This distinction is especially important in the LULUCF sector, where peat CO_2 respiration can vary by around ±100 per cent from the long-term mean over a five-year period (Wilson *et al.*, 2016). Understanding the GHG inventory's structure and limitations helps to identify where methodological advances are needed to underpin a fair and technically credible carbon land tax.

The Tier 2 approach used to determine national yearly GHG emissions from peat improves upon the default IPCC guidelines in the UK context (Hiraishi *et al.*, 2014; Evans, C. *et al.*, 2017). Evans, C. *et al*. (2017) updated emissions factors for UK-relevant peat emission categories in the IPCC drained land-use categories set out in the 2013 Wetlands Supplement (Hiraishi *et al.*, 2014). The IPCC organic-soil categories 'grassland' and 'extraction site' categories were disaggregated into drained and undrained areas, while 'heather-dominated' and 'grass-dominated' modified bogs were merged into a single 'modified bog' category. The approach also differentiates between near-natural and re-wetted bogs, improving on IPCC guidance.

Scientific evidence was collated to derive emissions factors per category, resulting in new UK-specific factors for all categories except CO_2 from fluvial export of dissolved organic carbon (DOC) and particulate organic carbon (POC), CH_4 from drainage ditches, and indirect N_2O emissions from downstream waters. Peat extent is currently defined using the 1:250,000 National Soil Map of Scotland (full coverage) and the 1:25,000 Soils of Scotland map (James Hutton Institute, partial coverage) in combination with the 1:50,000 British Geological Survey Geological Map of Britain, applying a slope threshold to downscale mixed land parcels in mountainous areas. This method achieved a true positive rate ('recall') of 0.68 and a true negative rate ('specificity') of 0.84 when validated against the National Soils Inventory of Scotland. Baseline (1990) peat emission categories are defined using the Land Cover Map for Scotland 1988 (LCS88) based on aerial photographs at 1:25,000 scale. LCS88 dominant categories were mapped to peat emission classes, though some distinctions could not be made due to limitations in source data. Yearly net emissions are obtained by multiplying the area of each peat category by its emissions factor.

Emissions factors were updated in Evans *et al.,* (2023) using new eddy covariance and chamber evidence. Changes in activity data, that is, changes in peat emission categories, are tracked through area accounting rather than mapped change detection, incorporating data on restoration activity (only those funded/supported by Peatland ACTION), afforestation and felling (from Forestry Commission records), cropland and grassland conversions (from land-cover data), and extraction areas (from licences and satellite imagery).

The current inventory has limitations for direct use in taxation, primarily due to unavoidable uncertainties in classifying peat extent and condition categories. If peat-extent classification uncertainties (recall and specificity) persist at rates reported in Evans *et al.* (2017) across Scotland, 32 per cent of peatland would remain untaxed and 16 per cent of non-peatland could be incorrectly taxed. Further uncertainty arises from peat condition classification, for which error has not yet been fully quantified.

The Peatland Code takes a related but more operational approach to quantifying avoided or reduced emissions. For bogs, it also uses emissions factors, directly aligned to the Tier 2 inventory, and applies them to condition categories that represent discrete ecological states. These categories, used in both the Peatland Code and UK GHG Inventory include 'actively eroding', 'drained', 'modified', and 'restored' states. The Peatland Code uses the difference in emission factors between these condition categories to estimate emission reductions from restoration activity, rather than attempting to model fluxes directly. This reduces the costs of monitoring at each site and makes the scheme operational. Each project is assigned baseline and post-restoration condition classes using field survey data and remote-sensing evidence, which is checked by independent third-party assessors, and the area within each condition category is then multiplied by the corresponding emissions factors to calculate net emission reductions. This discrete-category approach aligns conceptually with the national inventory but serves a different purpose. It prioritises verifiability at site scale and permanence over comprehensive spatial coverage, and updates emission factors periodically to reflect new evidence from flux-tower and chamber studies. However, like the Tier 2 approach, it is limited by the accuracy of condition classification and the assumption that all areas within a category share a uniform emissions factor, wherever they are located in the UK. This is acceptable for the Peatland Code and the UK inventory because applying a category mean across the national area is intended to balance over- and underestimation at aggregate scale. For taxation, the same averaging creates problems at site scale. Parcels in the same condition category can have materially different emissions depending on hydrology, vegetation and climate, so liabilities tied only to categories will not move with management until a reclassification threshold is crossed. In many cases reclassification may take years, during which landholders who have invested in effective re-wetting would face unchanged liabilities despite real reductions in emissions that are not yet reflected in a category change. It might also be observed that participation in the Peatland Code is voluntary whereas the payment of a tax is mandatory. A tax liability must therefore be based on a higher threshold of liability assessment.

Due to the lack of Tier 2 emissions factors in the UK GHG inventory the Peatland Code takes a different approach for fens. Here projects must measure their water table depth pre restoration and throughout the whole project lifetime. The average annual water table depth is then used in combination with the condition category to model the emissions, and from the difference in emissions pre and post restoration the emissions reductions are calculated.

8.3 Other Countries' National Inventory Approaches

Approaches used in Germany, Denmark and the Netherlands focus on the variables driving emissions. Germany reports emissions from organic soils with a spatial Tier 3 method that relates CO_2 and CH_4 to long-term mean annual water-table depth using response functions fitted to national chamber measurements, implemented on a national grid and compiled for UNFCCC submission (Bärbel Tiemeyer *et al.*, 2020; German Environment Agency, 2025). High-resolution maps of land use, organic soil type and WTD underpin country-specific response functions for CO_2 and CH_4, derived from a large chamber dataset and implemented in the national inventory (Bärbel Tiemeyer *et al.*, 2020; Fuß *et al.*, 2025; German Environment Agency, 2025). Although a constant (in time) map for mean annual WTD is used in the German inventory to align with IPCC reporting principles, the framework allows for the use of time-resolved WTD data to better capture the effects of re-wetting on emissions (German Environment Agency, 2025). This aligns well with data available from ongoing restoration monitoring and provides a potentially auditable signal for tax liability adjustments as water levels are raised.

Denmark has developed methods based on national WTD mapping and water-table-emission response functions fitted to Danish flux data, which are then used to estimate emissions and compare restoration scenarios (Koch *et al.*, 2023; Nielsen *et al.*, 2025). This has included the development of a high-resolution WTD map for Danish peat soils, non-linear CO_2 and CH_4 response functions with strongest sensitivity in the upper 0–0.5 m, and uncertainty analysis to test rewetted versus drained cases (Koch *et al.*, 2023) consistent with parallel national mapping efforts to update peat and organic-soil extent used in inventory workflows (Gyldenk *et al.*, 2023). In the proposed tax context, agricultural peat soils are generally assumed to be drained (and therefore high-emitting) where a field is classified as peat (commonly defined in Denmark as >6% C), with the highest CO_2 emissions associated with groundwater depths beyond c. 40 cm, consistent with Tiemeyer et al. and confirmed in Danish analyses; where peat is shallow (e.g. <40 cm), emissions may be treated as lower (for example, around half). The temporal aspect is not generally modelled directly unless land is taken out of agriculture, with liability instead linked to land status (e.g. continued agricultural use versus rewetting). Denmark's approach aligns technical inventory practice with a planned future carbon emissions land tax on non-energy agricultural emissions using uniform CO_2-equivalent pricing (which explicitly notes emissions from carbon-rich agricultural soils; Expert Group 2024). However, proposed peat-soil tax rates are substantially lower than those faced by ETS-covered industry, and the practical incidence of tax depends strongly on peat classification: if a field is mapped as peat but is actually mineral soil, the owner/user could be overcharged, reinforcing that the performance of the peat map is central to both fairness and dispute risk. As a consequence, work is underway on a sensor-based appeal system if earlier peat maps are used as the basis for taxation, and additional work has been proposed (not yet adopted) on improved high-resolution peat mapping (including approaches using drone-borne TEM and gamma sensors). Farmers may avoid the tax by entering an agreement to rewet land (with compensation), and may also sell land to government or receive replacement land. Taxation is planned to start on 1/1/2028, but it has not yet been decided whether the landowner or the user should be liable for the tax (pers. comm. Mogens Humlekrog Greve, 2 December, 2025).

The Netherlands splits organic soils into coastal peatlands, which cover about 72% of the organic soil area, and uplands. Coastal peatlands use a Tier 3, parcel-level ensemble (Erkens *et al.*, 2022) that couples a groundwater model (PP2D) with a carbon decomposition model (AAP), calibrated against the Netherlands Research Programme on Greenhouse Gas Dynamics in Peatlands and Organic Soils (NOBV) flux network (NOBV, 2019, 2023), with outputs used to derive emissions factors, which are used in GHG reporting (Schelhaas *et al.*, 2024; Baren *et al.*, 2025). Upland peatlands retain a Tier 2 method in which both methane and carbon dioxide emissions are derived from emissions factors (Baren *et al.*, 2025). However, it is worth noting that emissions factors for carbon dioxide were developed using measured or inferred ground-surface movements linked to ditch water level or mean lowest groundwater level, which could form the basis for future Tier 3 methods that could, similar to the SOMERS parcel outputs, provide hydrology-responsive CO_2 estimates at scales relevant to changes in land management.

In summary, the UK Tier 2 assigns fixed factors to categories such as near-natural, modified, drained and rewetted bogs, and tracks change mainly through area updates. In contrast, Germany and Denmark relate fluxes to WTD and the Netherlands links carbon dioxide emissions to subsidence in intensively drained peat, which may be altered via changes in management and are therefore easier to be adapted to the basis of a carbon tax. Continuous driver-based methods are more sensitive to management at parcel scale and better capture restoration effects between discrete category thresholds, which is relevant for a tax intended to reduce liabilities as water levels recover. The adoption of water-table-driven estimation for organic soils within the UK's inventory framework could align any liability calculation with inventory methods and update cycles used for reporting to UNFCCC, so that verified rewetting reduces assessed emissions and tax in step with inventory evidence.

8.4 Financing restoration

Consideration must also be given to the means available to landowners to finance restoration. The cost of restoration varies from site to site however is typically upwards of a thousand pounds per ha., meaning that for larger sites the total cost may run into hundreds of thousands of pounds (Glenk et al., 2022). Current financing options include capital investment grants available through the Peatland Action program and carbon finance utilising carbon credits awarded by the Peatland Code.

The introduction of a land carbon tax may complicate this funding environment by prompting a need to consider Peatland Code additionality. Additionality is a key concept underpinning the integrity of carbon finance, yet operational rules applied to determine additionality differ between codes. Recognising that the aim of introducing a tax would be to create an incentive toward restoration, it would be appropriate for this incentive to be accounted for in assessment of whether the anticipated emissions reduction is additional to the baseline trend. The current additionality rules within the Peatland Code utilise a carbon finance test which would not account for this incentive – as it relates more narrowly to the proportion of funding from carbon finance as compared to other sources. Were a tax to be implemented, it may be necessary however for the Peatland Code to reconsider this arrangement and potentially provide further justification of additionality. Were additionality to instead be assessed on the basis an investment test, as is currently the case for Woodland Carbon Code and international standards such as Verra and Gold Standard, it is likely that many projects would fail to pass and not be eligible for carbon credits, due to the fact that there would already be a strong incentive in place for landowners to engage in peatland restoration. Additional modelling would however be required in order to understand this outcome since without appropriate financing in place, from carbon finance or other sources, landowners may not be able to bear the cost of peatland restoration.

It might also be added that in its broadest sense, additionality requires that where an obligation has arisen then no further financial support (private or public) should be available. This would raise the further complication of the categorisation of a tax in terms of additionality. On the one hand as a measure to force land managers to restore land, the general principle of additionality may be offended; on the other hand as merely a financial obligation that can be avoided by management measures, additionality may not be regarded as an issue at all beyond the requirements of any financial tests in place.

8.5 Peat mapping baselines for tax administration

England's new Peat Map (Natural England, 2025) is a useful benchmark for improving Scotland's peat extent and condition baselines, but it also illustrates limits of national-scale modelling for regulatory use. The Natural England report documents a modelling stack that combines field surveys with satellite, LiDAR and ancillary predictors to map peaty-soil extent, depth, vegetation and upland erosion features, with published accuracy and confidence layers. Reported validation for peaty-soil extent is high and vegetation mapping is accurate overall, but agreement varies by vegetation class. The validated map outputs (specifically the peat-extent and vegetation-class rasters, together with their confidence layers) can provide an auditable screening baseline to identify where peat is likely, prioritise survey effort and plan restoration. Because some vegetation classes are harder to distinguish, such outputs should only be used to guide screening and targeting rather than determining liability without local verification.

The map reported high accuracy metrics but making it clear that not all predictions would be correct. This led to multiple public critiques, suggesting systematic misclassification by the England Peat Map, including predictions of peat on rocky outcrops, stone features and woodland, alongside omissions where peat is known locally (Envirotech Online, 2025; NFU, 2025; The Times, 2025). However, public reporting of misclassifications likely focused on places where the map was incorrect but it not clear if there is indeed systematic bias in the model. Likely causes, based on limitations identified by Natural England (2025) and well-documented constraints of optical and LiDAR peatland mapping (Kuhn et al., 2024; Honkavaara et al., 2023; Bonn et al., 2024), include class confusion between peaty and mineral soils, mixed pixels at 10–30 m, seasonal/phenological effects on optical signals, LiDAR artefacts on steep or rocky ground, noisy historic labels, and threshold choices that trade sensitivity for precision.

In parallel with Natural England's national modelling, Scotland-specific work led by the James Hutton Institute (JHI) is building a routinely refreshed peatland condition baseline using high-resolution imagery and machine-learning, intended for regular updating as new data arrive. It integrates recent satellite/UAV imagery, training data from field campaigns, and classifier ensembles to map condition states, with an explicit goal of supporting restoration planning and policy use at operational scales (The James Hutton Institute, 2024). However so far, there has only been one static mapping effort. A complementary JHI programme focuses on drainage and erosion features that drive emissions and restoration costs, using deep-learning models to detect grips, gullies and other surface indicators across Scotland at finer spatial resolution than legacy 100 m products. The team has released an open dataset and describes the rationale as enabling more precise inventory inputs and restoration targeting where surface variability is much finer than national soil maps capture (The James Hutton Institute, 2025b, 2025a). Recent JHI–National Library of Scotland work also mines historic Ordnance Survey maps with AI to identify “missing” Moorland, rough grassland, and peatland signatures, strengthening training/validation in areas where modern labels are sparse and helping reconcile discrepancies between historic and current condition signals (The James Hutton Institute, 2025b)

Both the JHI approach and Natural England’s England Peat Map aim to provide national, evidence-based screening layers for peatland extent, condition and surface features. Natural England’s approach focusses on providing national layers for each variable, with clear user guidance and data governance, whereas JHI’s approach puts more weight on frequently refreshed, higher-resolution detection of condition drivers such as drainage and erosion. Future development of the JHI map might usefully provide versioned releases with clear product definitions, confidence rasters and plain user guidance. Versioning would record what changed, when and why, so estimates used for tax can be traced and reproduced. Unambiguous product definitions would prevent disputes about what each layer represents and how it should be used. Pixel-level confidence rasters would allow tax authorities to treat high-confidence pixels as adequate for desk decisions, flag medium-confidence areas for targeted review, and mandate field checks where confidence falls below a stated threshold. User guidance should define those thresholds, specify appropriate use at parcel and holding scales, and list the evidence required to challenge or correct a classification. Together these measures would reduce ambiguity, support independent audit and simplify maintenance as methods and data are updated.

Appendix 3: Review methodology

9.1 Direct measurements

Chamber methods

Peat chambers have been used to measure emissions from soils for over 100 years (Pavelka et al., 2018). The aim is to cover a defined area of ground with a PVC chamber, allowing for the exchange of gases between the soil and chamber headspace. Measuring the change in concentration of gas over time then allows an estimate of the net flux of gases between soil and atmosphere (Pihlatie et al., 2013). Peat chambers are commonly used to measure CO_2, CH_4, N_2O, however the optimal chamber design and sampling strategy depends on the particular GHG gas targeted by study (Pihlatie et al., 2013).

A key difference in measurement technique is the choice of static (manual) versus dynamic (automated) system. Within static chamber systems gas is manually sampled by syringe and then transported from site for analysis by gas chromatograph. Automated chamber systems meanwhile use an in- situ gas analyser to measure gas concentration allowing for multiple repeated measurements. Automated systems need power supplies and are limited by the number of chambers versus the length of supply lines to and from the analyser while static chambers require frequent visits to the site. Greater frequency of measurement may better capture daily and seasonal dynamics in GHG cycles, however dynamic systems may not always be optimal and among measurement of peatland emissions, static systems continue to be most common (Boonman et al., 2024). Dynamic systems have been most commonly applied to measuring CO_2, since (typically) larger fluxes place less reliance on the sensitivity of the gas analyser and enable shorter enclosure intervals, while static systems are commonly used for measuring N_2O or CH_4 (Pihlatie et al., 2013). However, the development of faster gas analysers has enabled automatic systems to be used to estimate CH_4 and N_2O.

Whichever system is used, to provide an accurate estimate of annual emissions it would be necessary to ensure that sampling accounted for variation in conditions across site and was conducted throughout the year to capture seasonal changes in emissions. **Since this may entail hundreds if not thousands of individual chamber samples per site each year, peat chambers do not offer a practical means of nationwide monitoring to support a land carbon tax**.

Various factors have been identified in the literature as influencing the accuracy of estimated fluxes, and to reduce bias it is important to (Juszczak, 2013):

- use a fan to prevent stratification within the chamber
- allow for pressure compensation between chamber and outer atmosphere
- ensure chamber is properly sealed
- review chamber readings and address outliers which may reflect to mistakes of person conducting experiment (static chambers), improper closure of chambers (automatic), or result from chamber artefacts such as condensation
- rotate plot locations to reduce impact of chamber deployment on vegetation due to rain shadow (Boonman et al., 2024)
- avoid measurement on windy days (Yao et al., 2017)
- ensure appropriate application of linear/ exponential estimation technique.

Eddy Covariance

The Eddy Covariance (EC) method for measuring atmospheric fluxes of gasses uses a 3-dimensional wind speed detector (3D sonic anemometer) and an analytic method for measuring gas concentrations attached to tower to measure gas fluxes at the landscape scale. The measurements assume that the majority of gas transport to and from the atmosphere is via eddies (swirling parcels of air). By measuring the changes (covariance) in the upward/downward velocity of air with the concentration of gasses they can estimate gas, heat and vapour fluxes. In practice, EC tower alignment and data go through quality control because the method relies on several assumptions about the atmosphere, the landscape and tower height. When these assumptions break due to sudden weather changes, uneven terrain, low eddy activity, or winds coming from the wrong direction the measurements become less reliable. The tower height and location are selected to ensure that the measurements represent the ecosystem and above the messy airflow zone so that the air is well mixed and representative of the landscape rather than one small parcel of land. Additionally, quality control filtering identifies and removes periods of weather changes or when the wind is coming from the wrong direction so the final fluxes represent ecosystem behaviour. The literature generally find high correlations (R^2=0.86) with chamber measurements, even when footprint size and wind direction are not accounted for (Laine *et al.*, 2006). However, differences between chamber and EC measurements are expected, and interpreting these discrepancies requires specialist expertise.

The challenge in using EC as the basis for a carbon tax is achieving enough spatial coverage of peatlands while still meeting the strict quality-control requirements described above. To meet the tax-criteria, all emissions from peatlands owned by a landowner must be measured, and only emissions originating from peat under their ownership should be attributed to that landowner. Therefore, flux tower networks will have to be placed in coordination with ownership boundaries and the above factors to meet these two requirements resulting in hundreds or possibly thousands of towers (authors' interpretation based on complex geometry of ownership boundaries and Scotland's terrain). Furthermore, since all peat emissions should be measured, it will be hard to differentiate between peat and other GHG sources for peatland near roads, houses, agriculture or other GHG sources.

9.2 Methods Background and Search terms

Selection of proxy measurements

Proxy measurements were selected based on discussions with the Scottish Government and the funder. The search strings were broadened to include the variables that proxy measurements observe (called "proxy variables"). For example, InSAR (proxy measurement) measure temporal- and spatial- changes in surface elevation (proxy variable). Including proxy variables in the search string broadened the evidence review to include papers which used ground-based measurements as well as remote sensing techniques.

Peat Greenhouse Gas Emissions terms and definitions

Individual search strings were developed for each proxy measurement. However, they all shared common terms designed to capture studies which directly measured peat GHG emissions and compared them to another prospective measurement.

The vocabulary of peat emissions literature often uses jargon which we list here and use consistently throughout the report:

- Gross Primary Productivity (GPP): The total amount of carbon fixed by photosynthesis.
- Net Primary Productivity (NPP): The amount of carbon that remains in plants after what they use for their own respiration. NPP=GPP-R_a, where R_a is the rate of plant respiration.
- Gross Ecosystem Exchange (GEE): Measured total CO_2 uptake. Should be the same as GPP but is used when measuring carbon fluxes at the eco-system scale, e.g. with EC towers.
- Net Ecosystem Exchange (NEE): The net CO_2 flux between the ecosystem and the atmosphere accounting for respirations by autotrophs (plants) and heterotrophs (animals and microbes). NEE = R_{eco} – GPP, where R_{eco} = R_a+R_h and R_h is heterotrophic respiration. When NEE is negative, the ecosystem is a CO_2 sink, if its positive it's a CO_2 source. Net Ecosystem Productivity (NEP) is the negative of NEE while accounting for system offtake by animals etc.
- Net Ecosystem Carbon Balance (NECB): Balance of carbon in all its forms entering and leaving an ecosystem. NECB=-NEE-CH_4flux-DOC-VOCloss-Offtake where CH_4flux is the methane leaving the system, DOC is the dissolved organic

carbon leaving the system, VOCloss is loss of carbon as volatile compounds and Offtake is the carbon that is physically removed from an ecosystem by humans or animals. When NECB is *positive* the ecosystem is a carbon sink.

The peat GHG balance used this report can be expressed as

$$\begin{aligned} GHG = {} & (R_a + R_h - GPP) \\ & + CH_4^{Flux} \times GWP_{CH4} \\ & + N_2O^{Flux} GWP_{N_2O} \\ & + (DOC + VOC) \times p_{CH_4} GWP_{CH4} + (DOC + VOC) \times p_{CO2} \end{aligned}$$

where R_a and R_h [kgCO$_2$] are autotrophic and heterotrophic respiration respectively, GPP [kgCO$_2$] is the Gross Primary Productivity, CH_4^{Flux} [kgCH$_4$] is the net methane flux into the atmosphere, N_2O^{Flux} [kgN$_2$O] is the next flux of nitrous oxide into atmosphere, DOC and VOC [kgC] is carbon lost as dissolved and volatised organic matter respectively -p_{CH4} [kgCH$_4$ kg^{-1}C] and p_{CO_2} [kgCO$_2$ kg^{-1}C] are the proportions of that lost carbon which is converted to methane and CO$_2$ respectively[3] and GWP_{CH_4} and GWP_{N_2O} are the global warming potentials of methane and nitrous oxide respectively. The first line represents the (NEE), the second the methane balance, third the nitrous oxide balance and fourth the carbon loss downstream. These terms will be used in the summary of findings Table 4.

Table 4: Search terms shared amongst all proxy methods/measurements assessed

	Greenhouse gas exchange
Greenhouse gas language	“CH4 emission*” OR “CO2 emission*” OR “N2O emission*” OR “CH4 flux*” OR “CO2 flux*” OR “N2O flux*” OR “CH4 exchange*” OR “CO2 exchange*” OR “N2O exchange*” OR "methane" OR "carbon dioxide" OR "nitrous oxide" OR “GHG” OR "carbon flux*" OR “carbon exchange”
Ecosystem exchange language	“Net ecosystem carbon balance” OR “Net ecosystem exchange” OR “Net ecosystem production” OR "carbon balance" OR "carbon exchange" OR "ecosystem respiration" OR "soil respiration" OR "net primary production" OR “ecosystem carbon exchange” OR “Carbon uptake” OR “Carbon sequestration” OR
	(AND) Peatland
	“Peatland” OR “peat” OR “organo-mineral” OR “mire*” OR “fen*” OR “bog*” OR “wetland*”
	(AND) Direct measurement mode
Flux tower	“Eddy covariance” OR “Flux Tower” OR “Flux-tower” OR “Tall tower” OR “Tall-tower” OR

[3] These should be different for VOC and DOC respectively.

Chamber Method	"Chamber* system" OR "static chamber*" OR "dynamic chamber*" OR "automated chamber*" OR "closed chamber*" OR "open chamber*" OR "automatic chamber*" OR "manual chamber*"
(AND) Evaluation criteria	
Comparative accuracy	"Accuracy" OR "estimation" OR "*error" OR "measurement" OR "R-squared" OR "R squared" OR "Cost" OR "price" OR "expenditure" OR "uncertainty" OR "bias" OR "precision" OR "validation" OR "calibration" OR "agreement" OR "comparison" OR "evaluation" OR
Cost effectiveness	"Cost" OR "price" OR "expenditure" OR "viability" OR "feasibility"

9.3 Proxy Variables and Measurements

9.3.1 Water-table depth

The position of the water table is an important control on biophysical processes in peatland ecosystems. Waterlogged conditions limit soil oxygen availability. Water and oxygen availability together control plant and bacterial activity, which in turn affect CO_2 and CH_4 emissions.

Soil oxygen availability determines the pathways through which microbes can break down organic matter. Within waterlogged soils, a scarcity of oxygen and other electron acceptors means that microbes must commonly resort to less efficient methanogenic pathways, slowing the decomposition of organic matter (Bridgham *et al.*, 2013). Through this, sustained waterlogged conditions lead to long term accumulation of organic matter as peat. When the water table lowers, this creates more favourable conditions for microbes to break down organic matter in the soil, increasing CO_2 emissions to the atmosphere from bacterial respiration. However, since wetter conditions favour a shift to methanogenic pathways, a sustained increase in the water-table (i.e. shallower water table), tends to lead to an increase in methane emissions (while CO_2 emissions decrease) (Günther *et al.*, 2020a).

The availability of water and oxygen in soil also controls plant activity. Water is required in photosynthesis and therefore the water table influences plant growth and the level of CO_2 that is fixed by plants growing on peatlands. Meanwhile plant respiration is further limited by the availability of oxygen in soil and therefore the level of CO_2 emitted due to plant respiration is also indirectly controlled by the position of the water table.

The change in Net- Ecosystem Carbon Balance – that is, the change in CO_2 equivalent emissions – depends on the relative magnitude of changes in CO_2 and CH_4 emissions. While peatlands are normally found to be small net sinks, studies indicate that rewetting of drained/modified peatlands may result in a spike in methane production

(Kandel, Elsgaard and Laerke, 2017; Schaller, Hofer and Klemm, 2022; Antonijevic *et al.*, 2023; Kalhori *et al.*, 2024; Delwiche *et al.*, 2025). Over the short run, elevated methane emissions may be sufficient to cause a net increase in total GHG emissions (Kandel *et al.*, 2020), before emissions decline over the long run and the peatland becomes a net sink (Günther *et al.*, 2020b). It is, however, important to note that peatland restoration results in net GHG reductions of considerable magnitude by preventing losses of carbon from ongoing degradation in drained peatlands.

Modes of measuring water table depth

Water table may be measured using a dipwell (PVC lined perforated pipe) inserted into the ground, either manually using a dip meter, or continuously using a pressure transducer connected to a data logger. In the case of the latter, the pressure reading has to be corrected for changing air pressure either directly using a 'vented' system design, or via a data processing correction using a nearby air pressure sensor, so that the system reports water level changes, rather than just pressure changes. Multiple measurement points are required to ensure appropriate representation of site conditions. Modelled results in this section relate to mean annual water-table depth, indicating that a regular measurement regime would be required to capture variation in water table across the year (Table 5).

Table 5: Additional search terms regarding Water Table

	Water Table
Water Table	"“Water table” OR “Water table depth” OR “Moisture Probes” OR “dipwells” OR “dip-wells” OR “dip wells” OR “rewetting” OR “re-wetting” OR “restoration” OR “drained” OR “undrained” OR “ground water level”

9.3.2 Topography

Topography can be an important proxy for estimating emissions since changes in surface height can be used to assess erosion and features (hags) vulnerable to erosion. Additionally, small increases in height over time can be indicative of moisture changes events, accumulation of organic matter and methane ebullition events. It is important to measure topographic features at appropriate scales due to the fractal nature of ecosystem-surfaces. For example, hummocks (higher CO_2 emissions), hollows (lower CO_2 emissions) and erosion should be measured at the cm to m scale while gradients and pools at the 10s to 100s m of scale are important for watershed hydrology.

Aerial LiDAR (Light Detection and Ranging) measures topography through the bouncing of laser pulses off of objects in the terrain. Lasers are emitted towards the ground and the time it takes for the laser to return is measured, from which the relative height of the area that the laser interacted with can be calculated. The detector can measure multiple bounces (“returns”) from one pulse such that if deployed within a forest canopy, it can first measure the return from the canopy, then the return from the ground (provided enough signal can get to and from the ground). From this information, point clouds can be formed showing the geometry of both the Earth’s surface and vegetation layers. The intensity of the laser light returning in the pointcloud is indicative of surface reflectivity. This is useful for measuring vegetation depth and the topography of peat under forests (Yallop, Thacker and Clutterbuck, 2024). Digital Elevation Models (DEM) of topography are sub-divided into Digital Surface Models (DSM), which represent the elevation of the earth’s surface including ‘things’ on top of it such as buildings or trees, and Digital Terrain Models (DTM), which represent the elevation of the bare earth. The latter can be reliably constructed using LiDAR. Typically, DTMs are required to assess peat functionality including hydrology and emissions. Since laser light is never perfectly parallel, the footprint of the laser increases linearly with collection height. Typically, from an aircraft at 1,000 m above ground level, the laser will have roughly a 1m diameter footprint, (Yallop, Thacker and Clutterbuck, 2024).

Aerial photographs can also be used to evaluate surface height. If one location is viewed from at least two separate angles, parallax (depth perception) can be used to determine the height of the location. However, this method cannot measure objects beneath canopies.

Synthetic Aperture Radar (SAR) and Interferometric SAR (InSAR) are a satellite techniques that use microwave signals reflected from earths Surface. SAR measures the intensity of the microwaves returning (back-scatter) which depends on surface properties such as roughness, vegetation structure, and moisture content. In wetlands and peatlands, changes in WTD influence soil and vegetation moisture, which affects the dielectric properties of the surface which, in turn, affects how the microwaves interact with the surface. When the water table is close to the surface, soils and vegetation are wetter and tend to produce stronger backscatter signals. Conversely, when the water table drops, soils dry out, and backscatter generally decreases.

InSAR uses two separate signals of the same location and measures the phase (i.e. position in the wave cycle) of the returning signals are measured. Changes in phase between the signals can be used to determine changes in elevation. However, due to the repeating nature of the phase, if the phase shift is greater than half the wavelength, the exact change in elevation cannot be determined as there is no way to tell the difference between half-wavelength multiples of the phase shift (i.e,. it can only determine elevation changes modulo half-wavelength). This limitation can be overcome using a technique called phase unwrapping. By assuming elevation changes between neighbouring pixels are bounded, phase-shifts between nearby pixels can be used to distinguish between half-phase multiples and exact changes in elevations can be estimated.

Due to its high accuracy at small spatial scales, InSAR can detect bog breathing[4] (Tampuu *et al.*, 2022), which is believed to be indicative of peatbog function due its relationship to moisture content and loss of peat mass. Bog breathing may have a significant impact on peat carbon-stocks or mass loss via surface height measurements (Morton and Heinemeyer, 2019). Bog breathing is also linked to ebullition, the sudden release of gas stored below the soil surface. These short-time scale events can contribute significantly to yearly methane emissions but are hard to measure with InSAR due to temporal resolution. In addition, dense peat can trap gas bubbles for lengthy periods leading to the decoupling of methane generation (a function of temperature and moisture conditions) to methane release and measurement (Ramirez *et al.*, 2015), making it hard to correlate proxy variables to emissions. If instead the gas is released steadily, the methane within them can be consumed in the drier oxygen-rich layers converting the potent GHG into CO_2 thus reducing the net global warming potential (Rosenberry, Glaser and Siegel, 2006). and its measurement can improve and explain variability in emissions measurements (Table 6).

Table 6: Additional search terms regarding microtopography

	Microtopography
General Surface elevation	"bog breathing" OR "surface oscillation*" OR "peat surface motion" OR "peat surface movement" OR “surface elevation”
InSAR	“InSAR” OR
LiDAR	"LiDAR" OR “Light Detection and Ranging” OR "airborne laser scanning" OR "ALS"
Photogrammetry	"photogrammetry" OR "structure from motion" OR "SfM" "photometric stereo" OR "stereo photogrammetry" OR "stereophotogrammetry"

9.3.3 Spectral Earth Observations

Earth Observation (EO) refers to the collection and analysis of data about the Earth’s surface and atmosphere using sensors such as satellites and aerial drones. Spectral Earth observations, which rely on reflected or emitted light to infer vegetation and surface properties are particularly useful for assessing peatland photosynthetic activity and possibly hydrological status.

Vegetation indices (VIs) are functions of surface reflectance values from different wave-length bands (e.g. red, near-infrared (NIR), and shortwave infrared (SWIR)) derived from satellite or aerial sensors. They are designed to isolate the parts of reflected light that are associated with plant function. In the context of peat emissions, VIs act as proxies

[4] The rising and falling in peat elevation as the peat gets wetter in winter and drier in summer.

for photosynthetic activity (via chlorophyll absorption) and can be interpreted to be associated with water stress and plant health. All VIs used in papers cited in this review to predict GHG emissions from peat are summarised in Table 7.

Fluorescence and physiological indices, e.g. Solar-Induced Chlorophyll Fluorescence (SIF), directly measure plant function rather than light reflectance. While reflectance indices measure light reflected from leaves to infer greenness or water content, fluorescence and physiological indices capture light re-emitted or reflectance shifts linked to photosynthetic efficiency and light use efficiency (LUE). These indices can provide more direct insight into how plants convert absorbed photosynthetically active radiation (PAR) into carbon through photosynthesis.

Additional search terms for spectral earth observations used in the targeted literature search are found in Table 7.

Table 7: Definition of the most relevant commonly used reflectance-based vegetation indices to be approximate emissions from peat identified during review. Studies cited in this report may use different equations dependent on sensor used. This has not been compared in this report.

Index	**Full Name**	**Primary Sensitivity / Interpretation**
NDVI	Normalized Difference Vegetation Index	Classic greenness index; correlates with chlorophyll content and canopy density.
EVI	Enhanced Vegetation Index	Reduces atmospheric and soil background effects; performs better in dense vegetation.
EVI2	Two-band Enhanced Vegetation Index	Simplified EVI excluding blue band; used when blue reflectance is unavailable.
SR	Simple Ratio	Early greenness metric; directly related to canopy chlorophyll and leaf area.
kNDVI	Kernel Normalized Difference Vegetation Index	Nonlinear form of NDVI; enhances sensitivity to canopy structure.
NIRv	Near-Infrared Reflectance of Vegetation	Separates vegetation signal from background reflectance.

GRVI	Green–Red Vegetation Index	Sensitive to canopy greenness and seasonal phenological changes.
NGRDI	Normalized Green–Red Difference Index	Similar to GRVI; widely used for RGBRGB UAVs.
Red-edge CI	Red-edge Chlorophyll Index	Sensitive to chlorophyll concentration and photosynthetic potential.
NDWI	Normalized Difference Water Index	Indicates vegetation and canopy water content.
NDMI	Normalized Difference Moisture Index	Similar to NDWI; detects plant and soil moisture.
LSWI	Land Surface Water Index	Similar to NDWI. detects plant and soil moisture.
MWI	Modified Water Index	Sensitive to vegetation and canopy water content. Indicates vegetation moisture or stress levels.

Table 8: Fluorescence and Physiological Indices that have been found to be used to approximate emissions from peat in this review.

Index / Variable	**Definition**	**Primary Sensitivity / Interpretation**
SIF	Solar-Induced Chlorophyll Fluorescence	Weak red/far-red light (650–800 nm) emitted by chlorophyll during photosynthesis. Direct proxy for photosynthetic activity.
LUE	Light Use Efficiency	Ratio of carbon fixed to absorbed PAR (GPP = PAR × fAPAR × LUE). Often modelled using vegetation indices and environmental stress terms.

PAR	Photosynthetically Active Radiation	Portion of solar radiation (400–700 nm) available for photosynthesis; key input to LUE and photosynthesis models.

Table 9: Additional Search Terms Regarding Spectral Earth Observations

Spectral Earth Observation	
Satellites and research programs	
Vegetation Indices	"Vegetation indices" OR "NDVI" OR "MTCI" OR "EVI" OR "SAVI" OR "PRI" OR "LAI" OR "FAPAR" OR "NDWI" OR "Spectral index*" OR "Spectral indices" OR "remote sensing index*" OR "remote sensing indices" OR
Light use efficiency	

9.3.4 Erosion

Lost organic matter from erosion can be emitted as CH_4 or CO_2 downstream which is important when reflecting total GHG emissions from degraded peat.

Erosion of soil is typically measured using:

- Direct measurements such as erosion pins and stream water sampling.
- Isotopic tracers which can trace eroded material based on N or C isotope ratios.
- Fallout radionuclides (FRN) which measure concentrations of isotopes e.g. ^{210}Pb deposited on the land surface, in soil cores which can date soil layers.
- Geochemical fingerprinting where chemical fingerprints (e.g. ratios of rare earth elements) of eroded material can be traced back to its source.

Search terms used for systematic peat erosion are found in Table 10, we note that direct measurements of GHG and erosion measurements are typically not performed in single studies since the emissions occur off-site. Therefore, the strict search terms in Table 4 likely miss important literature on this topic.

Table 10: Additional Search Terms Regarding Erosion

Erosion	
Fallout radionuclides (FRNs)	
Geochemical fingerprinting	“rare earth element*” OR “REE tracer*”
Isotopic tracers	

Direct physical measurement methods	“erosion pin*” OR “erosion bridge*” OR “profile meter” OR “erosion marker horizon”

Appendix 4: Review findings

10.1 Drivers of Peat GHG emissions

The predominant proxy variables which control components of the Peat GHG balance are identified in Table 11 below. The drivers of each component were determined from the review of water-table depth and spectral earth observations which can be found in Section 9.3 and 9.4. The drivers are ranked (from left to right) according to their overall importance in predicting the GHG components. For instance, the most significant control on Gross Primary Productivity in most conditions is light and leaf area, followed by temperature, water-table depth, and soil nutrients and pH. This ranking seeks to provide an overall indicator of importance caveated that in reality, these rankings depend on site specifics and the relative contribution of drivers in specific circumstances continues to be debated within the literature.

As can be seen from Table 11, WTD and soil temperature are common drivers across all GHG components.

Table 11: Important proxy variables ("Drivers") for predicting individual component in the peat GHG balance at the yearly time scale. Drivers are listed in approximate order of importance; however, the order may vary dependent on conditions and are debated in the literature. Greenhouse Gas (GHG) components are Gross Primary Productivity (GPP); autotrophic and heterotrophic respiration (R_a and R_h respectively); methane flux (CH_4^{Flux}); nitrous oxide flux (N_2O^{Flux}). Drivers are Soil Temperature (Temp); Water Table Depth (WTD); soil nutrient status, particularly nitrogen Nutrients/pH); Ebullition refers to the sudden release of gas from peat. was not examined in this review and drivers are inferred from understanding of the mineral-soil nitrogen cycle.

GHG Component	**Key Drivers**
GPP	Light & leaf area index → Soil Temp → WTD → Nutrients/pH
R_a	GPP
R_h	WTD → Soil Temp → Nutrients/pH
CH_4^{Flux}	WTD → Soil Temp →Plant species →Ebullition
N_2O^{Flux}	Nutrients/pH (esp. N availability) → WTD ~ Soil Temp

10.2 Accuracy of measurement methods

Potential methods of measuring the drivers of peat GHG emissions are listed in the main text. The degree to which each measurement method accurately reflects drivers of each emissions component is given a qualitative score based on how successfully the measurement method has been used to approximate the driver within models of the emission components identified within the literature search. Importantly, this qualitative accuracy scoring is not indicative of how well the method predicts the full GHG balance, rather it relates to the ability to approximate that specific driver in emissions models.

Gross primary productivity: The amount of light a parcel of land receives and the quantity of leaves it contains could be well approximated by earth observations, and ground-based measurements are not required to target on this proxy variable. Using hyper-spectral sensors to detect Solar-Induced Fluorescence (SIF), for example, could possibly improve estimates of GPP compared to multispectral sensors. However, this increased spectral resolution often comes at the expense of temporal and particularly spatial resolution, which may diminish the ability to distinguish emissions between landowners in a tax context. Although not explicitly targeted in the literature search, temperature was often included in studies estimating GPP and NEE of peatland with authors often using land surface temperature (LST) derived from earth observations or interpolated/reanalysed meteorological data in models. Both can produce good estimates of GPP. Again, temperature can be measured sufficiently without relying on ground-based measurements.

Water-table depth: The only reliable country-wide approach for accounting for WTD was using ground-based dipwells. Therefore, achieving the spatial resolution required to handle ownership parcels would require the installation of several dipwells per site on a peat ownership basis. WTD, when measured with dipwells, can approximate NEE and CH_4 emissions well. Some authors find that WTD alone can approximate peat emissions well, but the current review would recommend the inclusion of VIs and temperature to ensure that GHG approximations are reliable across the range of vegetation and conditions found in Scottish peat. This would also be sensitive to changes in climate. A major conclusion of this review is that the lack of remote methods for measuring WTD is limiting the approximation of peatland GHG emissions at the national scale.

Several authors tried to include the effect of WTD on GPP, NEE and less often CH_4 emissions by approximating WTD with water-based indices derived from surface reflectance (LSWI/MWI). This approach infers WTD based on the drought-stress of the vegetation as detected by surface reflectance and from hyper-spectral sensors on aircraft. In Canadian peat bogs, this approach has been successful in predicting NEE at short time scales and for low and narrow ranges of WTD, but was shown to be a bad indicator of yearly NEE in Scandinavian peatbogs since its inability to detect seasonal changes in WTD. The review suggests that remote sensing methods using reflectance data alone are currently not accurate enough to predict WTD for the purposes of estimating CH_4 and R_h emissions from peatland in Scotland.

InSAR has recently been used to infer WTD in peatland to varying degrees of success depending on site properties and rates of drying and wetting. This research is in its early stage and would requires more validation and understanding of variability. Given the lack of remote measurements of WTD, we recommend further research into InSAR derived WTD, particularly research that links these measurements to NEE and CH_4 flux.

Process-based hydrological modelling as means of estimating WTD was not investigated in this report but it may be possible to interpolate coarser dipwell results to finer scales using physical modelling approaches. In general, standard models of groundwater hydrology should be adapted to account for the expansion of the media when applied to peat.

Theoretically, InSAR can detect bog breathing and ebullition events. However, we did not find studies which related InSAR signals to direct measurements of peatland GHG emissions[5].

N_2O emissions were not explicitly considered in this review but nitrogen concentrations, besides the drivers already mentioned, are known to be the major controller of these emissions. Soil tests, fertilisation and stocking density data are reliable approaches for determining nitrogen contents of peat. Remote methodologies for determining nitrogen concentrations in peat are left for another study (Table 1).

10.3 Comparison Matrix of Measurement Strategies

To assess cost and accuracy it was necessary to define measurement scenarios which combine multiple measurements, since effective modelling of some GHG components (e.g. soil respiration) requires information on multiple drivers. It was not possible/useful to score individual proxy measurements against the criteria since they could not predict peat emissions across the wide range of Scottish peat conditions as stand-alone measurements. The final table provides a comparison of four measurement scenarios, in relation to their cost and accuracy of measuring the full peat GHG balance.

Each scenario outlines a suite of methods that together may be used to measure key drivers of peat GHG emissions: light and leaf-area characteristics, surface temperature, and water-table depth (WTD), with optional soil sampling for nutrient and pH data. Each measurement scenario meets the criteria of providing sufficient spatial and temporal

[5] which is why InSAR has a score of Low in the ebullition column of Table 2.

resolution. Scenarios progress from low-cost, low-accuracy remote sensing (Scenario 1) to increasingly detailed hybrid ground/remote approaches incorporating on-site dipwells, soil analysis, and hyperspectral data (Scenarios 2–4). Costs are presented for two monitoring extents (ScotGov Target: 250,000 ha and the entire 1990-degraded peat area in UK National Inventory: 1,952,000 ha) and include annual operational and initial capital expenditures. Costing in Table 12 is indicative and reflects assumptions (detailed in subsequent section). Reported GHG coverage (CO_2, CH_4, N_2O) and indicative accuracy reflect each method's capacity to resolve drivers of emissions, as set out in Table 2.

Errors in WTD measurements will likely propagate nonlinearly (potentially even exponentially) into errors in estimates of NEE and CH_4, as many authors use nonlinear relationships between WTD and these fluxes to capture the underlying processes. Therefore, the absence of accurate remote measurements of WTD remains the key limitation, and we conclude that it is not currently feasible to provide an accurate measurement of the full peat GHG balance using only remotely sensed data (Scenario 1). Scenarios 2- 4 provide greater accuracy but at increased cost. The greatest improvement in accuracy is brought by incorporating site level measurement of water table in Scenario 2. However, this also marks the most significant contribution to cost, due to the cost installing and maintaining dipwells on peatland sites. Moving from Scenario 2 to 3 accounts for N_2O emissions with soil testing of peat under crops (not grass). Scenario 4 uses hyper-spectral detectors to improve estimates of photosynthesis, and possibly with further research to overcome WTD limitations, but comes at the expense of decreased resolution which may limit its ability to account for peat ownership.

Cost estimates provided in this report reflect a significant assumption that 3-5 dipwells would be required per 100ha. It should be noted however that this remains an area of unresolved uncertainty. An alternative costing of national peatland monitoring provided by Artz et al. (2023) calculated that 0.85 dipwells would be required per 100ha. Extrapolation of Artz et al.'s costing suggests that dipwell installation and monitoring costs could be 3-6 times lower than estimated in this report. Dipwell spacing in Artz et al. (2023) is extrapolated from monitoring at Flanders Moss, which is relatively flat and homogenous in comparison to the variety of peatland conditions and site topography present across Scotland. In addition, Artz et al.'s costing is presented in the context of a national monitoring framework rather than a parcel- or holding-level tax, and does not specify sensor models or performance characteristics in a way that allows direct comparison with the higher-specification pressure sensors and quality assurance assumptions used in this report. In a tax context, measurement design must be sufficiently robust to support independent verification, withstand audit and appeal, and minimise the risk that drift, missing data or local heterogeneity leads to systematic over- or under-assessment of liabilities; these requirements tend to increase both the density of instrumentation needed in complex terrain (e.g. around drains, slope breaks and heterogeneous management units) and the minimum sensor specification and QA procedures required to demonstrate data reliability.

At further extreme, Allot et al. (2009) calculated that 15 dipwells would be required to provide a reliable estimate at their highly eroded 30m by 30m site (which they specifically selected to represent the worst case scenario of maximum variation at site level). Beyond these estimates we could find no clear signal of required dipwell spacing in the literature, 3-5 per 100ha is presented as a best guess. This assumption is therefore used as a precautionary, tax-relevant standard intended to be broadly applicable across diverse Scottish peatland settings, rather than as an estimate for national-scale monitoring alone. It reflects the need for representative mean annual WTD estimates at holding scale, while limiting the risk that localised conditions dominate measurements, and it provides a transparent basis for costing and sensitivity testing in Table 9. This is broadly in line with actual dipwell spacing per 100ha (1.6, 3.2, 3.5, 5.7, 15) within the underlying studies analysed by Evans et al. (2021).

Table 12: Comparison matrix of measurement strategies for estimating peatland greenhouse gas (GHG) emissions. Each scenario outlines a suite of methods used to measure light and leaf-area characteristics, surface temperature, and water-table depth (WTD), with optional soil sampling for nutrient and pH data. Costs are presented for two monitoring extents (ScotGov Target: 250,000 ha and all degraded peat: 1,952,000 ha) and include annual operational and initial capital expenditures. Scenarios progress from low-cost, low-accuracy remote sensing (Scenario 1) to increasingly detailed hybrid ground/remote approaches incorporating on-site dipwells, soil analysis, and hyperspectral data (Scenarios 2–4). Reported GHG coverage (CO_2, CH_4, N_2O) and indicative accuracy reflect each method's capacity to resolve drivers of emissions.

Scenario	Assumed measurement protocol	Item	Annual operational cost		Initial capital cost		GHG Coverage	Accuracy
			250,000ha	1,952,000ha	250,000ha	1,952,000ha		
Scenario 1: Remote Sensing **Light and Leaf area**: Satellite derived VIs – Utilising open source MODIS, Landsat, Sentinel data **Temperature**: LST/ Meteorological data **WTD**: LSWI/MWI	Open source satellite and meteorological data obtained, inspected and processed annually. Initial model development and calibration using existing UK and Ireland site measurements drawn from literature.	Initial model development Annual data acquisition cost Data integration and processing	- Nil £42,000 Total: **£42,000**	- Nil £84,000 Total: **£84,000**	£3,000,000 - - Total **£3,000,000**	£3,000,000 - - Total **£3,000,000**	CO_2, CH_4 (Missing N_2O)	**Poor** LSWI provides an inconsistent approximation for water table over longer time periods, and modelling of respiration and CH_4 requires information on WTD.
Scenario 2: Remote Sensing with on-site water table measurement **Light and Leaf area**: Satellite derived VIs – Utilising open source MODIS, Landsat, Sentinel data **Temperature**: LST/ Meteorological data	Open source satellite and meteorological data obtained, inspected and processed annually. Initial model development and calibration using existing UK and Ireland site measurements drawn from literature.	Initial model development Dipwell construction cost Annual data acquisition cost Data integration and processing	- - Nil £63,000	- - Nil £126,000	£3,000,000 £8,305,000 - -	£3,000,000 £64,845,000 - -		

WTD: Dipwells installed at site. Remote monitoring of water table by pressure transducer.	Average annual water table depth determined from 3-5 dipwells per 100ha. installed at site and remote sensing by pressure transducer.	Annualised cost of 5 yearly dipwell servicing by ecological surveyor.	£450,000 Total: **£513,000**	£3,500,000 Total: **£3,626,000**	- Total: **£11,305,000**	- Total: **£67,845,000**	CO_2, CH_4 (Missing N_2O)	**Good and costly**
Scenario 3: Remote Sensing with on-site water table measurement and soil testing to target N_2O **Light and Leaf area**: Satellite derived VIs – Utilising open source MODIS, Landsat, Sentinel data **Temperature**: LST/ Meteorological data **WTD**: Dipwells installed at site. Remote monitoring of water table by pressure transducer. Annual calibration. **Nutrients and Ph:** Annual soil testing.	Open source satellite and meteorological data obtained, inspected and processed annually. Initial model development and calibration using existing UK and Ireland site measurements drawn from literature. Average annual water table depth determined from 3-5 dipwells per 100ha. installed at site and remote sensing by pressure transducer. Annual soil testing of 9,000ha cropped peatland area.	Initial model development Dipwell construction cost Annual data acquisition cost Data integration and processing Annualised cost of 5 yearly dipwell servicing by ecological surveyor. Annual soil testing	- - Nil £63,000 £450,000 £8,000 Total: **£521,000**	- - Nil £126,000 £3,500,000 £56,000 Total: **£3,682,000**	£3,000,000 £8,305,000 - - - - Total: **£11,305,000**	£3,000,000 £64,845,000 - - - - Total: **£67,845,000**	CO_2, CH_4, N_2O	**Good and costly** Improves applicability of Scenario 2 to better reflect N_2O emissions

Scenario 4: Hyperspectral data with on-site water table and soil testing **Light and Leaf area**: Hyperspectral data **Temperature**: LST/ Meteorological data **WTD**: Dipwells installed at site. Remote monitoring of water table by pressure transducer. Annual calibration. **Nutrients and Ph:** Annual Soil testing.	Hyperspectral data obtained, inspected and processed annually. Initial model development and calibration using existing UK and Ireland site measurements drawn from literature. Average annual water table depth determined from 3-5 dipwells per 100ha. installed at site and remote sensing of pressure transducers. Annual soil testing of 9,000 ha cropped peatland area	Initial model development	-	-	£3,000,000	£3,000,000		
		Dipwell construction cost	-	-	£8,305,000	£64,845,000		
		hyperspectral data acquisition cost	£110,000	£860,000	-	-		
		Data integration and processing	£63,000	£126,000	-	-		
		Annualised cost of 5 yearly dipwell servicing by ecological surveyor.	£450,000	£3,500,000	-	-		
		Annual soil testing	£8,000	£56,000				
			Total: **£631,000**	Total: **£4,542,000**	Total: **£11,305,000**	Total: **£67,845,000**	CO_2, CH_4, N_2O	**Good and costly** Improves accuracy at predicting GPP compared to scenario 3 but may lose spatial resolution.

10.4 Costing Assumptions

Initial model development

£3,000,000 research project

Satellite data

Satellite data acquisition cost is nil if using open source.

Annual data processing and integration of satellite, meteorological and landownership data: 1- 2 FTE roles. £42,000 – £84,000. Assume an additional 50% markup on data processing and integration, where processing and integration of water table data is further required. £63,000 - £126,000.

To tile Scotland would take 8 Landsat tiles. Landsat scene image size is 185km = 34,225km2.

To tile Scotland would take 18 HLS tiles. Harmonised Landsat and Sentinel (HLS) images are 109.8km =12,056km2.

To tile Scotland would take 2 MODIS tiles

Dipwell construction

Assume 3- 5 dipwells required per 100 ha. Average 4 per 100ha.

Cost of labour

Ecological surveyor visits site and develops schedule of works. Assume 1 day per 200ha = 0.5 days per 100ha.

Contractor visits site with materials. Augers well [either by hand/ with mini excavator], and fits dipwell and remote sensor.

Assume 1- 2 days required to construct 3- 5 dipwells. Average 1.5 days

Ecological contractor day rate: assume £300- £400. Average £350

Ecological surveyor day rate: assume £400 - £500. Average £450

Total cost of labour per 100ha = $0.5 \times 450 + 1.5 \times 350 = £750$

Cost of materials

Item	Cost	Detail
PVC pipe	£77.42	(half of 5m 4inch class E pipe)

Gravel	£11.40	25 kg sack
Bentonite	£26.00	(half of 25kg sack)
Sand and cement	£10	
Pressure sensor (commercial design)	£518.40	ALTA Wireless pressure meter [MNS2-8-W2-PS-300-SW]. 10 year battery life
Pressure sensor (commercial design)	£462.28	Druck PDCR 1830
Pressure sensor, temperature and data logger (commercial design)	£1050	TROLL 500

Total cost of dipwell materials £643

Total cost of dipwell installation

Cost of dipwell installation per 100ha = Cost of labour + cost of materials

Cost of dipwell installation per 100ha

$$= £750 + (£643 * 4) = £3322$$

Total cost of dipwell installation (1,952kha);

$$= 1952 \times \frac{1000}{100} \times £3322 = £64{,}845{,}440$$

Total cost of dipwell installation (250,000ha);

$$= 250{,}000 \times \frac{1}{100} \times £3322 = £8{,}305{,}000$$

Dipwell maintenance

Annual visit by ecological surveyor to change batteries on pressure sensor, check dipwell free and not choked and conduct response time tests.

Total peat area = 1952kha (1990)

Total Degraded Peat Area: 1461 kha (1990) [excluding near natural bog]

Ecological surveyor serviced area per day: 250 ha [walk 6-10k, service 6-10 dipwells]

Ecological surveyor daily rate: £400- £500. Average £450

Annual cost of yearly site visit for dipwell maintenance = 1952×1000/250 × 450 = £3,513,600 per annum.

Annual cost of yearly site visit for dipwell maintenance = 250,000/250 × 450 = £450,000 per annum.

Soil Testing

Soil testing required for proportion of peat that is cropped.

Peat Crop Area = 9kha

Soil samples collected by ecological surveyor.

Ecological surveyor serviced area per day: 300ha. [Walk 10- 16k.]

Ecological surveyor day rate: £400 - £500. Average £450

Labour cost of Total 9kha = $9 \times 1000 \times \frac{1}{300} \times 450 = £13{,}500$

Labour cost of part of 9kha = $9 \times \frac{250{,}000}{1{,}952{,}000} \times \frac{1}{300} \times 450 = £1{,}729$

Cost of sample analysis assumed to be £4.66 per ha. Eory et al. (2025) report an average value of £4.66 per ha to conduct soil testing for nitrogen

Cost of Total 9kha = $9 \times 1000 \times 4.66 = £41{,}940$

Cost of Part of 9kha = $9 \times 1000 \times \frac{250{,}000}{1{,}962{,}000} \times 4.66 = £5{,}344$

Total cost of 9kha = $£13{,}500 + £41{,}940 = £55{,}440$

Total cost of part of 9kha = $£1{,}729 + £5{,}344 = £7{,}073$

Hyperspectral data

Hyperspectral data is available at 50 euro per km2 = £44 per km2 (Leonie et al., 2025)

Annual cost of 250,000 ha = $250{,}000 \times \frac{1}{100} \times 44 = £110{,}000$

Annual cost of 1,952kha = $1{,}952{,}000 \times \frac{1}{100} \times 44 = £858{,}880$

Artz et al. (2023) costing

We are grateful to peer reviewers who provided an alternative costing. Artz et al. (2023) estimated the cost to maintain a national network of 100 monitoring sites, calculating that a network of 700 dipwells would be required to provide effective monitoring at those 100 sites.

They estimated that installing this network of 700 dipwells would cost.

Equipment:	£105,000
Dipwell construction materials:	£20,000
Labour:	200 person days

Artz et al. (2023) do not provide a value for labour cost. Assuming £350 day rate for ecological contractor, to enable comparison

Labour:	£70,000
Total cost for 700 dipwells	£195,000
Total cost per dipwell	£278.57

Artz et al. (2023) extrapolate required dipwell spacing from water table monitoring at Flanders Moss, where they calculated that a minimum of 7 dipwells would be required provide a reliable estimate of mean annual water table. Flanders moss is 821ha.

$$\frac{7}{821} = 0.85\ dipwells\ per\ 100ha$$

Total cost of dipwell installation (1,952kha)

$$= 1952{,}000 \times \frac{0.85}{100} \times 278.57 = \text{£}4{,}622{,}033$$

Total cost of dipwell installation (250,000ha)

$$= 250{,}000 \times \frac{0.85}{100} \times 278.57 = \text{£}591{,}196$$

Annual maintenance cost

Artz. et al. (2023) further specify that an annual site visit would be required to download data and perform a manual water table calibration and dipwell displacement check. No value for cost of labour is provided. Assuming £450 day rate for ecological surveyor, to enable comparison, this implies a further annual cost of £450 per 7 dipwells, or £64.28 per dipwell.

Annual cost of dipwell maintenance (1,952kha)

$$= 1952{,}000 \times \frac{0.85}{100} \times 64.28 = \text{£}1{,}066{,}533$$

Annual cost of dipwell maintenance (250,000ha)

$$= 250{,}000 \times \frac{0.85}{100} \times 64.28 = \text{£}136{,}595$$

Costing Comparison

		250,000ha		1,952,000ha	
	Dipwells required per 100 ha	Installation Cost	Annual maintenance	Installation Cost	Annual maintenance
This report	4	£8,305,000	£450,000	£64,845,000	£3,513,600
Authors estimate extrapolating from Artz et al. (2023) with additional assumption on cost of labour	0.85	£591,196	£136,595	£4,622,033	£1,066,533

10.5 Topography

The search terms yielded 32 hits in the Web of Science Database and an additional 23 hit in the SCOPUS database. Of the 55 unique articles, 7 were deemed suitable for further reading after reading the abstract.

Key Findings: Topography

- No studies compared topographic measurements (InSAR, LiDAR, photogrammetry etc) to peat GHG emissions quantitatively.
- Often, topographic measurements were used to explain differences in measurements qualitatively.
- Topographic features could affect EC measurements by their effect on airflow.
- No studies linked bog-breathing to yearly emissions estimates.
- InSAR shows promise as a means for estimating water table depth, however, more research is required to understand variability across sites.
- No study in the targeted literature review linked InSAR derived surface motion to peat GHG emissions directly.
- Time-resolved LiDAR surveys show promise for estimating GPP in agriculture by measuring changes in crop height, however, this has not been transferred to peat ecosystems. Spectral earth observations are currently the cheaper and more established approach to capture these phenomena.

Several papers deemed relevant used measurements of micro-topography to explain emissions differences between hummocks and hollows (Lees *et al.*, 2021). With authors find that hummocks have greater CO_2 emissions but less methane emissions than hollows (Wu *et al.*, 2011). In general, NEP is higher in hummocks but they are known to consume atmospheric methane at low rates (Frenzel and Karofeld, 2000). Many of these results can be derived from understanding of the control of water table depth on CO_2 and methane production, however, some authors find that living vegetation differences between the microforms are important for understanding net CO_2 flux (Krohn *et al.*, 2017). Results such as these could be used to further refine National Inventory type methodologies by including additional peat conditions categories which account for micro-topographic features. However, measurements of micro-topography are unlikely to be a stand-alone proxy of emissions.

Other papers concern how surface topography could affect EC measurements due its effect on airflow. For example, (Herbst *et al.*, 2011) found that friction velocity[6] (turbulent shear stress) caused by airflow interacting with the micro-topography in the EC footprint had a large effect on measured methane emissions from a restored wetland in Denmark. Footprints with a high proportion of low-lying peat had the largest deviation between modelled and EC measured methane emissions due to low friction velocities causing insufficient mixing and unreliable eddy-covariance measurements (Herbst *et al.*, 2011). Zhang *et al.* (2020) compared measurements of CO_2 and CH_4 emissions between chamber and EC methods from wetlands on the Qinghai-Tibetan Plateau and used temperature dependent models fit to each set of measurements to extrapolate results to historic emissions. The choice of measurement mode caused large differences in projected emissions. The 4 chambers used were not representative of all microtopographic features found in the seemingly-homogenous wetland while the EC method averaged out spatial heterogeneity of the footprint making it hard to translate the result to other locations without accounting for spatial features with modelling (Zhang *et al.*, 2020).

LiDAR has recently shown promise as a means of estimating GPP in arable systems by measuring changes in crop height from point clouds produced by LiDAR time series (Revenga *et al.*, 2024). However, the literature search found no examples of these techniques being transferred to peat ecosystems. Additionally, this technique requires several LiDAR surveys per month which is not cost effective at the national scale. Spectral earth observations are a more established methodology for estimating GPP in peat (see later sections).

Measurements of bog-breathing by InSAR seemed the most likely mode of measuring topography to predict annual GHG emissions due to its ability to measure bog breathing

[6] $\sqrt{(\overline{u'w'})^2 + (\overline{v'w'})^2}$ in the language of equation

and long- and short-terms changes in elevation thought to be indicative of subsidence and water table depth (Alshammari *et al.*, 2020). The literature search suggests that there is no literature relating InSAR measured bog-breathing to direct measurements of GHG emissions from peat.

Since the literature search on InSAR's correlation with direct measurements of GHG emissions was limited, additional searches were conducted to evaluate how well InSAR can detect soil moisture. Both InSAR and SAR have shown promise for estimating peat moisture under certain conditions, with reported R^2 values ranging from 0.12 to 0.72 for SAR and from 0.05 to 0.67 for InSAR, depending on site characteristics in Irish peatbogs (Hrysiewicz *et al.*, 2023). The authors found that InSAR derived surface motion could not accurately detect the low soil moisture in drought conditions and lagged-behind the increases soil moisture and water table depth following rewetting. The lag could be explained by phase ambiguity (See Appendix 3 Topography section) when surface motion is large (Hrysiewicz *et al.*, 2023). InSAR coherence, the 'similarity'[7] of two sequential InSAR signals, has been shown to be related to soil moisture, particularly in spring/summer months and in banket bogs (R^2=0.83) (Walker *et al.*, 2025). However, coherence was out-of-phase with WTD resulting in lower correlation. Frozen ground was found to affect the Radar response causing poorer correlation in winter months (Walker *et al.*, 2025). The authors investigated several pre-processing options to account for seasonal changes in conditions that could affect the measurement. Hrysiewicz *et al.* (2023) found a negative correlation of coherence with soil moisture while Walker *et al.* (2025) found a positive correlation with the later authors offering several mechanisms for the differences. Using InSAR and SAR to estimate peat moisture and WTD is still in its infancy and further research is required to make it a reliable proxy for these variables.

10.6 Water-table depth

The search terms yielded 314 hits in the Web of Science Database and an additional 220 hits in the SCOPUS database. Two further articles were identified through cross-citation, one further was provided by a peer reviewer. Of the 537 unique articles, 53 were deemed suitable for further reading after reading the abstract.

Among these, several recent meta-analyses were identified which had made assessment of environmental controls on GHG emissions from peatlands. Given the large volume of primary studies, the review focussed on relating findings from meta-analyses. Primary studies were reviewed selectively, with a focus on articles dated post 2020.

[7] Cross-correlation

Key Findings: Water table, CO_2 and CH_4

UK and Ireland

- A recent UK meta- analysis of environmental controls on emissions from UK and Ireland peatlands (16 sites) conducted by Evans *et al.* (2021) found that mean annual effective water table depth (WTDe) was a reliable predictor of both NEP (CO_2 flux adjusted for grazing and other carbon offtakes) (R^2=0.9) and CH_4 (R^2=0.55) emissions, concluding that mean annual effective water table depth alone was sufficient as predictor and including additional control variables did not improve the predictive power of their model (where water table depth was measured as mean effective water table depth, i.e. not exceeding the depth of peat).
- Similar functional relationships were reported by Tiemeyer *et al.* (2020) analysing a German national dataset (118 sites), however the strength of the relationship was not reported. Tiemeyer *et al.* (2020) did not investigate further environmental controls due to data availability.
- Evans et al.'s strong results contrast to those observed in an earlier analysis by Levy *et al.* (2012) utilising annual flux data from peat chamber measurements at 21 UK sites, which observed water table to be one among several environmental controls on CH_4 fluxes. When assessed as univariate predictors Levy *et al.* (2012) found a species composition index to the strongest univariate predictor of CH_4 fluxes.

Global

- Findings from global meta- analyses are overall more mixed.
- Evans et al. (2021) further report findings from an extended dataset, incorporating flux measurements from a further 49 eddy covariance studies located globally, they found a similar linear and positive relationship for CO_2, though with a lower gradient, and poorer model fit (R^2 = 0.65).
- Contrastingly a meta- analysis of CO_2 fluxes from global wetlands conducted by Lu *et al.* (2017) (43 wetland sites) found no statistically significant effect of water table depth on CO_2 emissions. Within their study, mean annual temperature followed by Mean annual precipitation were found to be strongest univariate predictors of annual carbon fluxes across all wetland types.
- Considering the full GHG balance, Zou et al., (2022) conducted a global review of wetland GHG fluxes collating findings from 1,875 sites (3,704 site years). Across their global dataset (complete records available for 174 site years), they find that a near surface level water table (-1 to -30cm) minimised GHG emissions, while emissions peaked in both flooded and drained conditions, reflecting a parabolic relationship between GHG emissions and water table level. They similarly observed a parabolic relationship between CO_2 emissions and water table level,

while CH_4 emissions increased linearly with water table level, and N_2O emissions decreased linearly with water table level. The general form of these relationships held across temperature regimes, boreal, temperate, and tropical sites. Fitted relationships were not overwhelmingly strong however. Across all sites, the relationship between water table level and net GHG flux was (R^2= 0.29, n=103 site years). Relationships for specific GHG components were sometimes stronger than this, but these were overall poorer for temperate sites.

- Other meta-analyses of CH_4 fluxes from peatlands have found water table to be one among several controls on CH_4 emissions across the temperature regimes and wetland types that are present at global scale. At the global scale some studies instead found temperature or vegetation to be stronger univariate predictors of methane fluxes than water table.
- Turetsky *et al.* (2014) (71 wetland sites) additionally found that functional forms depended on type of wetland and management.
- Similarly Li *et al.* (2024) (38 wetland sites) found that response of methane emissions to water table depth and temperature varied between vascular plant wetlands and moss plant wetlands, which differed in both direction and magnitude of response to variation in water table depth.

Findings from primary studies

Studies of GHG emissions at peatland sites post rewetting have indicated that methane emissions may increase in the short run following rewetting (Kandel, Elsgaard and Laerke, 2017; Schaller, Hofer and Klemm, 2022; Antonijevic *et al.*, 2023; Kalhori *et al.*, 2024; Delwiche *et al.*, 2025). In one case the increase in methane dominated, resulting in a net increase in CO_2 equivalent emissions in the short term (Kandel et al., 2020).

Summary Table: Water table findings from meta- analyses

Table 13 Summary findings from meta-analyses

Source	Geographic scope	Flux measure	Water Table: CO_2	Water Table: CH_4	Overall/ Best Fit Model
Evans et al. (2021)	UK and Ireland (16 sites)	Eddy Covariance (CO2) Static chamber (CH4)	linear relationship R^2 =0.9	exponential relationship R^2 =0.55	Mean annual effective water table depth sufficient as single predictor both for CO_2 and CH_4, including other variables did not improve predictive power.
Tiemeyer et al. (2020)	Germany (118 sites)	Static Chamber	Approximately linear response up to -0.4m	Exponential relationship	-

Levy et al. (2012)	UK (21 sites)	Peat chamber	-	linear relationship R^2 = 0.15 to 0.25	Water table one of several environmental controls on CH_4 and had relatively low predictive power in comparison to other variables when assessed as univariate predictor. A species composition index found to be strongest univariate predictor where data available, peat depth otherwise. Parsimonious multivariate models included soil temperature, soil moisture and soil carbon.
Lu et al. (2017)	Global (22 inland and 21 coastal wetland sites)	Eddy covariance	Not significant		Water table was not found to be a significant predictor of variation in CO_2 fluxes. Mean annual temperature (MAT) followed by Mean annual precipitation (MAP) were found to be strongest univariate predictors of annual carbon fluxes across all wetland types. Their best fit model included MAT, MAP and an interaction between MAT and MAP and explained 71% variation in GPP and 57% variation in NEP.
Zou et al. (2022)	Global (3,704 site years, 1,875 sites)	Eddy covariance, Static chamber, Automatic chamber			-

Wu et al. (2025)	Global (371 wetland observations)	Eddy covariance	-0.35 standardised coefficient in SEM	-	Water table depth was the most important factor regulating methane exchange from wetlands, while mean annual temperature was the second most important predictor. Methane fluxes also related to carbon cycle measures, GPP, NEE and R_{eco} likely due to common underlying drivers.
Li et al. (2024)	Global (38 wetland sites)	Eddy covariance	-	0.47 standardised coefficient in SEM	Water table depth, followed by mean annual temperature most important regulators of net methane in wetlands.
Knox et al. (2019)	Global (60 sites)	Eddy covariance	-	Moss plant wetlands: linear relationship (R^2=0.24) Vascular plant wetlands: (R^2= 0.18-0.35)	Li et al. (2024) present results from various modelling approaches, concluding overall that response to environmental controls differs between moss plant wetlands and vascular plant wetlands, which differed in both direction and magnitude of response to variation in water table depth.
Turetsky et al. (2014)	Global (71 wetland sites)	Static chamber	-	linear relationship R^2 = 0.31 (excluding sites which are permanently inundated)	Water table significant predictor, however mean annual temperature strongest single predictor.

Meta analysis findings, Water table and CO_2

Drawing on site level measurement of annual GHG fluxes, several recent meta-analyses have sought to assess the extent to which differences in water-table depth (among other environmental control variables) can explain variation in annual fluxes between sites.

Meta- analyses differed in their geographic scope (UK versus Global) as well as type of primary studies included (eddy covariance/ static chamber). Most looked at evidence for environmental controls on methane, two assessed the evidence for CO_2 in addition to methane. None of the reviews identified looked at N_2O, or the full GHG balance. Summary findings from meta-analyses are presented in Table 13 above.

UK and Ireland

Evans *et al* (2021) found a strong linear relationship between water-table depth and CO_2 emissions from UK and Ireland peatlands (16 sites). Analysing annual flux measurements from sixteen eddy covariance studies at sites in UK and Ireland they found that net ecosystem productivity (NEP) increased linearly with water table depth. They report $R^2 = 0.9$, indicating that variation in WTDe alone between sites explained 90% of variation in NEP. Extending this dataset with flux measurements from a further 49 eddy covariance studies located globally, they found a similar linear and positive relationship, though with a lower gradient, and poorer model fit ($R^2 = 0.65$).

Evans *et al.* (2021) analysis of variation in annual CO_2 flux was limited to eddy covariance studies. Other primary studies utilising peat chamber measurements to measure CO_2 emissions were not included in their analysis. We are not aware of any meta-analysis which has been conducted of findings from UK peat chamber measurements to date.

Tiemeyer *et al.* (2020) describe the methodology for determining GHG emissions factors from drained organic soils within Germany. In line with findings within Evans et al. (2021) the primary environmental control underpinning German emission factors is a national map of water table depth. Emissions factors draw on a national dataset of GHG balances (CO_2, CH_4 and N_2O) from 118 sites across land-use categories and types of organic soils. Fluxes were measured using manual chambers following harmonised protocols. GHG response was statistically analysed in relation to land use category, type of organic soil and mapped water table depth. Other drivers such as soil properties, dynamic water table, land use intensity and fertilisation were considered but not utilised due to data availability at national level.

Across their dataset, CO_2 emissions increase steeply with increasing water-table depth before levelling out at a water-table depth of around -0.4m where additional drainage would not on average increase CO_2 emissions. Among shallow drained sites, CO_2 emissions increased almost linearly with deeper water table. Modelling this relationship they fit a Gompertz function. They found no clear difference in water table response across land classes.

Global

Lu *et al.*, (2017) conducted a global meta- analysis of CO_2 flux measurements from eddy covariance studies finding no statistically significant effect of water table depth on annual CO_2 fluxes, whether assessed as GPP, R_{eco} or NEP. Data for their study was compiled from a literature review in 2014 comprising 143 site years from 22 inland and 21 wetland sites. Mean annual temperature (MAT) followed by Mean annual precipitation (MAP) were found to be strongest univariate predictors of annual carbon fluxes across all wetland types. Their best fit model included MAT, MAP and an interaction between MAT and MAP and explained 71% variation in GPP and 57% variation in NEP. They further observed a positive relationship between leaf area index and GPP (R^2= 0.53) and leaf area index and R_{eco} (R^2= 0.37) however no significant relationship was observed for NEP.

A subsequent review by Zou *et al.*, (2022) presents contrasting results. Zou *et al.*, (2022) conducted a global review of wetland GHG fluxes, developing a global database (3,704 site years, 1,875 sites) of net wetland GHG fluxes (C_{O2}, C_{H4} and N_{2O}). Across their global dataset, which encompassed a range of temperature regimes, they find that a near surface level water table (-1 to -30cm) minimised GHG emissions, typically resulting in a near- neutral GHG flux. In contrast net greenhouse gas exchange rates peaked in flooded and drained conditions.

Sites were categorised on six levels of water table depth; below (negative number) and above (positive) the surface: WTL ≤ –70 cm; –70 cm to –50 cm; –50 cm to –30 cm; –30 cm to –5cm; –5 cm to 40 cm; and >40 cm. Sites were further categorised on long term average air temperature; boreal (<4°C) temperate (4- 17°C) and tropical (> 17°C). Complete records of C_{O2}, C_{H4} and N_{2O} fluxes were available for 174 site years, enabling assessment of the full GHG balance. The degree of data underpinning other flux assessments is not stated, though each draws on the full database of 3,704 site years.

Assessing net GHG fluxes across all sites they observed a parabolic relationship between water table level and net annual GHG emissions (sum of C_{O2}, C_{H4} and N_{2O}). Median net GHG emissions were lowest within the near surface water table level category (-30 to -5cm) and increased relative to this within both deeper water table categories, and shallower (flooded) categories. A similar parabolic relationship was observed for NEE which was also minimised within the near surface category. Meanwhile C_{H4} and N_{2O} both displayed linear relationships. Net annual C_{H4} emissions were found to increase across all water table categories, while N_{2O} emissions were found to decrease across all water table categories. The parabolic relationship between water table level and net annual GHG emissions was maintained when sites were split by temperature regime, though the minimum point was at a higher water table level among tropical sites (-5 to 40cm), than for boreal or temperate sites (-30 to -5cm).

Meta analysis findings, Water table and methane

Meta-analysis findings for the relationship between water-table depth and methane emissions are overall more mixed.

UK and Ireland

Analysing annual flux measurements from 41 static chamber studies in UK and Ireland, Evans *et al.* (2021) found an exponential relationship between water-table depth and net methane flux ($R^2 = 0.55$). Adding additional variables did not improve the model fit. They conclude that water-table depth was sufficient as a single predictor of CH_4 emissions.

Within their analysis of 118 sites on drained organic soils in Germany, Tiemeyer *et al.* (2020) similarly find an exponential response of CH_4 to water-table depth, model fit statistics were not however reported. Among deep drained soils annual CH_4 fluxes were approximately zero, and increased as water table approached the soil surface. Modelling this relationship they fitted an exponential response of CH_4 emissions to water-table depth. CH_4 response to water table was observed to vary across land use classes; forest land, cropland and grassland, and unutilised wet organic soils.

In contrast to Evans et al. and Tiemeyer et al., an earlier study by Levy *et al.* (2012) found water-table depth to be but one of several environmental controls on CH_4, and that water-table depth had relatively low predictive power in comparison to other variables when assessed as a single predictor. Levy *et al.* (2012) reported that when considered as univariate regressors several variables showed reasonably close relationships with CH_4 flux, particularly soil carbon, peat depth, soil moisture and plant species composition. In relation to other potential control variables however, water-table depth was found to explain a relatively low proportion of variation in methane flux (15- 25%) when assessed in this way. They found that water table explained a greater proportion of variation in methane flux when assessed at plot level ($R^2 = 0.25$, n= 130 plots) as compared to when averaged at the level of each study ($R^2 = 0.15$, n= 10 studies). Restricting their analysis to studies where species composition data were available, species composition was the strongest univariate predictor. Otherwise, considering the full data set, peat depth was found to be the best single predictor.

When assessed within multivariate linear specifications, Levy et al (2012) reported that parsimonious models included soil temperature, soil moisture and soil carbon, however the best combination of these depended on the averaging level (whether averaged across plot, sub- site or study). Meanwhile a model including an exponential response to temperature, combined with a power function for soil moisture and a linear function for soil carbon provided similar explanatory power to those from best sub- sets linear regression.

Global

Wu *et al.* (2025) conducted a meta- analysis of annual CH_4 fluxes reported in peer reviewed literature. Utilising a structural equation modelling framework they assess joint controls on net CO_2 and net CH_4 exchange from peatlands. They report that water table depth was the most important factor regulating CH_4 exchange from wetlands, while mean annual temperature was the second most important predictor. Among the factors tested water table depth (standardised coefficient 0.47), mean annual temperature (0.42), mean annual precipitation (-0.18) and ecosystem respiration (-0.10) all exerted direct effects on CH_4 exchange. Methane exchange was strongly related to carbon cycle measures GP, ER and NEE- CO2, which they surmise is due to common underlying drivers, particularly microbial activity, and may also be due to transfer of CH_4 through plant tissue and aerenchyma, as well as plant feeding of microbes in the rhizosphere.

Li *et al.* (2024) carried out a meta-analysis of environmental controls on methane emissions in natural wetlands finding that response to environmental controls differed between vegetation types. Drawing on the flux net database, as similarly used by Knox *et al.* (2019), they evaluate data from 38 sites covering 160 site years. They characterised sites as either vascular plant wetlands or moss plant wetlands based on primary vegetation type, finding that CH_4 response to water-table depth differed between the two types of wetlands. When the water table was below the surface, vascular plant wetlands had high CH_4 emissions while moss plant wetlands had CH_4 emissions close to zero. The direction of response further differed with emissions increasing as water table lowered among vascular plant wetlands, and conversely increasing among moss plant wetlands. As a univariate predictor water table depth explained 24% of variation in emissions from moss plant wetlands and 18- 35% variation in emissions from vascular plant wetlands.

Variance decomposition analysis further indicated diverging environmental response between moss plant wetlands and vascular plant wetlands. Among moss plant wetlands, their model was able to explain 88% of variation in CH_4 emissions; temperature (28.4%) and hydrological conditions (24.9%) best explained CH_4 emissions, followed by soil cation exchange capacity (14.6%). Among vascular plant wetlands, their model was able to explain 56% of variation in methane emissions; solar radiation best explained CH_4 emissions (41.3%), followed by temperature (19.3%) and latent heat (15.8%).

Li *et al.* (2024) further explore direct and indirect effects of environmental controls on CH_4 though structural equation modelling across all wetland types. Within their structural equation model soil physicochemical properties, water table and temperature each had direct effects. Water-table depth further indirectly affected CH_4 emissions by influencing wetland temperature and soil pH.

Analysing CH_4 flux measurements from 60 global sites within the fluxnet network of eddy covariance towers, Knox *et al. (*2019) assess potential environmental control on annual methane flux across sites – controls included biome or ecosystem type, mean seasonal water table depth, mean annual soil temperature, and mean annual air temperature. At global scale, they report that temperature provided the best predictor of CH_4 emissions: mean annual soil temperature or mean annual air temperature each explained approximately 65% variation in (log transformed) annual methane flux. Assessed as a univariate predictor, they find a positive linear relationship between water table depth and CH_4 flux, however only among sites which are not permanently inundated. When assessed across all sites, no significant relationship was found between average water table depth and methane flux, whereas excluding permanently inundated sites they find a positive linear relationship.

An earlier analysis by Turetsky *et al.* (2014) analysed CH_4 measurements from 71 global sites identified by literature review in 2009. In contrast to Knox *et al.* (2019) most flux measurements were taken by static chamber, only four sites were taken by eddy covariance. Turetsky *et al.* (2014) explored various model specifications and overall their analysis identified "general controls on wetland methane emissions from soil temperature, water table, and vegetation, but also show that these relationships are modified depending on wetland type (bog, fen, or swamp), region (subarctic to temperate), and disturbance." Water table was found to be a significant predictor within several model specifications, however the strength of effect varied depending on wetland type and prior management. An interaction of mean water table depth and wetland type was found to be a significant predictor within their best fit model of annual CH_4 flux, which included water table X wetland type, mean annual temperature X wetland type, and mean annual precipitation, and explained 49% of variation in log transformed mean flux.

Suggesting that functional relationships vary across wetland types, when assessed across wetland types, Turetsky et al (2014) found that mean water-table position was the only significant predictor of CH_4 flux averaged by site ($R^2 = 0.33$, $F = 28.62$, $P < 0.0001$; log10 CH_4 flux = 2.1 + 0.03x), while within wetland types, mean water-table position was a significant predictor of CH_4 flux for bogs and poor fens but not rich fens or swamps.

Using a mixed effects model they further explored whether drainage disturbance alters functional relationship between CH_4 flux and water table. The best-fit model of log transformed instantaneous CH_4 flux included several treatment (drainage vs. pristine) effects, suggesting that the same relationships between CH_4 flux, water-table position, and soil temperature were not adequate for explaining variation in flux across pristine and disturbed sites. Excluding the random variable, this final model explained 65% of variation in log transformed instantaneous CH_4 flux. Using a similar mixed effect modelling approach, they find no evidence that functional relationships differed between pristine versus flooded sites however, only water table position and soil temperature were retained in the final model, which (excluding the random variable) explained 40% of log transformed instantaneous CH_4 flux across the pristine and flooded sites.

Findings from primary studies

Primary studies were reviewed selectively, with a focus on articles dated post 2020.

Short term versus long term dynamics post- rewetting

Studies of GHG emissions at peatland sites following rewetting have indicated that methane emissions may increase in the short run. Among these, longer term studies of emissions post rewetting have observed that CH_4 emissions can remain elevated for some time following rewetting. In one case the increase in CH_4 emissions dominated the GHG balance resulting in an increase in CO_2 equivalent emissions.

Measuring the change in GHG fluxes at a rewetted agricultural fen during two initial years of paludiculture, Kandel et al. (2020) observed elevated emissions and a net increase in CO2 equivalent emissions. CH_4, CO_2 and N_2Owere measured using static chambers, enabling assessment of the full GHG balance. Average annual CH_4 emissions from both flooded and semi- flooded treatment plots were significantly higher than control plots. The increase in methane emissions dominated the GHG balance, resulting in a net increase in CO_2eqv emissions in the two years post rewetting.

Similarly, (Antonijevic *et al.*, 2023) reported a long period of elevated methane emissions following rewetting at a two fen sites near Zarnekow in the Peene valley, Germany. Methane emission remained high for 14 years following rewetting, only subsiding following the emergence of helophytes. They hypothesise this occurred due to large injection of leaf litter, which more gradual rewetting may have avoided.

Also studying the Zarnekow peatland site, Kalhori et al. (2024) also reported changes in CO_2 alongside CH_4 emissions over sixteen years post rewetting. During this time the site transitioned from being a CO_2 source to a CO_2 sink, while methane emissions have declined (though to a lesser extent). Evaluating the time trend of measured emissions they observed that the site level emissions only approached IPCC default emissions factors after 13- 16 years. They further evaluate environmental controls on interannual variation in emissions. At their site interannual variation in CO_2 was primarily driven by vegetation development (R^2=0.62) and soil temperature (R^2=0.46). Water-table depth did not significantly control interannual variation in methane. They surmise this was due to high water table at their site which generally remained above soil surface. One severe drought year in 2018 provided an exception. Following this both annual cumulative and daily median CH_4 emissions dropped sharply in 2019.

Schaller et al. (2022) measured GHG exchange at a peatland in Uchte, NW Germany 18 years after rewetting, finding the peatland was still a significant GHG source 18 years post rewetting. While the site remains a net source, emissions at the study site were lower than IPCC emissions factor for a peatland recently drained for peat extraction. The study site was an oligotrophic raised bog, drained for peat extraction in the 1950s and rewetted in 1999. GHG fluxes (CO_2, CH4 and N_2O) were measured by eddy covariance tower over 18 months in 2016 and 2017. Applying 100 year GWP conversion factors they estimate the balance of CO_2, CH_4 and N_2O as +500 ± 120 g CO_2-equiv m^{-2} a^{-1} in 2017. Among this CH_4 dominated, contributing 78% to the flux. Further including measurement of O_3 (net cooling effect), resulted in a slightly smaller estimated flux of +430 ± 120 g CO_2-equiv m^{-2} a^{-1}. Within this 18 month measurement period observed no significant response of CH_4 to variation in water-table depth (further investigation of environmental controls on emissions to follow in subsequent work).

Delwiche et al. (2025) analysed fourteen years of (near continuous) eddy covariance data from a flux tower located in the Mayberry wetland California. Following rewetting in 2011, annual methane emissions spiked in 2012, reaching 63.3 g C m^{-2} yr^{-1}. Since 2012 methane emissions declined, reaching 10.6 g C m^{-2} yr^{-1} in 2023. R_{eco} showed a similar trend. Water-table depth was relatively constant for the first five years but then experienced frequent pronounced drops due to abstraction. Vegetation ingrowth rapidly occurred, with open water dropping from 70% to 40% between 2012 and 2014. Developing a random forest model they explore drivers of the observed decline in methane flux. The most important predictors were vegetation coverage, followed closely by sediment temperature, while latent temperature, water table depth and R_{eco} had lesser importance.

Bockermann et al. (2024) found contrasting results. Evaluating the effect of rewetting and warming on greenhouse gas emissions from intensive and extensive grasslands in Germany, they found that rewetting and use as Carex paludiculture resulted in net- sink within the first year. Dynamic and static chambers were used to measure CO_2, CH_4 and N_2O enabling assessment across the full greenhouse gas balance. Rewetted plots were observed to have lower NEE, greater CH_4, and lower N_2O (though N_2O higher than expected). When considering the full GHG balance rewetted plots were found to have substantially lower emissions than drained. Emissions further depended on crop treatment with rewetted plots on extensive grass becoming a net sink. Plots under warmed treatment (closed chambers) were observed to have greater emissions reduction potential.

Hei et al. (2025) compare NECB between a recently rewetted minerogenic peatland and two undisturbed fen mires in Northern Sweden over the first three years post rewetting, integrating eddy covariance measurement of CO_2 and CH_4 exchange along with estimates of dissolved C to export to estimate NECB. The rewetted peatland was found to be a net source with a mean annual NECB of +77 (±34) g C m^{-2} $year^{-1}$ over the initial 3 years following rewetting. In contrast, nearby undisturbed mires were nearly C neutral or a net sink. Net CO_2 emissions declined by about 50% over the three years, while annual CH_4 emissions steadily increased year on year but remained at about half that of the undisturbed mire in the third year. CO_2 and CH_4 response functions further differed. Half hourly R_{eco} showed a stronger response to temperature, while (daily) CH_4 showed a weaker response to temperature as compared to natural mire sites. The observed reduction in net CO_2 emissions during first three years was largely due to an increase in GPP rather than a reduction in R_{eco}. The seasonal and interannual pattern of GPP increase further corresponded with NVDI suggesting that the change resulted from response of vegetation to rewetting. Changes in biomass were not recorded, however they observed an increase in cottongrass abundance. Contrastingly, annual R_{eco} remained similar over the three years, suggesting that an increase in autotrophic respiration due to increasing plant growth, counterbalanced the (likely) reduction in soil heterotrophic respiration due to wetter soils.

Ratcliffe et al. (2020) measured CO_2 emissions at a *drained* New Zealand peatland finding that emissions had *decreased* relative to measurement sixteen years prior and that the site had transitioned to being a C-sink. During the 19^{th} C, Moanatuatua was around 7,500 ha in size. Drainage for pasture began in 1930s and by 1979 the bog reached its current size of around 140 ha, less than 2% of its original extent. Water table measurements in 1976 and 1977 showed water table to be close to the surface, varying 0.8cm to 3.8cm below the surface. Repeat measurements in 1995 indicated a sharp decline in water table, reaching -60cm in summer 1994 and -65cm in 1995. Within their four measurement years summer water table depth ranged 20cm to 1m (approx), with 20cm reflecting an anomalous wetter summer with high precipitation, within the other three years summer water table depth ranged 75cm to 1m. Measurement of CO_2 by eddy covariance was conducted over two periods, first in 1999 and 2000, then in 2016 and 2017. Measured NEP was much greater in the recent monitoring period. During 1999 and 2000 the bog was a C source, yet by the later period of measurement in 2016 and 2017 the bog had become a C sink. The reduction in emissions was primarily due to greater C uptake by GPP and to a lesser degree resulted from lower C emissions from respiration.

Contrasting findings on environmental controls

Heiskanen *et al.*, (2021) found that drier (deeper water table) Finnish sub-arctic fens were larger CO_2 sinks than wetter ones, contradicting the results of Evans et al. (2021). Further contradicting UK results, Heiskanen *et al.* (2021) found using *daily* flux tower measurements that Green Chromatic Coordinate (GCC, an optical measure greenness investigated in later sections) was a more important predictor of both Net Ecosystem Exchange (NEE) and Gross Primary Production (GPP) than water table, with fixed effect models explaining 34 and 64% of the variations respectively. Differences between the peat bogs of Evans et al. (2021) and fens of Heiskanen *et al.* (2021) are explained by the nutrient status and plant community. The nutrient-poor acidic peat bogs likely limit rates of photosynthesis under dry conditions, and the specialist species are not adapted for water-limited conditions, decreasing rates of photo synthesis. Additionally, the drier conditions exposes the organic-mater to microbial consumption, increasing carbon loss. On the other hand, fens are relatively nutrient rich and pH neutral to alkali, containing vascular plants and photosynthesis dominating the carbon balance (Nielsen, Elsgaard and Lærke, 2024). Lowering the water-table depth can increase rates of photosynthesis (possibly by improved oxygen transport around roots) but not cause water limiting conditions due to the deeper roots of the vascular plants. These contradictory results suggest that water table depth may not be the sole-driver of CO_2 flux in all peat conditions and that nutrient status and ground cover of certain peat classifications (e.g. extensive/intensive grass) may need to be considered along-side water table depth to accurately determine GHG emissions.

Heiskanen *et al.* (2021) found that soil temperature was the best indicator of *daily* methane flux from Finish fens, followed by water table depth and leaf area index metrics having similar weightings in their linear model. However, environmental controls on *daily* emissions at a single site may be expected to differ from environmental controls on *annual* emissions between sites, and the UK and Ireland climate is overall more temperate. Additionally, because the model of Heiskanen *et al.* (2021) does not include an exponential relationship between water table depth and methane flux, it may lose some explanatory power. Therefore, these results do not necessarily contradict the dominance of water table depth on *annual* methane flux found by Evans et al. (2021).

Cultivated peat

Two recent studies among cultivated peatlands report similar findings to Evans et al. (2021), while another found no effect of water table depth on estimated carbon budget.

Heikkinen et al. (2024) measure CH_4 and CO_2 fluxes in a cultivated peatland in Finland over three growing seasons, finding that CO_2 emissions decreased linearly as the water table increased, while CH_4 emissions increased, though remained comparably insignificant relative to CO_2. Their study design featured two drained and two undrained plots equipped with control wells, fluxes were measured using static chambers. They found an approximately linear relationship for CO_2 emissions and water table. CO_2 increased as water table became deeper, though with indication of a levelling off which they hypothesise was due to soil temperature gradient in relation to depth. Observed monthly CH_4 fluxes ranged from negative to positive but insignificant, being two orders of magnitude below those for CO_2. From classification tree modelling they suggest that "risk for CH_4 emissions increases when water level is less than 30 cm from the soil surface and [soil water content] exceeds the threshold value of 0.6 m^3 m^{-3}." Though noting that estimates are site-specific and depend on the peat type, degree of peat decomposition, and soil compaction.

Boonman et al. (2024) evaluated the effect of subsoil irrigation and drainage on CO_2 emissions from peatlands used for dairy farming in the Netherlands, finding that sites with higher water table had reduced annual average CO_2 eq. emissions. Emissions were measured over three years by both peat chamber and eddy covariance, enabling a comparison of measurement techniques. Sites with subsoil irrigation and drainage were generally observed as having lower cumulative CO_2, though with one anomalous site year where the CO_2 flux from the (wetter) sub soil irrigation site very slightly exceeded those from the control. A similar pattern was observed when additionally accounting for C import (manure) and C export (harvesting) to measure Net Ecosystem Carbon Balance (NECB). They further observed a relationship across subplots between mean summer water table depth, NEE and NECB. NECB as measured by Eddy Covariance and Automatic Chambers showed overlapping confidence intervals when accounting for C import (manure) and C export (harvesting)).

Nijman et al. (2024) investigated the effects of drainage on carbon budgets on thirteen degraded peatlands used for grazing in the Netherlands finding no effect of water table depth on estimated carbon budget. Sites were selected across different water table depth (WTD), drainage-irrigation management, and soil moisture. NEE was measured over two years in 2021 and 2022 using automated chambers 1 to 2 times per month, for 2 to 3 days each measurement campaign. Remaining days were gap-filled using a random forest model. Contrary to expectation they found no relationship between variation in WTD and annual C budget. Variation in C budgets was also independent from drainage-irrigation management. Shallow drained and deep drained had similar C budgets and sites with irrigation did not have statistically lower C budgets than control sites.

10.7 Spectral earth observations

The search terms yielded 129 hits in the Web of Science Database and an additional 102 hits in the SCOPUS database. Two further articles were identified through cross-citation. Of the 231 unique articles, 36 were deemed suitable for further reading after reading the abstract after prioritising articles published after 2020.

Key Findings: Spectral earth observations, CO_2 and CH_4

- Large number of studies using earth observations to estimating GPP, less estimating NEE and even less estimating methane emissions from peat.
- Due to their nature of measuring reflected solar radiance or light emitted by plants (florescence) earth observations are good at accurately estimating GPP (i.e. rates of photosynthesis.) in peat across several climates.
- Generally, additional variables such as temperature and less-often water conditions are required for accurate estimates of GPP. However, there are cases when temperature and water conditions do not vary, either because of limited spatial variability or short measurement duration, and spectral earth observations alone are a good predictor of GPP.
- Like with GPP, temperature is an important additional variable when making predictions of NEE (Microbial and plant respiration minus GPP). Land Surface Temperature (LST) can be determined from earth observations at approximately ± 2 K in (general) making it easy to include as an additional variable in models. However, temporal frequency of measurement is low and temperature is a snapshot when satellite passes over the area and may not be representative.
- Predictions of NEE with earth observations are less accurate than GPP since water-table depth is a major controller of bacterial respiration in peat and is difficult to accurately measure from earth observations.
- To overcome this issue, attempts have been made to use reflected earth observations to detect drought stress in the vegetation as a proxy for WTD to varying degrees of success. Short time-scale studies looking at sub-daily changes in NEE have good agreement with EC measurements whereas longer-scale studies find this approach cannot capture seasonal changes in water table depth *resulting in usually poor approximations of NEE*.
- Hyper-spectral observations of light *emitted* from plants during photosynthesis (SIF) provides a more direct measure of photosynthetic activity that can partially account for temperature and moisture stress effects on GPP, potentially reducing the need for ancillary data. However, it remains limited by retrieval noise in peatland environments and does not capture respiration components required for NEE estimation.
- Methane emissions are less often approximated with earth observations. Like NEE, these fluxes depend heavily on water table depth which are hard to

approximate remotely. Best attempts to measure methane emissions using earth observations use meteorological data as additional variables to approximate soil/peat moisture conditions, often finding that the meteorological rather than spectral observations are the main driver of methane emissions.

- Models of methane tried to capture ebullition events indicating that more auxiliary (microtopography/InSAR) data may be needed to improve estimates.

Gross Primary Production (GPP)

Earth Observations are inherently suited for predicting GPP (rates of photosynthesis), often achieving high accuracy, but generally require additional variables like temperature and water conditions. Studies using various Earth Observations platforms and indices demonstrate good performance in predicting GPP. MODIS GPP was the strongest predictor of EC-derived GPP in northern peatlands, explaining 68% to 89% of the variation (Kross et al., 2013). Higher resolution data from Landsat (R^2 0.53–0.69) outperformed lower-resolution MODIS (R^2 0.40–0.63) in predicting GPP in wetlands (Cao *et al.*, 2025). Finer temporal and spatial resolution approaches, like camera-derived GRVI ($R^2 = 0.96$) or UAV/Phenocam VIs (R^2s > 0.70), showed strong correlations with GPP, often outperforming coarser satellite products in capturing seasonal dynamics (Gatis et al., 2017; Simpson et al., 2025).

Generally, additional variables are required to make good predictions of GPP, as spectral observations alone often struggle to capture non-light limitations. A model using Photosynthetically Active Radiation (PAR) (measured on the ground), temperature, and water table depth (WTD) achieved an R^2 of 0.85 (Albert-Saiz *et al.*, 2025). Cumulative air temperatures were used alongside solar radiation to mollify GPP, achieving an R^2 of 0.94 across several sites (He *et al.*, 2025). One study found that a combined metric of a red-edge chlorophyll index and 90-day-average rainfall (as a WTD proxy) was the best linear predictor of GPP, with an R^2 of 0.93 (Spinosa, Fuentes-Monjaraz and El Serafy, 2023). A Random Forest model for Gross Ecosystem Productivity (GEP/GPP) included spectral bands, VIs, LST, air temperature, shortwave radiation, and soil moisture achieved an R^2 of 0.76 across multiple drained peatland sites (Khan et al., 2025). However, in cases of limited temporal or spatial variability, such as during the peak growing season in a Scottish peatland, meteorological conditions (temperature and WTD) rather than vegetation greenness have been found to control GPP (DuBois et al., 2018). WTD and temperature were identified as the key controls on Light Use Efficiency (LUE) in northern peatlands (Wu et al., 2020).

Hyperspectral observations of Solar-induced Chlorophyll Fluorescence (SIF), for example, can provide a more direct measure of photosynthetic activity. SIF is a glow of light produced as an inefficiency of photosynthesis, and thus reduces when factors like water or nutrients limit photosynthesis, potentially reducing the need for ancillary data (Balogun *et al.*, 2023). Hyperspectral imagery improved GPP prediction performance (adjusted R^2 = 0.71) and reduced bias compared to broadband MODIS GPP (adjusted R^2 = 0.68), with the improvement potentially due to capturing plant physiological effects without relying on external meteorological inputs (Dubois et al., 2018). Ground-measured SIF could predict GPP with high accuracy (R^2 = 0.98) over 16-day aggregates (Buareal *et al.*, 2024). SIF was found to be a better indicator of NEE than EVI in Canadian peat bogs, although the difference in RMSE was modest (0.51 vs 0.53 μmol CO_2 m^{-2} s^{-1}) (Balogun *et al.*, 2023). SIF remains limited by signal-to-noise ratios due low photon fluxes and cannot fully capture soil respiration components required for NEE estimation (Balogun *et al.*, 2023). The marginal improvement in GPP estimations with hyper-spectral sensors may not always be worth the reduced spatial resolution to capture more flux in certain peat use-cases.

Net Ecosystem Exchange (NEE) and Water Table Depth (WTD)

Predictions of NEE with spectral EO are less accurate than GPP primarily because WTD is a major controller of bacterial respiration and is difficult to accurately measure remotely. Neither MODIS NDVI nor MODIS SR performed well at predicting NEP (–NEE), explaining only 25% to 53% and 29% to 39% of the variation, respectively (Kross et al., 2013). A machine learning model predicting GEP/TER/NEE achieved an overall R^2 of 0.79, but noted high RMSE compared to other studies (Khan et al., 2025). However, the study only used one site for model validation and did not account for autocorrelation indicating the possibility of over-fitting so the model cannot be generalised across sites. Like with GPP, Land Surface Temperature (LST) can be determined from EO in NEE models and is an important additional variable when making predictions (Khan et al., 2025).

Attempts have been made to use reflected EO VIs (e.g., LSWI, MWI, NDWI) as a proxy for WTD or peat moisture in models of NEE by measuring vegetation drought stress (Xiao *et al.*, 2004; Junttila *et al.*, 2021). Short time-scale studies looking at sub-daily changes in NEE using satellite-derived WTD showed good agreement, with R^2 up to 0.92 over a 3-month period (Balogun, Bello and Higuchi, 2023). The Modified Water Index (MWI) used as the sole predictor of NEE found strong correlations (R^2 between 0.6 and 0.78) over several years (Kalacska *et al.*, 2018). However, these proxies are effective under conditions corresponding to the onset and peak of vegetation water stress and are often inaccurate proxies for WTD estimation outside these conditions (Kalacska *et al.*, 2018; Balogun, Bello and Higuchi, 2023). For example, hyperspectral NDWI1240 performed well at predicting WTD in ranges between ~-30 -40 cm but could not predict WTD in summer months where WTD was lower (Kalacska *et al.*, 2018). Longer-scale studies show that this approach cannot capture seasonal variation in WTD across all peatland types, resulting in poor yearly estimates of NEE (e.g., R^2 = 0.36 using LSWI and temperature in Swedish and Finnish peatbogs (Junttila *et al.*, 2021).

Methane (CH_4) Emissions

Methane emissions are less often approximated with Earth Observations than CO_2 fluxes and depend heavily on WTD. Best attempts use meteorological data as additional variables to approximate soil/peat moisture conditions, finding that these auxiliary data are the main drivers (Watts et al. 2014). Watts et al. (2014) used satellite data alongside reanalysis data from MERRA (which includes soil moisture estimates) to model CH_4 fluxes based on temperature, soil moisture, and soil carbon. MERRA data accounted for approximately 75% of variation in CO_2 and CH_4 fluxes. SIF, argued as a proxy for substrate, only modestly increased the R^2 from 0.75 to 0.76 in a linear model already containing soil temperature and WTD (Buareal *et al.*, 2024). Watts et. al., (2014) model of CH_4 flux included features of gas transport and ebullition the peat, indicating that more auxiliary (microtopography/InSAR) data may be needed to improve estimates.

Summary Table: Spectral Earth Observations Literature Review

Table 14: Spectral earth observations literature review summary table

Study	Site Type	Carbon Metric	Proxies	R^2	CO_2 data	Spectral data	Other variables
Khan et al. (2025)	Agricultural peatlands in East Anglia England	NEE	NDVI, EVI, NDMI among other predictors	0.87 (Grass) 0.66 (Crops) 0.64- 0.89 (across sites)	EC	Landsat and Sentinel 2 (at 30 m resolution)	Land surface temperature estimated from Landsat data. No water table depth measurement but uses daily soil moisture product produced by CEH.
Cao et al. (2025)	Ten ecosystems within fluxnet	GPP	Various vegetation indices**	0.40- 0.69 (Wetlands)	EC	Landsat (30m) and MODIS (500m)	
He *et al.*, 2025	Canadian northern peatbogs	GPP	Various vegetation indices	0.94	EC	MODIS EVI and NDVI	Temperature dampens VI derived GPP
(Buareal *et al.*, 2024)	Japanese Peat	GPP and CH_4	Ground measured SIF	GPP=0.93 to 0.93 CH_4 = 0.77	EC	Ground based	GPP – only SIF. CH_4 Temperature and WTD. Non-linear model.
Gariosain et al. (2024)	Pyrenean mountain peatland	GPP R_{eco} CH4	Chlorophyll index	GPP= 0.69 R_{eco}= 0.84 CH_4 = 0.59	Static chamber	Sentinel 2	Site measurement of water table, DOC. Temperature site and reanalysis.
(Balogun, Bello and Higuchi, 2023)	Canadian peatland	NEE	SIF + various VI including EVI	0.92-0.98	EC	MODIS and OCO2	Temperature. R2 for Diurnal NEE
(Junttila *et al.*, 2021)	Swedish and Finish peatland	GPP + NEE	NDWI,EVI	GPP=0.7, NEE=0.36	EC	Sentinel-2 and MODIS	Temperature (MODIS-LST)
(Lees *et al.*, 2021)	Scottish peatland	GPP	NDVI	Chamber= 0.57-0.71, EC= 0.76-0.86	EC +Chamber	MODIS	Temperature (MODIS-LST)

(Kalacska *et al.*, 2018)	Canadian peatland	NEE +WTD	MWI and hyperspectral NDWI1240	WTD=0.79, NEE=0.68-0.78	EC	Airborne	None
Dubois et al. (2018)	Various ecosystems across California, forests, grassland savannas, wetlands and shrubland	GPP	Hyper sepctral signals	0.71	EC	hyperspectral data (VSWIR, 400–2,500 nm)	
Gatis et al. (2017)	Drained peatland in Exmoor, England	GPP	GRVI	0.96 (camera) 0.79 (MODIS)	Static chamber	Digital camera, MODIS	
Watts et al. (2014)	Six sites in Russian and Eurasia	CO_2 and CH_4	LUE model using reanalysis data from MERRA And MODIS GPP	0.75 0.69	EC	MODIS MERRA	Soil moisture and surface temperature estimates obtained from MERRA archive, gridded at 1/2 × 2/3° spatial resolution.
Kross et al. (2013)	Raised ombrotrophic bog, Moderately rich treed fen, Open minerotrophic moderately rich fen,	GPP NEP	MODIS GPP MODIS GPP	0.68- 0.89 across sites 0.43- 0.75 across sites	EC	MODIS	

Mesotrop
hic sub-
arctic
poor fen

10.8 Erosion

The search terms yielded 4 hits in the Web of Science Database and an additional 4 hits in the SCOPUS database. Of the 8 unique articles, 2 were deemed suitable for further reading after reading the abstract. The lack of hits in the erosion literature search is due to the necessity that papers included a direct measurement of direct GHG emissions. These search terms were designed to capture on-site emissions while carbon lost from erosion as POC/DOC is mostly emitted off-site. The criteria were intentionally strict to ensure that the evidence would be defensible within a tax-dispute context and to limit paper-count within this short project. Indeed, removing this restriction yields over 200 papers in the WOS database which were not possible to review in this project.

Five excluded papers considered CH_4 isotopic ratios to investigate aerenchyma flux pathways which discriminates ^{13}C-CH_4 (Marushchak *et al.*, 2016). The two relevant papers used ^{210}Pb to date soil layers and thus determine rates of organic-matter accumulation (Adkinson, Syed and Flanagan, 2011; Arias-Ortiz *et al.*, 2021). Arias-Ortiz *et al.*, (2021) could estimate organic carbon accumulation rates and show that the majority of organic carbon in a Californian marshland was fixed since restoration activity. Unlike measurements of NEE with EC, carbon accumulation rate in this context includes fluxes of CH_4 and NEE as well as carbon lost as DOC and POC. By comparing carbon accumulation measurements with EC measurements Arias-Ortiz *et al.*, (2021) argued they could estimate carbon loss via DOC and POC. We recommend caution with this interpretation since errors or site-dependent topography variations in EC measurements could easily be attributed to erosion. Additionally, unquantified errors in ^{210}Pb dating likely do not co-vary with EC errors due to differing methodological principles. Similarly, Adkinson, Syed and Flanagan (2011) used ^{210}Pb peat dating to quantify long-term carbon burial and compared those results with EC-derived NEE to test whether GPP (short-term carbon sink) translates into actual long-term peat accumulation. They find that the two measurement approaches yield the same qualitative results regarding two contrasting Canadian peatlands but are more cautious and do not interpret quantitative differences between the two measurement modes as DOC or POC loss.

Using ^{210}Pb dating to determine rates of organic carbon-accumulation/loss in peat could be a useful monitoring tool to determine success of restoration activity. Unlike EC, this measurement is indicative of gaseous and POC/DOC loss/gain and could help capture more of the peat GHG balance.

The IPCC wetlands supplement offers Tier 1 emissions factors for DOC based on concentrations found in rivers and drainage waters by assuming that 90% of DOC is oxidized to CO_2 but offer no emissions factors for POC (Hiraishi *et al.*, 2014). The mass of DOC is derived from climate-based Tier 1 emissions factors for drained peatland only. To include DOC emissions, the UK National Inventory used long-term data from

POC monitoring and assumed 100% of POC oxidises to determine emissions factors per area of bare peat (Evans, C. *et al.*, 2017). Direct measurement of erosion-derived emissions is rarely (never?) available, emissions accounting must therefore rely on proxy measurements (DOC/POC loads in drainage) and emission conversion assumptions which introduce substantial uncertainty. Methodologies to measure DOC/POC loads are outside the scope this study but will be required to capture the full GHG balance in eroded peat. Evidence from a meta-analysis suggests that DOC loss is correlated with WTD in peat bogs but not fens (Xu *et al.*, 2023). It may be possible to determine DOC losses based on WTD and use emissions factors to convert to CO_2 and CH_4 emissions downstream. However, we can conclude that in any GHG-tax, emissions estimates for eroded peat must be treated as conservative due to the lack of direct link to measured emissions.