Defusing the 'carbon bomb': A smart-data approach to assessing and managing risk of abrupt greenhouse gas emissions from peatlands

Background: The most essential terrestrial ecosystems for climate action are peatlands. Peatlands occupy only 3% of the Earth's surface but store at least two-fold more carbon (C) than standing forests, or one-third of all soil C [(1)]. Alongside other types of wetlands, peatlands are the largest and most uncertain natural source of the greenhouse gas (GHG) CH_4 [(2)]. Peatland GHG emissions (CO_2, CH_4 and N_2O) are strongly influenced by extensive human and natural disturbance (e.g., drainage, wildfire) and by rapid climate change (e.g., permafrost thaw). Conserving intact peatlands is an effective way of avoiding GHG emissions, whilst restoring disturbed peatlands offers a cost-effective 'natural climate solution' to reduce GHG emissions [(3)]. Without protection, peatland vulnerability to climate change and disturbance raises concerns that slowly-accumulating C stocks could be released to the atmosphere very rapidly, further accelerating global warming – a potential 'carbon bomb'. To assess uncertainty and manage risk of abrupt GHG emission from peatlands, policy-makers need 'smart data' on their GHG fluxes.

The smart-data approach applies causal knowledge and real-world understanding to develop models driven by information required for prediction rather than by data availability [(4)]. Prediction of future peatland GHG emissions remains highly uncertain for at least two reasons. First, although a few peatlands have been instrumented with eddy covariance (EC) flux towers enabling high-frequency (10-20 Hz), automated monitoring of gas exchange with the atmosphere, uncertainties in aggregated half-hourly GHG fluxes have been quantified based on overly simplistic assumptions [(5)] and by ignoring systematic and structural uncertainties. Second and more fundamentally, EC-based GHG emission data are scarce geographically and shorter in duration than relevant controls and interactions, and hence understanding of peatland GHG response to climate change and disturbance is weak and incomplete. We do know that peatland dynamics are mediated by system feedbacks that either dampen or amplify external perturbations [(6, 7)]. For example, a sustained but weak increase in precipitation can lead to rapid and dramatic changes in peatland surface structure and C sequestration [(8)]. We have qualitative understanding of some of the feedbacks responsible for such non-linear behaviour, but we lack full understanding of how feedbacks interact with external forces [(9)] to control GHG fluxes.

The **aim** of the proposed research is to integrate quantitative information on GHG fluxes and environmental factors with semi-quantitative understanding of controls and interactions and qualitative information on land management. This AI-based 'smart data' approach will enable better understanding of interactions between environmental, climatic, social and economic processes that drive policy and management of peatlands and their GHG emissions. Stakeholders will be involved directly in model development, ensuring their trust in the data and results.

Description of the proposed research: The project team brings together critical expertise in ecosystem dynamics and modelling; measurement and modelling of GHG fluxes; and application of AI techniques to problems of risk and uncertainty. The **specific objectives** of the proposed research are: (i) to build an accurate model of peatland GHG fluxes and uncertainties, addressing the challenges of unknown or unobserved processes as well as uncertainty in model choice and model structure; and (ii) to incorporate external factors and natural mechanisms of resilience into a high-level causal Bayesian network (BN) of peatland GHG fluxes, thereby providing a smart-data approach to assessing and managing the risk of abrupt GHG emissions from peatlands. We will trial this approach using EC flux and environmental data (meteorology, hydrology, vegetation) at two well-studied peatlands in the UK GHG flux network: Auchencorth Moss, a transitional lowland raised bog in southern

Scotland with a near-continuous 20-year record; and Forsinard, a blanket bog in the Flow Country of northern Scotland with a record spanning six years. Data for these contrasting sites have been published previously [10, 11] and are curated and managed by CEH. Auchencorth Moss is part of the Integrated Carbon Observation System (ICOS), an international organisation that aims to quantify the pan-European GHG balance.

Tools and methods: Building an accurate model of EC-based GHG fluxes is challenging because of both uncertainty in correct model structure and unobserved/unmeasured processes and interactions. We will tackle these issues using cutting-edge Bayesian and Machine Learning (ML) techniques. Robust predictions will be produced by model ensemble approaches, combining multiple models using model boosting and model stacking to create unbiased estimates with low variance [12, 13]. Unobserved processes and feedbacks will be constrained using Approximate Bayesian Computation [14], a likelihood-free modelling approach, and will assimilate environmental data and their associated uncertainties using data assimilation approaches on dynamic model output (e.g. Ensemble Kalman Filter, 4DVar) [15]. To future-proof our approach, we will construct a framework capable of assimilating future data-streams, such as remote sensing data, through careful design of model state variables.

We will extend this data-driven GHG flux model with expert opinion on peatland functioning and management. Insights gained during an expert workshop will enable us to elicit causal and explanatory risk factors and interventions (including, e.g., political and process/people factors) that have, up until now, been either ignored or assumed too difficult or controversial to measure. The objective of the workshop will be to identify the most appropriate model variables and structure, arriving at a high-level causal Bayesian network (BN) [4]. As BNs are based on directed acyclic graphs, cyclical causality (i.e., feedbacks) cannot be incorporate directly. Instead, we will carry out qualitative analyses of sign-directed graphs of key feedbacks, obtaining prediction weights that will be converted to conditional probabilities in the BN models [16]. Using such a model with the approach proposed in, e.g., Pearl and Mackenzie [17], we could in principle more rigorously evaluate the effect of various interventions, including the effects of sustained change in one or more model variables (e.g., precipitation or temperature), as well as extreme events (e.g., the hot, dry summer of 2018 and the extremely wet winter of 2015/16). It will also enable us to consider counterfactual questions, such as how observed outcomes might have changed if some previous intervention had been different. At Forsinard, for example, we can use GHG flux data from contrasting sites [18] to explore the impact of restoring peatlands that were afforested in the 1970s/80s as tax refuges.

Relevance and beneficiaries: Conserving and restoring peatlands will be an important component of UK and international climate action, driven by, e.g., the Paris Agreement to reduce emissions of GHGs and to conserve or enhance existing C sinks and stocks. This project will demonstrate how an innovative, smart-data approach can provide the intelligence needed for this action, despite gaps in knowledge and data. Our analyses of GHG fluxes will feed via CEH into protocol development and future analyses at ICOS, as well as to the BEIS-funded process of verifying the UK inventory of annual GHG emissions. A range of stakeholders will participate in the expert workshop, including NGOs active in peatland conservation and restoration (e.g., RSPB, IUCN) as well as policy-makers funding climate action and reporting on progress (e.g., Scottish government, BEIS).

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