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A Conceptual Framework for Remote Sensing Solution for Peatland Greenhouse Gas Emission Estimation in Latvia

Maksims FEOFILOVS[1*], Linda GULBE-VILUMA[2], Andrei GRISHANOV[3], Ilze BARGA[4], Amrutha RAJAMANI[5], Nidhiben PATEL[6], Francesco ROMAGNOLI[7]

[1,5–7]*Institute of Energy Systems and Environment, Riga Technical University, 12/1 Azenes iela, Riga, LV1048, Latvia*

[2–4]*Baltic Satellite Service, 29 Miera str., Jurmala, LV-2015, Latvia*

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***Abstract* – Peatlands play a critical role in the global carbon cycle, acting as long-term carbon sinks but becoming significant greenhouse gas sources when drained or degraded. Accurate estimation of carbon dioxide and methane emissions from peatlands is essential for climate change mitigation and land management. Traditional field-based measurement techniques, such as eddy covariance and chamber systems, are spatially limited and resource intensive. Remote sensing provides a scalable and cost-effective alternative for monitoring surface and vegetation characteristics linked to carbon dynamics. This study presents a comprehensive review of remote-sensing-based methods for estimating greenhouse gas emissions from peatlands and evaluates the data readiness in Latvia for national-scale implementation. Two primary approaches are identified: land-cover-based estimation using emission factors and regression-based modelling of carbon fluxes derived from vegetation and temperature indices. Latvia possesses extensive open-access datasets, including Sentinel-2 satellite imagery, Light Detection and Ranging data, and national habitat inventories, which enable reproducible and transparent monitoring. The proposed conceptual framework integrates these resources into a unified, automated workflow for Greenhouse Gas emission estimation, establishing a foundation for operational peatland greenhouse gas monitoring and reporting.**

***Keywords* – Carbon flux; climate change; emission factors; GHG accounting; peatlands; remote sensing.**

1. Introduction

Greenhouse gases (GHG) such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) are the main contributors to global climate change. Monitoring these gases is essential for understanding their sources and sinks, developing effective mitigation strategies, and meeting international climate targets such as the Paris Agreement [1]. Reliable GHG emission estimation helps countries to assess progress toward sustainability goals and supports evidence-based environmental policies [2], [3]. Traditional field-based methods, including chamber measurements and eddy covariance systems, provide highly accurate estimates of carbon and methane fluxes from ecosystems. However, these methods are limited in spatial

* Corresponding author.
E-mail address: Maksims.Feofilovs@rtu.lv

coverage, are labour-intensive, and require substantial financial and technical resources [4], [5].

In Latvia, as in many Northern European countries, peatlands and organic soils are major sources of GHG emissions [6], but field measurements cover only a few representative sites. Because peatlands are spatially diverse, point-based measurements cannot fully represent their variability [7]. This limitation has encouraged the use of remote sensing technologies to complement or replace extensive field campaigns.

Remote sensing offers a scalable, repeatable, and cost-effective means of observing environmental conditions related to GHG emissions. Using satellite, aerial, or drone-based sensors, remote sensing provides continuous spatial coverage over wide areas and long periods [8]. Existing available technologies such as Sentinel-2, Landsat, and MODIS enable consistent monitoring of land-surface properties such as vegetation, soil moisture, and temperature [9]–[11]. Although satellites cannot directly measure gas fluxes, they capture spectral and thermal information that can be correlated with surface processes such as photosynthesis, evapotranspiration, and soil respiration [4]. For Latvia, which maintains full national coverage of Sentinel-2 imagery and other open-access spatial data, remote sensing offers an efficient way to scale GHG estimation from individual sites to national applications.

Peatlands are unique ecosystems that store vast amounts of carbon as partially decomposed organic matter. In their natural state, peatlands act as carbon sinks, absorbing CO_2 through plant growth and sequestering it in the soil over long periods [2]. When drained or degraded through human activities such as agriculture, forestry, or peat extraction, they become major sources of carbon emissions [4]. In Latvia, peatlands are an essential component of the country's natural environment. These ecosystems play a key role in biodiversity conservation, hydrology, and the national carbon balance. Disturbance or drainage of peatlands contributes to Latvia's total GHG emissions, while restoration and rewetting can help reverse these effects [12]. The assessment of peatland restoration depends on high-resolution monitoring of environmental variables, which can be efficiently achieved using remote sensing techniques.

Two main methodological approaches have been applied to estimate GHG emissions from peatlands using remote sensing data. The first, regression-based GHG emission modelling, employs empirical or machine learning models to relate satellite-derived variables such as vegetation and land-surface temperature indices to field-measured GHG emissions. These models have been successfully used in Nordic peatlands to predict spatial patterns of CO_2 exchange [13]. The second, land-cover-based emission factor estimation, involves classifying peatland areas by land-cover type and applying corresponding emission factors derived from field observations. The Intergovernmental Panel on Climate Change (IPCC) provides global guidelines for emission factor tiers [14], while Latvia has developed country-specific Tier 2 values through the *LIFERestore* project [15], enabling national-scale application of this approach.

Despite international progress, there is still a lack of regional-scale applications using freely available datasets and integrated national data. Latvia has a particularly strong foundation for remote sensing implementation with open-access Sentinel-2 imagery, Light Detection and Ranging (LiDAR) canopy models, and detailed national habitat maps [8], [12]. The aim of this paper is to (a) review and synthesize remote-sensing approaches for estimating GHG emissions in peatland, (b) assess data readiness and available resources in Latvia, and (c) propose a conceptual framework linking these datasets with GHG emission estimation methodologies. The developed conceptual framework provides a basis for implementing national-scale monitoring of peatland GHG emissions in Latvia.

2. State of the Art: Remote Sensing and Modelling of Peatland GHG Emissions

2.1. Role of Remote Sensing in GHG Emissions Estimation

Remote sensing provides a non-invasive spatially continuous method to observe environmental conditions that influence GHG emissions [16]. Although remote sensing does not measure CO_2 or CH_4 fluxes directly, they record spectral and thermal energy from the Earth's surface that can be related to land-surface properties affecting carbon exchange [17]. Parameters such as vegetation indices, land-surface temperature, and soil moisture are frequently derived from optical and thermal sensors to infer the processes of photosynthesis, respiration, and decomposition [4].

According to Lees *et al.* [4], satellite data enable the estimation of gross primary productivity (GPP), ecosystem respiration (ER), and net ecosystem exchange (NEE) when combined with empirical models and field-based calibration. Remote sensing is therefore a practical approach for large-area and long-term carbon-balance studies where field campaigns are limited. Peatlands are particularly suitable for such applications because of their extensive coverage and high spatial variability. Traditional field methods, such as flux chambers and eddy-covariance (EC) towers, provide precise data but only at the plot scale, while remote sensing can generalize these results across entire peatland complexes. By integrating satellite and in-situ data, it becomes possible to evaluate emissions and removals from natural and managed peatlands at national scales. GHG related studies employ several target variables to be estimated by the means of remote sensing data:

- CO_2 emissions (t CO_2 – Cha^{-1} y^{-1} or total emission amount t CO_2 – Cy^{-1});
- CH_4 emissions (kg CO_2 – Cha^{-1} y^{-1} or total emission amount kg CO_2 – Cy^{-1});
- Net Ecosystem Exchange ((gC m^{-2} yr^{-1}, gCO_2 m^{-2} yr^{-1}).

Multispectral instruments, including Sentinel-2 (MSI) and Landsat OLI, supply vegetation information through indices such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Normalized Difference Water Index (NDWI), which are proxies for canopy activity and moisture conditions [18], [19]. MODIS provides complementary temporal coverage for monitoring seasonal dynamics [20], [21]. These indices, coupled with land-surface temperature, are the most common predictors in GHG emission estimation models [4]. Two typical approaches on remote sensing based GHG emission estimation are: (a) Land cover-based approaches, which classifies land cover classes using remote sensing data as input and then applying emission factors for each land cover class; these emission factors are acquired in field experiments and can be applied with accurate land cover information, and (b) Using regression-based models estimating GHG emissions which takes different remote sensing-based products as input.

2.2. Land-Cover-Based Approaches

The land-cover-based approach is the most widely applied method for remote sensing–based estimation of peatland GHG emissions because of its simplicity and compatibility with international reporting frameworks. This method consists of two main steps, first is the classification of peatland land-cover types using remote sensing data and second, application of emission factors (EFs) for each class to estimate fluxes of CO_2 and CH_4 based on existing literature sources [2]. In the Land cover-based approach, remote sensing data is used solely to obtain more up-to-date and detailed land cover maps through machine learning classification methods. Remote sensing provides the most spatially detailed information on land cover, and satellite data enables regular monitoring of large areas at a low cost. Total emissions are calculated by simple equation, see Eq. (1) [22]:

$$CO_2 \text{ emissions } (\text{t } CO_2 - Cy^{-1}) = \text{land use area (ha)} \times \text{EF } (\text{t } CO_2 - \text{C ha}^{-1}\text{ y}^{-1}), \quad (1)$$

where EF is the land cover/use specific emission factor.

One source of EF is a system proposed by the Intergovernmental Panel on Climate Change (IPCC) consisting of three tiers [2], Tier 1 (T1) includes default EF specially for wetlands, Tier 2 (T2) includes country specific EFs and based on emission data from case studies, and Tier 3 (T3) use more complex and dynamic EFs models [22]. However, the *LIFERestore* project [15] provided adjusted EFs specific to Latvia. Although nitrous oxide (N_2O) can be emitted from peatlands under specific conditions, its contribution to total GHG emissions in Latvian peatlands is generally minor compared to CO_2 and CH_4.

The *LIFERestore* project determined CO_2, CH_4, and N_2O EFs for the following land cover classes: 1) transitional mire, 2) raised bog, 3) active peat extraction, 4) abandoned peat extraction, 5) rewetted peatland, 6) afforested peatland (coniferous), 7) afforested peatland (deciduous), 8) restored or renaturalised bog, 9) reclaimed with blueberry, 10) reclaimed with cranberry, 11) cropland on former peat extraction site – legumes, 12) cropland on former peat extraction site – cereals, 13) perennial grassland on former peat extraction sites, 14) bioenergy production former peat extraction sites.

The cover classes can be estimated by using remote sensing data and machine learning methods. Land cover classification using remote sensing can be done by any machine learning classification method. Accuracy is more highly dependent on quality of training data and representativeness of the data features than the choice of machine learning methods themselves. A lot of shallow machine learning methods are available in Python libraries, like sklearn. There are three types of resolutions, which are the most important characteristics of multispectral satellite images: spatial, spectral, and temporal.

The spatial resolution determines the size of the smallest detectable object on the ground, often expressed in meters per pixel. Higher spatial resolution allows for finer detail, making it suitable for applications like urban mapping or small-scale vegetation analysis, while lower resolution is often used for large-scale environmental monitoring. The spectral resolution refers to the number and width of wavelength bands captured by the satellite. Multispectral sensors typically collect data in a few broad bands (e.g., visible, near-infrared, and shortwave-infrared), which are crucial for distinguishing different surface features, such as vegetation, water bodies, and soil types. The temporal resolution describes how often a satellite revisits the same location. High temporal resolution is critical for monitoring dynamic changes, such as vegetation growth, land cover changes, or seasonal trends in water bodies [23].

This approach is widely applicable for national GHG inventories, though its precision is limited by classification accuracy and emission-factor variability. Further improvement can be achieved by integrating flux-based modelling methods.

2.3. Carbon Flux Modelling Approaches

Regression-based or carbon flux modelling approaches aim to estimate GHG fluxes directly by linking remote sensing derived predictors to field-measured CO_2 exchange components. These methods rely on statistical, or machine learning models calibrated with flux measurements from EC towers or chamber systems [4], [13]. This approach estimates gross primary productivity (GPP), net ecosystem exchange (NEE), autotrophic respiration (R_a), heterotrophic respiration (R_h), and ecosystem respiration (R_{eco}) which uses multiple independent variables, such as land-surface temperature and remote-sensing based vegetation indices. These coefficients are usually determined through regression methods and need to be tailored to specific geographic and climatic conditions for improved accuracy.

An empirical model of the CO_2 balance GPP, NEE, and ecosystem respiration (ER) that could be used for upscaling CO_2 fluxes with remotely sensed data [13], which is constructed for five peatlands in Sweden and Finland using Sentinel-2 vegetation indices and MODIS land-surface temperature. Their results indicated coefficients of determination (R^2) of 0.70 for GPP, 0.56 for ER, and 0.36 for NEE, with normalized root mean square errors (NRMSE) between 13 % to 15 %. These outcomes are the consistent, where R^2 value range from 0.09 to 0.77, reflecting high spatial variability among ecosystems.

Regression models generally incorporate multiple independent variables, such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Land Surface Temperature (LST), and surface albedo along with coefficients derived through regression or machine-learning training. These coefficients quantify the sensitivity of carbon fluxes to each variable and are often site-specific. Therefore, model transferability across climatic zones requires recalibration [4].

For Latvia, empirical modelling can be supported by data from EC towers and chamber measurements established in national research projects [15]. These field datasets provide the calibration and validation base for developing localized regression equations linking Sentinel-2 spectral indices and Moderate Resolution Imaging Spectroradiometer (MODIS) temperature products to CO_2 fluxes. MODIS provide high-frequency observations of vegetation and surface temperature at moderate spatial resolution, making them particularly suitable for large-scale and temporal analyses of carbon flux dynamics.

Another valuable group of input variables for carbon-flux modelling is provided by the Copernicus Global Land Service, which supplies harmonized biophysical parameters derived from Sentinel and PROBA-V missions [24]. These include vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), and Fraction of Absorbed Photosynthetically Active Radiation (FAPAR).

Vegetation indices are mathematical combinations or ratios of spectral bands in satellite or aerial imagery that are used to measure and monitor the condition, health, and density of vegetation on Earth's surface. They are derived from the way plants interact with light, particularly in the visible and near-infrared (NIR) parts of the electromagnetic spectrum. In addition, Phenology layers provide valuable information about the timing and progression of key vegetation life-cycle events derived from satellite data. These layers capture indicators related to the start of growing season, end of growing season, annual productivity, offering insights into the seasonal dynamics of ecosystems on a global scale [25], [26].

Overall, carbon-flux modelling approaches offer a dynamic and data-driven method to upscale field measurements of GHG exchange. Their effectiveness depends on careful calibration with ground data and the selection of reliable remote-sensing predictors, such as those now available through the Copernicus programme. Together, these developments provide a solid foundation for integrated modelling frameworks that can support national-scale peatland emission monitoring.

2.4. Knowledge Gaps and Challenges

Despite substantial methodological progress, several knowledge gaps limit the operational use of remote sensing for Peatland GHG emission estimation. The first challenge is the scale mismatch between field measurements and satellite observations. Flux chambers capture fluxes at the plot scale, while eddy-covariance (EC) systems represent footprints of hundreds of meters, and satellite sensors record at pixel sizes from 10 m to 1 km, creating spatial aggregation errors and complicating validation [27]. The second limitation concerns uncertainty in emission factors and model parameters. Emission factors are often derived from a small number of field sites and may not fully capture variability across climatic zones or land-management conditions [28]. Likewise, regression coefficients in empirical models are frequently site-specific and require regional recalibration to maintain accuracy [13].

Temporal inconsistencies present an additional obstacle. Frequent cloud cover, especially in Northern Europe, causes data gaps in optical imagery and hinders time-series continuity. Although radar observations mitigate this problem, they increase data-processing complexity and require specialized expertise [29]. Moreover, the lack of standardized field validation protocols restricts the comparability of studies. Integrating remote-sensing outputs with field data requires careful geolocation, and mismatches between sensor footprints and measurement plots can introduce systematic bias [30].

From a regional perspective, Baltic Peatlands remain underrepresented in flux and modelling studies compared with Scandinavia [13]. Nevertheless, Latvia's rich spatial data infrastructure comprising Sentinel-2 imagery, LiDAR coverage, and national emission factor datasets obtained in The *LIFERestore* project provides a strong foundation for overcoming many of these limitations [15]. Addressing current gaps will require harmonized field campaigns, open data sharing, and hybrid modelling frameworks that combine optical, radar, and environmental variables. Such coordinated efforts are essential to advance reproducible, nationally consistent GHG monitoring for peatlands.

3. CONCEPTUAL FRAMEWORK FOR PEATLAND GHG ESTIMATION IN LATVIA

The findings within literature serve as basis for development of conceptual framework, which establishes the link between remote sensing data, GHG emission modelling, and user interaction within an integrated, automated workflow. The framework proposed in this study is designed to serve as an operational application that supports peatland users, planners, and analysts in estimating greenhouse gas emissions from peatland areas based on their actual land-use composition. The framework is built around the practical use case in which a user manages or assesses a peatland area that consists of one or more predefined peatland land-cover classes. The conceptual design of framework integrates three essential components:

A. Remote sensing data: Pre-calculated land-cover maps derived from Sentinel-2 imagery processed through supervised machine-learning classification.
B. Emission modelling: Application of EFs corresponding to each peatland land-cover type to estimate CO_2 and CH_4 emissions.
C. User interaction: A cloud-based application programming interface (API) that allows analysts to submit spatial data and retrieve results through an automated Python-based environment.

The framework enables the linking of user-defined spatial units with national-scale geospatial datasets that describe peatland types and land-use status. It operationalizes the methodological principles described in Section 2 by transforming them into a functional cloud-based system for national-scale GHG emission estimation. The system is designed to estimate CO_2 and CH_4 emissions from peatlands through a streamlined process that connects user-defined spatial inputs with a centralized geospatial database containing pre-processed remote sensing–derived land-cover maps. Within the framework, peatland classes are derived from existing national habitat and land-use datasets, while active peat extraction is manually defined:

- Afforested peatland, coniferous – derived exclusively from the national forest inventory database by selecting mature, pure coniferous stands.
- Afforested peatland, deciduous – derived exclusively from the national forest inventory database by selecting mature, pure deciduous stands.

- Transitional mire – obtained from open data provided by the Nature Conservation Agency, corresponding to habitat type 7140. This class was omitted in later stages of the research due to insufficient classification accuracy.
- Raised bog – obtained from open data provided by the Nature Conservation Agency, corresponding to habitat type 7110.
- Abandoned peat extraction – obtained from open data provided by the Nature Conservation Agency, corresponding to habitat type 7120.
- Active peat extraction – delineated manually based on visual interpretation of high-resolution satellite imagery.

These datasets serve as the foundation for reproducible and consistent GHG calculations across the entire territory of Latvia. Each peatland class can be subsequently linked to land-cover-specific emission factors obtained from onsite measurements or generalised emission factors for country-wide applications (e.g., *LIFERestore* project).

This design ensures a seamless flow of data between user-defined polygons, the GHG emission estimation model, and the visualization of outputs in GIS software. The framework promotes transparency, reproducibility, and scalability, aligning with national goals for monitoring peatland carbon balance and supporting Latvia's reporting under climate policy frameworks. The process is divided into four main stages:

- Stage 1: User Input and Preprocessing – the user prepares polygons of interest representing the areas for which GHG emissions will be calculated. The polygons are created and checked in GIS and then exported to file containing an identification of the area required for processing.
- Stage 2: After preparing the polygons, a specifically developed script for the recognition of land cover type is executed. This process is enabled through a cloud service that hosts the database of land-cover maps obtained from satellite.
- Stage 3: GHG Emission Estimation – for the obtained land-cover information from the database, the GHG emission estimation is performed taking into account land-cover type and the area of each land-cover type within the polygon.
- Stage 4: Output Download and Examination – the output contains spatial land-cover classification layers and the calculated GHG-emission results for each user-defined polygon.

By explicitly accounting for the exact area of each land-cover class in the defined polygon, the framework allows peatland users to quantify emissions associated with their fields and plan better for necessary restoration measures in a spatially explicit and reproducible manner, while accounting for potential emission reductions or increases resulting from rewetting, renaturalisation, or other land-use change measures.

4. Discussion on Implementation Potential and Challenges

4.1. Remote Sensing for Scalable Peatland GHG Emission Estimation

This study positions remote sensing as a key enabling technology for scalable, reproducible estimation of GHG emissions in peatlands. The integration of spectral, radar, and ancillary geospatial data into GHG emission estimation frameworks reflects a growing trend in environmental monitoring toward multi-sensor, data-driven approaches. The conceptual framework developed in this work aligns with such global directions, providing an operational pathway for automated, national-scale GHG assessments.

Recent studies highlight that combining remote sensing with geospatial modelling enhances both temporal and spatial representativeness of emission estimates [31]. Unlike traditional methods that rely on plot-scale flux measurements, remote sensing solutions enable continuous monitoring of large regions, capturing the hydrological and vegetation dynamics that drive GHG emissions [32]. This is particularly relevant for Northern European peatlands, where seasonal water table fluctuations strongly influence CO_2 and CH_4 emissions [3], [33].

4.2. National Applicability and Data Readiness in Latvia

The proposed framework addresses these dynamics by linking land-cover classification, emission factors, and cloud-based computation into a reproducible workflow, bridging the gap between scientific modelling and operational reporting. Latvia's environmental data infrastructure provides a strong foundation for implementing such an approach. The availability of Sentinel-2 multispectral imagery**,** Sentinel-1 radar data, and national LiDAR coverage, along with country-specific emission factors from the *LIFERestore* project [15], enables Tier 2–level GHG emission estimation following IPCC guidelines [14].

Comparable national-scale systems have been piloted successfully in Finland [13], where open satellite archives and standardized emission databases have improved reporting accuracy and transparency. Latvia's integration of these datasets represents a significant step toward regional harmonization of peatland GHG inventories.

4.3. Limitations and Future Directions

Despite these advantages, several challenges remain in scaling remote-sensing-based GHG emission estimation systems. Uncertainty propagation arising from land-cover misclassification and spatial mismatches between satellite pixels and field plots continues to limit model accuracy [33]. While regression-based models offer flexibility, their coefficients are often site-specific and require local calibration to account for climatic and management variability [13].

Cloud cover remains a persistent limitation for optical time-series analysis in Northern Europe. Integrating radar backscatter and surface temperature data may help improve temporal continuity. In addition, validation remains a key bottleneck due to the limited availability of eddy-covariance towers and chamber-based flux measurements for independent comparison [27].

The conceptual framework demonstrates both regional applicability and international relevance. Future research should focus on improving model transparency through hybrid approaches that combine machine learning techniques with process-based simulations. Expanding collaborative databases that integrate flux-tower, soil, and remote sensing data would further support cross-regional calibration of emission factors and improve the robustness of national GHG inventories. However, field measurements remain essential for calibration and validation as even locally fitted models often exhibit modest accuracy for estimating GHG emissions.

5. CONCLUSION

Depending on the availability of datasets, two primary approaches are identified for utilizing remote sensing data in GHG emission estimation. The first is the land-cover-based emissions factor approach, where remote sensing data are used to create accurate land-cover maps, and emission factors from existing studies are applied to estimate emissions based on the distribution of land-cover classes. This method is particularly suitable when only limited field data are available. The accuracy of this approach depends not only on classification precision but also on the reliability and representativeness of the applied emission factors.

The second approach is the carbon flux, where relationships between remote sensing derived variables and GHG emissions are established using regression-based or machine-learning models. Although these approaches allow to capture complex interactions between vegetation, temperature, and carbon exchange processes, their coefficients and parameters are often site-specific and may not generalize well to across different regions.

The conceptual framework developed in this study integrates both approaches within a unified, automated system that connects user input, remote sensing data, and emission factor modelling. This design enables reproducible and transparent estimation of GHG emissions from peatlands at the national scale, utilising openly available datasets such as Sentinel-2 imagery, national LiDAR coverage, and emission factors that meet Tier 2 requirements. By combining automation with standardized data sources, the framework bridges the gap between theoretical modelling and operational implementation, supporting consistent, large-scale emission assessment and monitoring. Latvia's strong spatial data infrastructure provides an ideal foundation for applying this system to national GHG accounting and peatland restoration evaluation.

Future research must focus on implementing and validating the framework using real peatland sites, integrating radar and environmental variables, and refining model accuracy through continuous calibration. The developed framework provides a basis for applying remote sensing based GHG emission estimation methods to real-case studies at the national and regional scales.

It is recommended that future work focus on the practical implementation of the framework in selected peatland areas in Latvia to evaluate its performance under diverse ecological and management conditions. Combining optical, radar, and environmental datasets will improve temporal continuity and model accuracy, while closer integration with field monitoring programs will enhance validation and reliability. The proposed approach can therefore serve as a transferable model for other countries aiming to establish transparent, automated, and reproducible GHG emission estimation systems for peatland ecosystems.

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FLPP FUNDAMENTAL AND APPLIED RESEARCH PROJECTS

Peat4Res

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES USED IN THE WRITING PROCESS

During the preparation of this work the author(s) used OpenAI's ChatGPT and Grammarly in order to improve the language and readability of the manuscript. After using these tools/services, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

References

[1] IPCC. Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Core Writing Team, Lee H., Romero J. (Eds.); IPCC: Geneva, Switzerland, 2023:35–115. https://doi.org/10.59327/IPCC/AR6-9789291691647

[2] Gitarskiy M. L. The Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (Utochneniye rukovodyashchikh printsipov natsional'nykh inventarizatsiy parnikovykh gazov MGEIK). *Fundam. Appl. Climatol.* 2019:2. https://doi.org/10.21513/0207-2564-2019-2-05-13 (In Russian)

[3] Rydin H., Jeglum J. K. *The biology of peatlands*, 2nd ed.; Biology of Habitats Series; Oxford University Press: Oxford, UK, 2013. https://doi.org/10.1093/acprof:osobl/9780199602995.001.0001

[4] Lees K. J., Quaife T., Artz R. R. E., Khomik M., Clark J. M. Potential for Using Remote Sensing to Estimate Carbon Fluxes across Northern Peatlands – A Review. *Science of the Total Environment* 2018:615:857–874. https://doi.org/10.1016/j.scitotenv.2017.09.103

[5] Hooijer A., Page S., Canadell J. G., Silvius M., Kwadijk J., Wösten H., Jauhiainen J. Current and Future CO_2 Emissions from Drained Peatlands in Southeast Asia. *Biogeosciences* 2010:7:1505–1514. https://doi.org/10.5194/bg-7-1505-2010

[6] Vanags-Duka M., Bārdule A., Butlers A., Upenieks E. M., Lazdiņš A., Purviņa D., Līcīte I. GHG Emissions from Drainage Ditches in Peat Extraction Sites and Peatland Forests in Hemiboreal Latvia. *Land* 2022:11(12):2233. https://doi.org/10.3390/land11122233

[7] Kou D., *et al*. Peatland Heterogeneity Impacts on Regional Carbon Flux and Its Radiative Effect within a Boreal Landscape. *Journal of Geophysical Research: Biogeosciences* 2022:127(9). https://doi.org/10.1029/2021JG006774

[8] ESA. Sentinel-2 User Handbook. European Space Agency: Paris, France, 2015.

[9] Bartkowiak P., Castelli M., Notarnicola C. Downscaling Land Surface Temperature from MODIS Dataset with Random Forest Approach over Alpine Vegetated Areas. *Remote Sensing* 2019:11(11):1319. https://doi.org/10.3390/rs11111319

[10] Wang Q., Li J., Jin T., Chang X., Zhu Y., Li Y., Sun J., Li D. Comparative Analysis of Landsat-8, Sentinel-2, and GF-1 Data for Retrieving Soil Moisture over Wheat Farmlands. *Remote Sensing* 2020:12(17):2708. https://doi.org/10.3390/rs12172708

[11] Priede A., Gancone A. Kūdras ieguves ietekmētu teritoriju atbildīga apsaimniekošana un ilgtspējīga izmantošana (Sustainable and Responsible After-Use of Peat Extraction Areas). Rīga, Latvia, 2019. In Latvian.

[12] Junttila S., Kelly J., Kljun N., Aurela M., Klemedtsson L., Lohila A., Nilsson M. B., Rinne J., Tuittila E. S., Vestin P., *et al*. Upscaling Northern Peatland CO_2 Fluxes Using Satellite Remote Sensing Data. *Remote Sensing* 2021:13(4):818. https://doi.org/10.3390/rs13040818

[13] Sato A., Vitullo M., Gschwantner T. Chapter 8 Settlements. In 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories; Cambridge University Press: Cambridge, UK and New York, NY, USA, 2019.

[14] LIFE Peat Restore. [Online]. [Accessed 28.05.2024]. Available: https://life-peat-restore.eu/en/

[15] Khan M. A., Rahman M., Ali S., Chowdhury N. Integration of Remote Sensing and GIS for Environmental Assessment. *Environ. Res. J.* 2025:12:45–60.

[16] Xiao J., Chevallier F., Gomez C., Guanter L., Hicke J. A., Huete A. R. Remote Sensing of the Terrestrial Carbon Cycle: A Review of Advances over 50 Years. *Remote Sensing of Environment* 2019:233:111383. https://doi.org/10.1016/j.rse.2019.111383

[17] Neigh C. HLS Operational Land Imager Vegetation Indices Daily Global 30 m v2.0; NASA EOSDIS Land Processes Distributed Active Archive Center: Sioux Falls, SD, USA, 2025. https://doi.org/10.5067/HLS/HLSL30_VI.002

[18] Neigh C. HLS Sentinel-2 Multi-Spectral Instrument Vegetation Indices Daily Global 30 m v2.0; NASA EOSDIS Land Processes Distributed Active Archive Center: Sioux Falls, SD, USA, 2025. https://doi.org/10.5067/HLS/HLSS30_VI.002

[19] Dubovyk O., Landmann T., Erasmus B. F. N., Tewes A., Schellberg J. Monitoring Vegetation Dynamics with Medium Resolution MODIS-EVI Time Series at Sub-Regional Scale in Southern Africa. *Int. J. Appl. Earth Obs. Geoinf.* 2015:38:175–183. https://doi.org/10.1016/j.jag.2015.01.002

[20] Ganguly S., Friedl M. A., Tan B., Zhang X., Verma M. Land Surface Phenology from MODIS: Characterization of the Collection 5 Global Land Cover Dynamics Product. *Remote Sensing of Environment* 2010:114(8):1805–1816. https://doi.org/10.1016/j.rse.2010.04.005

[21] Habib W., Ingle R., Saunders M., Connolly J. Quantifying Peatland Land Use and CO_2 Emissions in Irish Raised Bogs: Mapping Insights Using Sentinel-2 Data and Google Earth Engine. *Scientific Reports* 2024:14:1171. https://doi.org/10.1038/s41598-024-51660-0

[22] Gray J., Song C. Mapping Leaf Area Index Using Spatial, Spectral, and Temporal Information from Multiple Sensors. *Remote Sensing of Environment* 2012:119:173–183. https://doi.org/10.1016/j.rse.2011.12.016

[23] Fuster B., Sánchez-Zapero J., Camacho F., García-Santos V., Verger A., Lacaze R., Weiss M., Baret F., Smets B. Quality Assessment of PROBA-V LAI, fAPAR and fCOVER Collection 300 m Products of Copernicus Global Land Service. *Remote Sensing* 2020:12(6):1017. https://doi.org/10.3390/rs12061017

[24] Viña A., Gitelson A. A., Nguy-Robertson A. L., Peng Y. Comparison of Different Vegetation Indices for the Remote Assessment of Green Leaf Area Index of Crops. *Remote Sensing of Environment* 2011:115:3468–3478. https://doi.org/10.1016/j.rse.2011.08.010

[25] Berra E. F., Gaulton R. Remote Sensing of Temperate and Boreal Forest Phenology: A Review of Progress, Challenges and Opportunities in the Intercomparison of In-Situ and Satellite Phenological Metrics. *Forest Ecology and Management* 2021:480:118705. https://doi.org/10.1016/j.foreco.2020.118705

[26] Levy P., Clement R., Cowan N., Keane B., Myrgiotis V., van Oijen M., Smallman T. L., Toet S., Williams M. Challenges in Scaling Up Greenhouse Gas Fluxes: Experience from the UK Greenhouse Gas Emissions and Feedbacks Program. *J. Geophys. Res. Biogeosci.* 2022:127. https://doi.org/10.1029/2021JG006743

[27] Chen J., Gao M., Huang S., Hou W. Application of Remote Sensing Satellite Data for Carbon Emissions Reduction. *J. Chin. Econ. Bus. Stud.* 2021:19(2):109–117. https://doi.org/10.1080/14765284.2021.1920329

[28] Boniface K., Gioia C., Pozzoli L., Diehl T., Dobricic S., Fortuny Guasch J., Greidanus H., Kliment T., Kucera J., Janssens-Maenhout G., *et al*. Europe's Earth Observation, Satellite Navigation and Satellite Communications Missions and Services for the Benefit of the Arctic: Inventory of Current and Future Capabilities, Their Synergies and Societal Benefits. Publications Office of the European Union: Luxembourg, 2021.

[29] Boesch H., Liu Y., Tamminen J., Yang D., Palmer P. I., Lindqvist H., Cai Z., Che K., Di Noia A., Feng L. *et al*. Monitoring Greenhouse Gases from Space. *Remote Sensing* 2021:13(14):2700. https://doi.org/10.3390/rs13142700

[30] Montgomery J., Brisco B., Chasmer L., Devito K., Cobbaert D., Hopkinson C. SAR and LiDAR Temporal Data Fusion Approaches to Boreal Wetland Ecosystem Monitoring. *Remote Sensing* 2019:11(2):161. https://doi.org/10.3390/rs11020161

[31] Millar D. J., Cooper D. J., Dwire K. A., Hubbard R. M., Ronayne M. J., von Fischer J. Hydrological Dynamics and Associated Greenhouse Gas Fluxes in a Mountain Peatland under Different Climate Scenarios. *Ecohydrology* 2023:16(5):e2536. https://doi.org/10.1002/eco.2536

[32] Halme P., Allen K. A., Auniņš A., Bradshaw R. H. W., Brumelis G., Čada V. *et al*. Challenges of Ecological Restoration: Lessons from Forests in Northern Europe. *Biological Conservation* 2013:167:452–453. https://doi.org/10.1016/j.biocon.2013.07.020

[33] van Beijma S., Chatterton J., Page S., Rawlings C., Tiffin R., King H. The Challenges of Using Satellite Data Sets to Assess Historical Land Use Change and Associated Greenhouse Gas Emissions: A Case Study of Three Indonesian Provinces. *Carbon Management* 2018:9(4):399–413. https://doi.org/10.1080/17583004.2018.1511383