

Detecting peat-like behaviour areas using European Ground Motion Service data

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Abstract

Peatlands are natural terrestrial carbon stores that play a key role in climate change mitigation. Accurate mapping of these ecosystems remains challenging due to their complex surface characteristics and the limitations of traditional optical-based methods. This paper presents a method for the detection of peatland-like displacement dynamics using open-source advanced differential interferometric synthetic aperture radar data from the European Ground Motion Service. Vertical displacement time series are analysed using a two-step unsupervised framework that integrates principal component analysis and *k*-means clustering in Great Britain to identify areas exhibiting peat-like displacement behaviour. This provides a process-based complement to traditional optical peatland mapping approaches. The results reveal distinct subsidence trends and seasonal deformation patterns typical of peat soils, even in regions not classified as peatlands in existing land cover databases. Cross-correlation analysis with climatic variables further highlights the sensitivity of peatlands to moisture and temperature variations. Three case studies are shown to validate the approach and demonstrate its potential for refining peatland inventories: (i) Hatfield Moors, (ii) New Forest and (iii) an area north of Tilshead not classified as peatland in the land cover database. The proposed solution exploits the potential of Sentinel-1 data to enhance peatland identification, characterise their response to environmental parameters and support the updating of existing land cover maps. A more precise identification of peatland ecosystems is relevant for climate change analysis and resilience. This methodology provides a robust, cost-effective tool for identifying peat-like behaviour areas and for significantly enhancing conservation and restoration efforts.

KEYWORDS

climate change, cross-correlation analysis, European Ground Motion Service (EGMS), peatlands, peat-like behaviour areas (PBAs), remote sensing, Sentinel-1, time-series analysis

1 | INTRODUCTION

Peatlands are a specific type of wetland ecosystem where waterlogged conditions prevent plant material from fully decomposing. As a result, the production of organic matter exceeds its decomposition, leading to a net accumulation of peat (International Peatland Society, 2024). Peatlands attract considerable attention due to their essential function within the global carbon cycle, particularly in terms

of mitigating climate change by removing carbon dioxide (CO₂) from the atmosphere (Fang et al., 2016; Kimmel & Mander, 2010; Xu et al., 2019). These carbon-rich ecosystems also play a key role in water resource management and habitat provision (Xu et al., 2018). By supporting a variety of rare, threatened and declining species, peat soils play a key role in maintaining global biodiversity (Posa et al., 2011). Moreover, they contribute to human well-being by delivering valuable ecosystem services at both national and international

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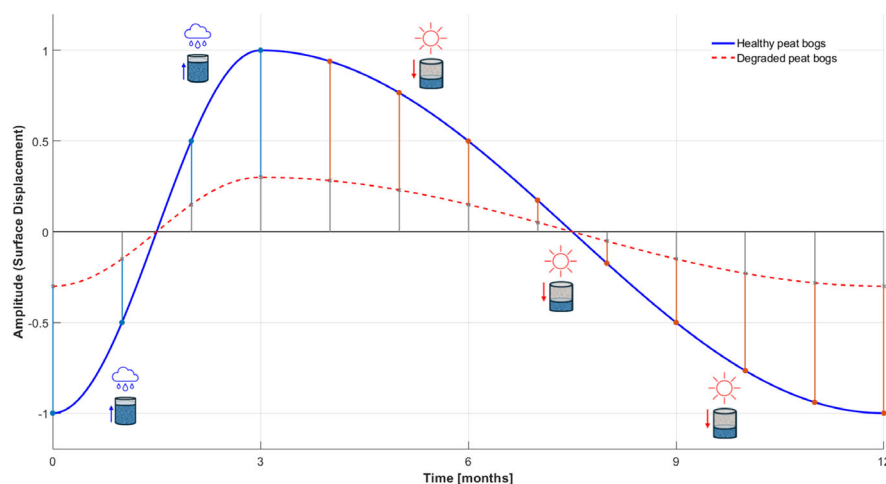


FIGURE 1 Conceptual schematic representation of the theoretical dynamic surface motion in a peat bog environment, driven by water content fluctuations, also known as ‘bog breathing’. The curves highlight the characteristic asymmetric response, with rapid uplift occurring during wet periods and slow, gradual drawdown during dry periods, contrasting the high-amplitude response of a healthy peat system with the muted, low-amplitude behaviour of a degraded one.

levels (Reed et al., 2014), including flood regulation (Holden et al., 2004), agricultural production, energy resources, habitats for rare species and cultural services (Bonn et al., 2016). Despite their ecological significance, peatlands are increasingly threatened by human activities (Arroyo-Mora et al., 2019; Xu et al., 2018). Drainage (Gibson et al., 2009; Holden et al., 2004), agricultural conversion (Carlson et al., 2013), peat extraction and burning (Clay et al., 2012; Page et al., 2002; Turetsky et al., 2015; Yallop & Clutterbuck, 2009) have severely degraded many peatland ecosystems, transforming them from long-term carbon sinks into active carbon sources and thereby exacerbating climate change (Food and Agriculture Organization of the United Nations, 2020).

Peatlands occur in a variety of climatic regions, including boreal, temperate and tropical zones, with their distribution and extent primarily governed by hydrological and climatic factors. They are typically classified into three major types based on their hydrology, nutrient availability and vegetation composition (Abdelmajeed & Juszcak, 2024): (i) bogs, (ii) fens and (iii) transitional mires. Bogs, also known as ombrogenous mires, are peatlands exclusively relying on precipitation water input, making them highly sensitive to climatic variations. These ecosystems are characterised by nutrient-poor, acidic conditions and are dominated by *Sphagnum* mosses (Guo et al., 2017). In contrast, fens, or minerotrophic peatlands, receive water from both rainfall and mineral-rich groundwater, creating nutrient-rich environments that support a more diverse plant community (Mahdianpari et al., 2020). Transitional mires show a mix of characteristics from both bogs and fens, depending on local hydrological and environmental conditions (Xu et al., 2018). Peat bogs tend to show a more pronounced response to hydrological changes than other types of peatlands, particularly in relation to the moisture index, resulting in dynamic seasonal surface fluctuations, a phenomenon commonly referred to as ‘bog breathing’ (Scotland’s Nature Agency, 2023) (Figure 1).

This process is influenced by seasonal rainfall and temperature variations, and it is a key indicator of peatland health, reflecting changes in water content, gas storage and peat thickness over time (Howie & Hebda, 2018; Wilson, 2025). Despite their recognised importance, accurate quantification of peatland extent remains challenging due to limited data availability at both local and continental scales. Filling these gaps is essential for implementing effective peat conservation strategies and assessing their role in climate regulation.

In the literature, estimates of global peatland coverage vary between 3.97 and 4.43 million km², depending on the data sources used. Andriess (1988) estimated that organic soils, commonly referred to as peatlands, cover about 4.36 million km² with an average depth of 80 cm. More recently, Xu et al. (2018) conducted a geospatial meta-analysis incorporating data from various global, regional and national sources, estimating the total area of peatlands to be approximately 4.23 million km², equivalent to 2.84% of the global land surface. These values exceed those reported by other studies, which suggest a global peatland area ranging from 3.97 to 4.00 million km² (Immirzi & Maltby, 1992; Page et al., 2011; UN Environment Programme [UNEP], 2008).

The importance of peatlands is widely recognised (Denman et al., 2007; Froking et al., 2006), but current methods for the estimation of global peatland cover remain highly uncertain, limiting the ability to accurately assess their role in soil carbon storage, water regulation and other ecosystem services (Xu et al., 2018). Peatlands are particularly challenging to detect due to their variable composition and their abundant vegetation. Traditional mapping approaches, based on aerial photography, optical images and manual delineation, often lead to inconsistencies and underestimation of peatland extent. Large-scale land cover datasets also frequently omit or misclassify peatlands due to their subtle morphological characteristics. The reliance on optical imagery further complicates peatland mapping; in fact, the spectral signatures of peat soils often overlap with those of other vegetation types.

Remote sensing technologies, particularly advanced differential interferometric synthetic aperture radar (A-DisAR), are emerging as powerful tools for monitoring peatland dynamics (Bradley et al., 2022; Wilson, 2025). Interferometric synthetic aperture radar (InSAR) can detect vertical displacement trends and patterns, allowing researchers to assess peatland conditions, identify degradation processes and detect peat-like behaviour areas (PBAs). On the other hand, the widespread use of InSAR has been limited by the high cost and complexity of data processing. The European Ground Motion Service (EGMS) of the Copernicus Land Monitoring Service (CLMS), managed by the European Environment Agency (EEA) since 2021, provides freely available and open-source ground displacement data from the Sentinel-1 satellites, offering a cost-effective solution for large-scale peatland analysis (Copernicus, 2025). The aim of this study is to exploit the EGMS vertical (Level 3 Ortho data) displacement data

(EEA, 2024) for detecting the dynamic surface behaviour of peatlands, identifying peat soil areas not classified as peatlands in existing databases and refining their distribution. In order to achieve this goal, the integration of InSAR analysis with land cover datasets to enhance peatland detection accuracy and update peatland mapping is proposed. An analytical framework combining a two-step unsupervised approach, based on principal component (PC) analysis (PCA) (Jolliffe & Cadima, 2016), followed by *k*-means clustering (Wu, 2008), is employed to identify and interpret non-stationary displacement trends across Great Britain (GB).

2 | STUDY AREA

GB hosts extensive peatland ecosystems, covering over 10% of its land surface. However, most of these environments are in a degraded state due to various anthropogenic activities, such as drainage, peat extraction, burning and overgrazing (International Union for Conservation of Nature [IUCN], 2011). In England, approximately 87% of peatlands are classified as damaged, leading to extensive carbon loss and increased greenhouse gas emissions (GOV.UK, 2023).

The transition of degraded peatlands from long-term carbon sinks to active carbon sources is a significant driver of climate change. GB has recognised the ecological importance of peatlands, incorporating their protection into several conservation policies, including the United Kingdom Peatland Strategy (IUCN, 2011) and the 25-Year Environment Plan (25YEP) (GOV.UK, 2018). In response to ongoing degradation, Defra and Natural England launched the Nature for Climate Peatland Grant Scheme in 2021 (Natural England, 2021), providing financial support for peatland restoration. This initiative aims to accelerate habitat recovery and enhance carbon sequestration (UK Centre for Ecology & Hydrology, 2023). In Wales, the National Peatland Action Programme provides a 5-year plan funded by the Welsh Government, aiming to coordinate restoration efforts across the country (The National Peatland Action Programme, 2020). In Scotland, a target has been set to restore 250 000 ha of degraded peatland by 2030 (Scottish Government, 2023). In addition to serving as carbon storage sites, peatlands provide habitats for a diverse array of species in GB, many of which are endemic. To address peat soil degradation, initiatives such as the South West Peatland Partnership (2024) have employed innovative restoration techniques, including the construction of leaky wooden dams to regulate water flow and sediment traps to reduce erosion. These interventions have facilitated the regeneration of peat-forming vegetation, thereby promoting the recovery of biodiversity.

Focusing on peatland dynamics in GB and leveraging EGMS data to improve the identification of peatland areas, three case studies are selected to illustrate the methodology and results. Each site represents a key step in the research approach, with a detailed analysis integrating cross-correlation techniques to gain deeper insights into peatland behaviour and its environmental drivers. The selected sites are as follows: (1) Hatfield Moors, located within the Humberhead Peatlands (Humberhead Peatland, 2023); (2) New Forest, part of an extensive wetland restoration initiative (IUCN, 2023); and (3) an area north of Tilshead, not classified as peatland in the land cover database (Figure 2).

3 | DATA AND METHODS

This study applies an open-source methodological framework designed to detect and classify peat-like ground displacement patterns across GB using A-DInSAR time-series data from the EGMS. The workflow combines an unsupervised classification of InSAR displacement time series, based on PCA (Jolliffe & Cadima, 2016) and *k*-means clustering (Wu, 2008). The approach is subsequently extended to a multi-disciplinary cross-correlation analysis to explore the relationship between peatland dynamics and climatic or environmental conditions (Figure 3).

In the first stage, vertical displacement data from the EGMS were downloaded and filtered to exclude measurement points (MPs) located in urban areas, on roads or near infrastructures based on the CORINE Land Cover (CLC) 2018 (CLC2018) classification (EEA, 2019). PCA and *k*-means clustering algorithms were then applied, leading to the identification of different time-series behaviour classes. The classification procedure identified four distinct classes, referred to as UP-1 to UP-4. To refine the classification, known peatland sites such as Hatfield Moors were used as reference areas. These peatland sites have been extensively investigated in previous studies focusing on peatland displacement processes (Fibbi et al., 2024; Whitehouse, 2004) and therefore provide a reliable benchmark for peat-like behaviour in GB. Based on this comparison, clusters UP-2 and UP-3 were identified as representative of typical peatland displacement behaviour in GB, characterised by pronounced seasonal oscillations and long-term subsidence trends. On the other hand, clusters UP-1 (positive displacement trend without seasonal variability) and UP-4 (negative trend without seasonal patterns) were excluded, as their temporal characteristics are inconsistent with known peatland dynamics in GB. By combining these reference behaviours with seasonality factors, a data screening process was carried out to detect MPs showing peat-like displacement patterns. At this stage, a clustering analysis was performed to highlight areas with a high density of identified MPs, while discarding regions with more dispersed occurrences. The resulting clusters were then analysed against the CLC2018 dataset (EEA, 2019) to determine whether they corresponded to already catalogued peatlands or potential new peatland areas. Finally, a multi-disciplinary approach was used to conduct a cross-correlation analysis integrating rainfall, temperature and moisture index data. This analysis was used to validate the results and to identify the atmospheric factors controlling peat-like displacement behaviour.

3.1 | InSAR data

This study uses open-access A-DInSAR data provided by the EGMS, an initiative under the CLMS (Copernicus, 2025). EGMS represents the first large-scale application of A-DInSAR technology for continuous ground deformation monitoring across Europe, including all Copernicus-participating states and the United Kingdom, and is based on full resolution processing of all Sentinel-1 satellite acquisitions (Costantini et al., 2021). This study employs the Level 3 Ortho Vertical product covering the period from January 2019 to December 2023 across GB. The Level 3 data are derived from multiple Level 2b products (ascending and descending geometries anchored to the global navigation satellite system reference network in a common reference

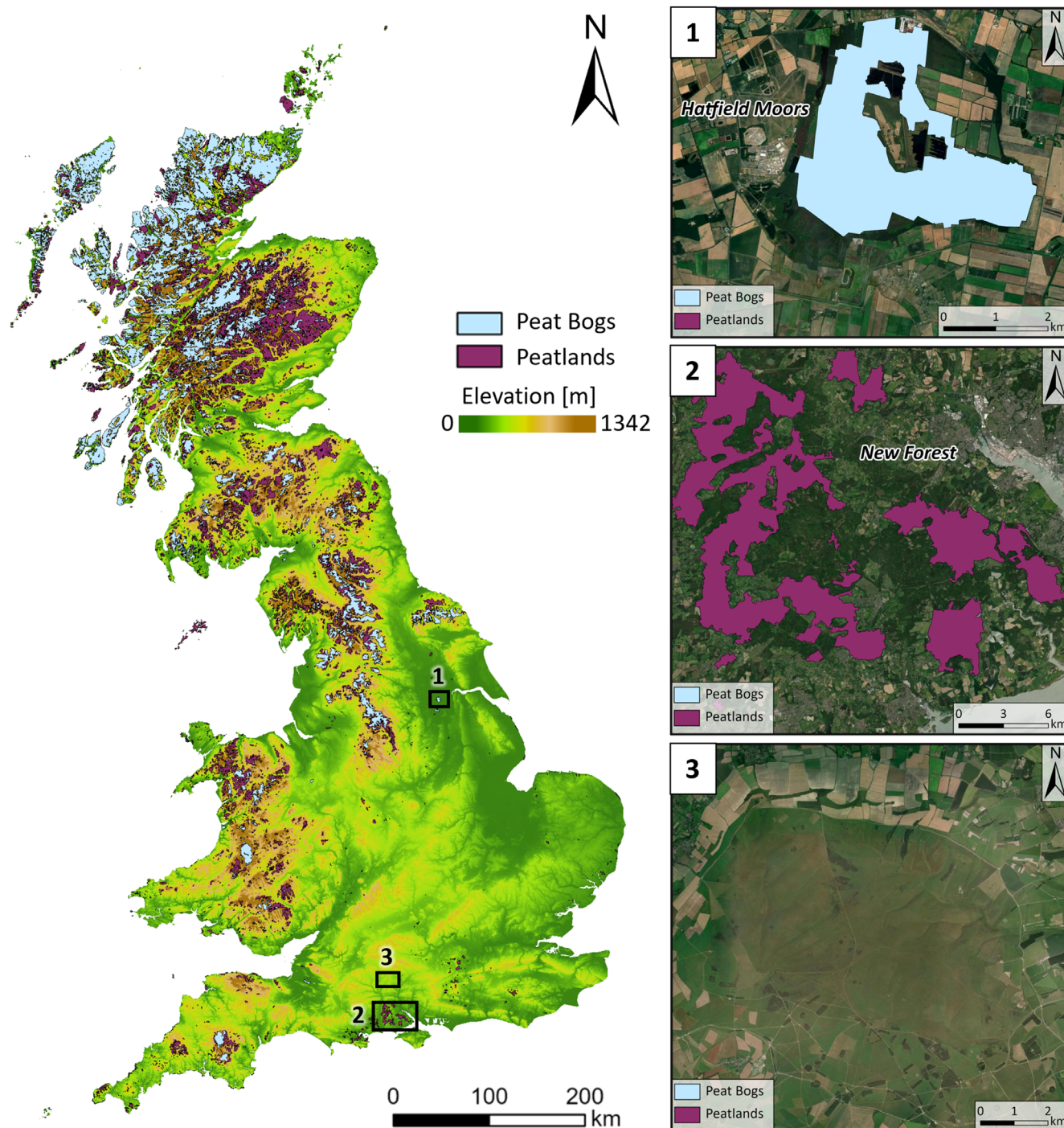


FIGURE 2 Peatland distribution across Great Britain (GB) based on the CORINE Land Cover 2018 (CLC2018) dataset (European Environment Agency, 2019). Peat bogs are shown in light blue, while other peatland types are represented in purple. The background displays the digital terrain model (DTM). The boxes highlight three focus areas: (1) Hatfield Moors, (2) New Forest and (3) a newly identified area not classified as peatland in the CLC2018 database.

frame) from complementary geometries (EEA, 2024). Unlike the Level 2b products, which are distributed according to a single-burst logic, the EGMS Level 3 Ortho products are organised into regular spatial tiles of 100×100 km. Point-based information in tabular format is provided for each tile (Figure 4). The EGMS data are accessible via the EGMS Explorer (Copernicus, 2025) and processed by the Operational Ground motion INsar ALLiance (ORIGINAL) consortium (EGMS, 2024), ensuring high-quality results through advanced processing algorithms, including PSP-IFSAR (Costantini et al., 2009), SqueeSAR (Ferretti et al., 2011), GSAR-GTSI (Dehls et al., 2019) and persistent scatterer

interferometry (PSI) performed with the integrated wide area processor (Yague-Martinez et al., 2016). EGMS data were extracted in this study using the EGMSStream Webapp, which provides access to displacement products and associated metadata (Becattini et al., 2025).

3.2 | Land cover datasets

Land cover information is used both to pre-filter InSAR MPs and to evaluate the spatial correspondence between detected peat-like areas

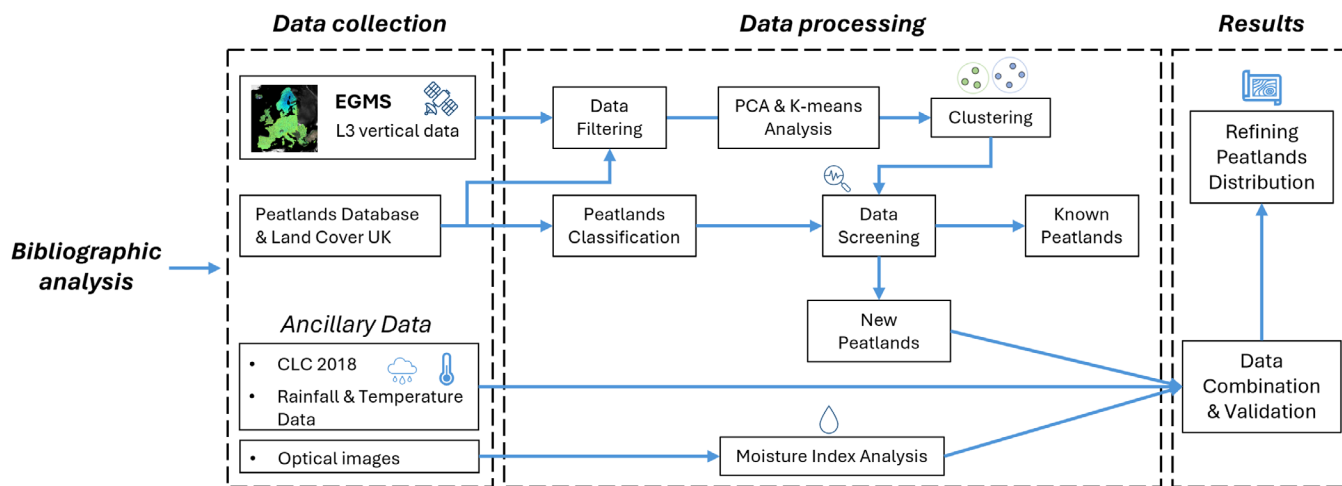


FIGURE 3 Flow chart showing the adopted methodology for PBA detection.

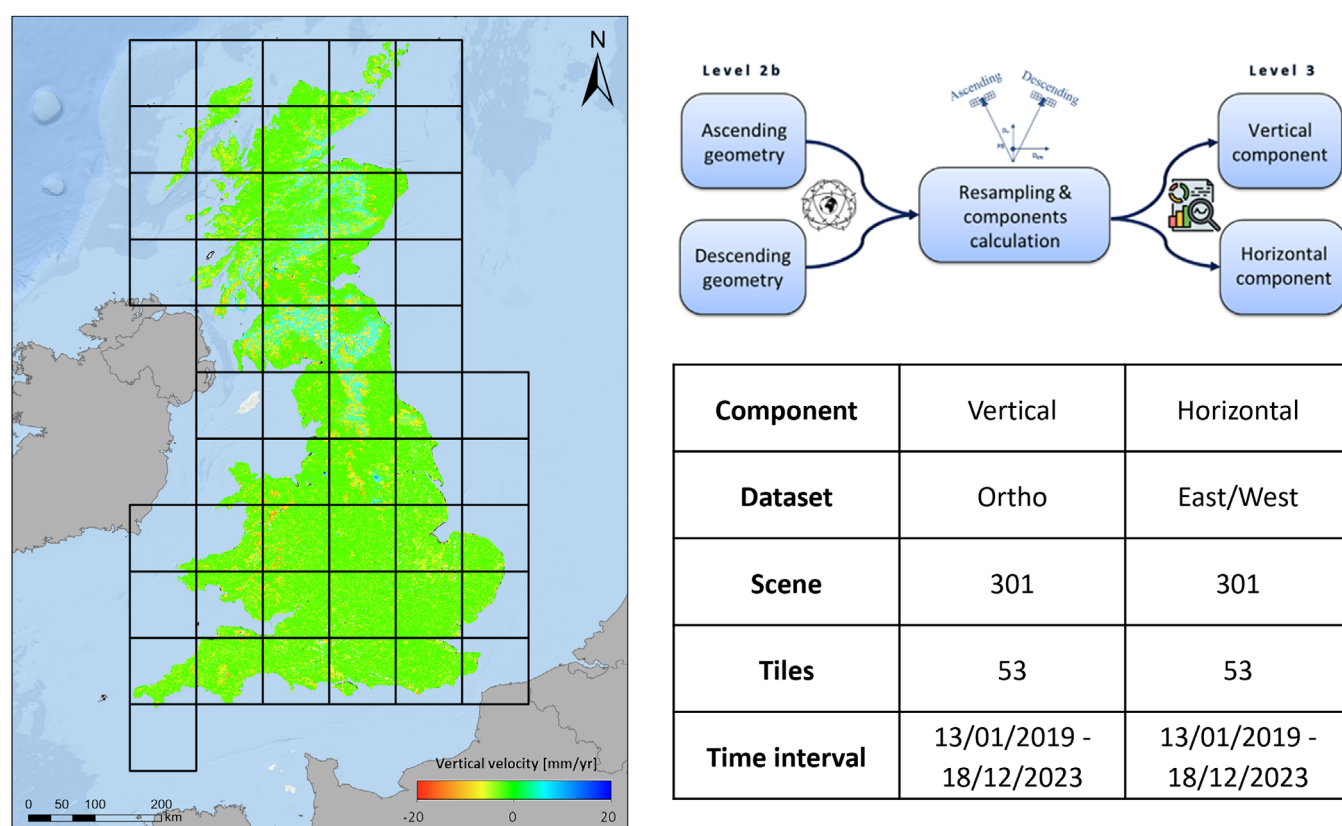


FIGURE 4 Spatial distribution of the EGMS Level 3 Ortho tiles selected for the analysis across GB and main characteristics of Sentinel-1 dataset used in this study.

and existing peatland inventories. Specifically, the CLC2018 dataset (EEA, 2019) is used to exclude MPs located in urban areas, roads and infrastructure and to assess whether peat-like clusters overlapped with previously mapped peatlands. This land cover dataset, based on satellite image interpretation by national authorities, follows a standardised classification system with 44 classes in the hierarchical three-level CLC nomenclature. In addition, the national GB Land Cover Map provides an independent reference for comparing the PBAs identified through the InSAR-based analysis. The land cover classes are categorised into 21 groups based on the UK Biodiversity Action Plan (Morton et al., 2024). It provides a continuous national

dataset of land cover classes, ranging from grassland and woodland to urban and suburban built-up areas.

3.3 | Rainfall and temperature data

Monthly rainfall and temperature data, covering the period from January 2019 to December 2023, are obtained from the national meteorological service, the UK Met Office (Met Office, 2024), to investigate the potential climatic drivers of seasonal ground displacement in peatlands. Time series from the Waddington and Hurn

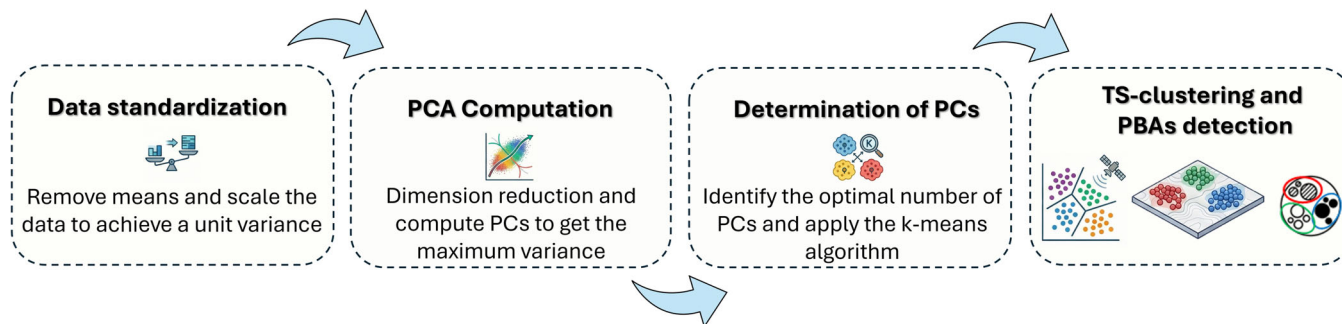


FIGURE 5 Flow chart of the PCA and *k*-means clustering approach applied to A-DInSAR displacement time series.

weather stations are selected to represent the regional climatic conditions in the analysed case studies.

3.4 | Sentinel-2 optical images

Optical images from the Sentinel-2 constellation (Sentinel-2A and Sentinel-2B), operated by the European Space Agency (ESA, 2025), are used to derive the normalised difference moisture index (NDMI) in order to monitor surface moisture variations and support the interpretation of peatland dynamics. Sentinel-2 provides global high-resolution multispectral optical data freely available (ESA, 2025). Two bands with a 20-m spatial resolution are selected: (i) Band 8a (Near InfraRed [NIR]) and (ii) Band 11 (Short-Wave InfraRed [SWIR]). These bands allow for vegetation red-edge analysis, which is essential for assessing the biological and hydrological condition of vegetation. Data are retrieved via the Sentinel Hub EO Browser (EO Browser, 2025), which is now known as the Copernicus Browser (Copernicus Browser, 2026), filtering for cloud cover. NDMI values are computed, ranging from -1 to $+1$, where lower values indicate water stress, while higher values suggest water saturation.

3.5 | PCA and *k*-means clustering approach

The proposed methodology employs a two-step unsupervised classification framework combining PCA (Jolliffe & Cadima, 2016) and *k*-means clustering (Wu, 2008) to identify and classify ground displacement patterns from A-DInSAR time series. PCA is first applied to reduce the dimensionality of the displacement time series, while preserving the dominant temporal variability. The optimal number of PCs is selected to retain most of the cumulative variance, ensuring both data integrity and computational efficiency. The retained PCs provide a concise representation of the main displacement behaviours across the study area. Subsequently, the *k*-means clustering algorithm is applied to the reduced PCA space to group MPs exhibiting similar displacement time series. The algorithm partitions the dataset into *k* clusters by minimising the within-cluster sum of squared Euclidean distances between individual time series and their cluster centroids, maximising similarity within each cluster. The optimisation of this sum is advantageous, given its indication of data concentration and increased similarity among points within the cluster. The number of clusters is automatically determined based on the optimal number of PCs. Each MP is assigned to a cluster of displacement time series with

analogous patterns (Figure 5). This selection process enables MPs displaying peat-like displacement patterns to be isolated for subsequent spatial and temporal analyses.

3.6 | Spatial clustering

The spatial clustering is performed to delineate coherent areas characterised by peat-like displacement patterns, distinguishing spatially meaningful peatland units from isolated or scattered MPs. The analysis employs the density-based spatial clustering of applications with noise (DBSCAN) algorithm, which is implemented in MATLAB (R2024). DBSCAN groups MPs into clusters based on their spatial proximity and local point density (Ester et al., 1996), requiring two key parameters: (i) the maximum distance between neighbouring points (ϵ) and (ii) the minimum number of points to form a cluster. Based on sensitivity tests and the 100×100 -m spatial resolution of the EGMS Level 3 Ortho dataset, an ϵ value of 400 m and a minimum of 5 MPs are selected as optimal parameters to identify spatially coherent and meaningful clusters. DBSCAN can detect clusters of arbitrary shape, making it well suited for irregular peatland areas. The resulting clusters are subsequently smoothed using a buffer operation in a geographic information system (GIS) environment. These areas, referred to as PBAs, represent spatially coherent regions with displacement patterns consistent with peatland dynamics.

3.7 | Cross-correlation analysis

Cross-correlation analyses are performed between the InSAR time series and environmental variables, including rainfall, temperature and NDMI, to investigate the potential atmospheric and hydrological controls on peat-like displacement behaviour. All datasets are normalised to remove differences in scale and units, allowing direct comparison of their temporal variability. The linear Pearson cross-correlation coefficient (Pearson, 1896) is computed for each pair of time series across a range of temporal lags using MATLAB software (MATLAB R2024). Positive lag values indicate that variations in the environmental variable precede ground displacement, while negative lag values indicate that displacement leads the environmental signal. For each pair of time series, the maximum correlation coefficient and its corresponding time lag are identified, providing quantitative insights into both the strength and timing of the interactions.

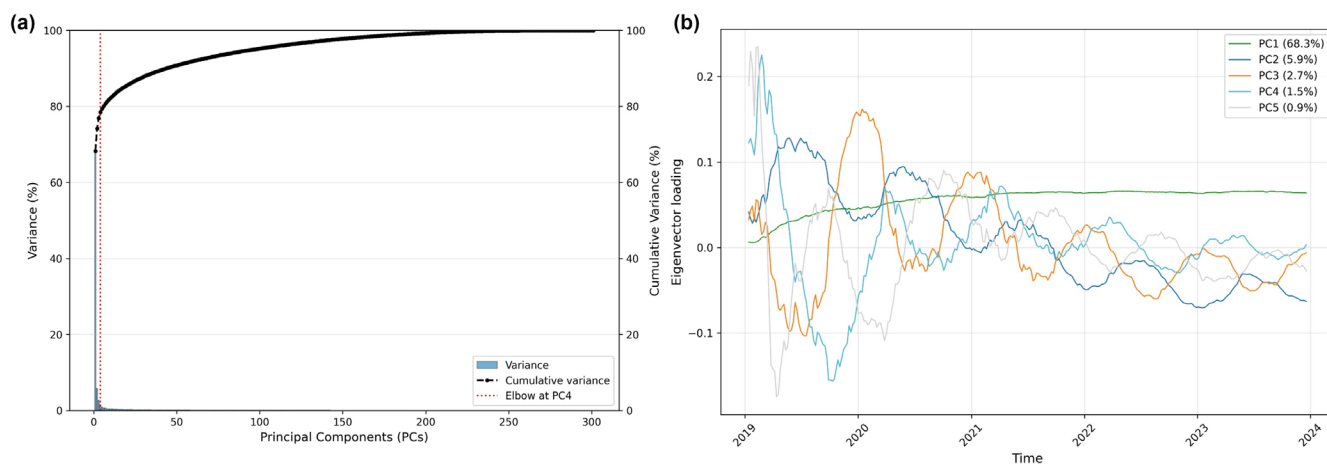


FIGURE 6 Explained variance associated with each principal component with the red dashed line highlighting the elbow at the fourth component (a). Temporal loadings of the first five principal components (b); PC5 (shown in grey) represents the first discarded PC.

4 | RESULTS

The PCA results show a sharp decline in the eigenvalue spectrum after the first PC, indicating that PC1 alone explains 68.3% of the total variance. The first four components cumulatively account for approximately 80% of the variance (Figure 6a), while subsequent components each contribute less than 1%, suggesting that the temporal behaviour of the displacement time series can be effectively represented in a low-dimensional space (Figure 6b).

PC1 (68.3%) displays a monotonic and regular trend, and it captures the dominant long-term deformation signal. PC2 (5.9%) and PC3 (2.7%) demonstrate oscillatory patterns with annual periodicity that can be interpreted as seasonal effects, while PC4 (1.5%) and the higher components (e.g., the PC5 discarded) represent short-term variations and residual noise. These results demonstrate how PCA can isolate the primary dynamics of deformation, facilitating a clear distinction between long-term trends, seasonal cyclicity and local fluctuations.

The application of the proposed methodology at the GB scale results in the identification of 1 065 542 MPs showing peat-like displacement patterns (Figure 7a). Clustering analysis further refines the results, grouping the MPs into 1529 distinct clusters (Figure 7b). The clusters highlight areas characterised by subsidence trends and clear seasonal patterns (Figure 7c) and are distributed across the GB (Figure 7d). The complete set of the identified PBAs and associated MPs is made available through an interactive web-GIS application developed using Esri ArcGIS Online (2026). The platform allows users to explore, visualise and query the spatial distribution of PBAs at different scales and is freely accessible through the creation of a standard Esri account. The application is accessible at <http://bit.ly/4uihDND>.

4.1 | Hatfield Moors—Peat bog landscape

Hatfield Moors is a remnant of a once-extensive wetland complex, located in South Yorkshire, England (Fibbi et al., 2024; Humberhead Peatland, 2023; Mitchell et al., 2020). It lies within the Humberhead Peatlands National Nature Reserve, which spans

28.87 km² and represents the largest expanse of lowland raised bog wilderness in Britain (Humberhead Peatland, 2023). The land cover of Hatfield Moors is primarily composed of peat bogs (55%), followed by non-irrigated arable land (17%), water bodies (6%) and inland marshes (4%). Ongoing decomposition processes and climatic variations drive significant seasonal surface dynamics and subsidence effects in this landscape (Morton et al., 2024).

The results obtained demonstrate a strong correspondence between the areas identified by the InSAR analysis and those catalogued as peatlands in the existing database (Figure 8). The red and blue points represent the MPs detected through PCA and *k*-means clustering analysis, while the grey areas highlight the resulting PBAs, indicating regions with a high density of MPs. A total of 32 MPs with peat-like displacement behaviour are identified in the Hatfield Moors peat bog area, forming two distinct PBAs. The northernmost cluster consists of 17 MPs, while the southernmost cluster contains 15 MPs. Notably, all detected MPs fall within areas classified as peat bogs in the national land cover dataset (Morton et al., 2024).

The InSAR time-series analysis of the average vertical ground displacement shows a subsidence trend due to ongoing peat bog degradation and a clear seasonal pattern, highlighting a strong relationship with meteorological conditions (Figure 9a). The red and blue bars at the top represent the temporal evolution of maximum and minimum temperatures, while rainfall is shown with light blue bars at the bottom. The moisture index is represented by the green line and the average vertical InSAR time series by the red line.

In addition, the cross-correlation analysis between vertical InSAR data and soil moisture is performed, and it provides two key values. First, the maximum normalised correlation value represents the highest correlation between InSAR displacement time series and the moisture index after normalisation within a range of 0 to 1. This value quantifies the degree to which the two datasets show similar temporal patterns. Second, the optimal lag indicates the time delay (in days) between the two datasets that maximises the correlation. The cross-correlation result shows a strong correlation with a time lag close to 0 (Figure 9b), indicating that the surface dynamics of Hatfield Moors are highly influenced by soil moisture variations, confirming the 'bog-breathing' phenomenon.

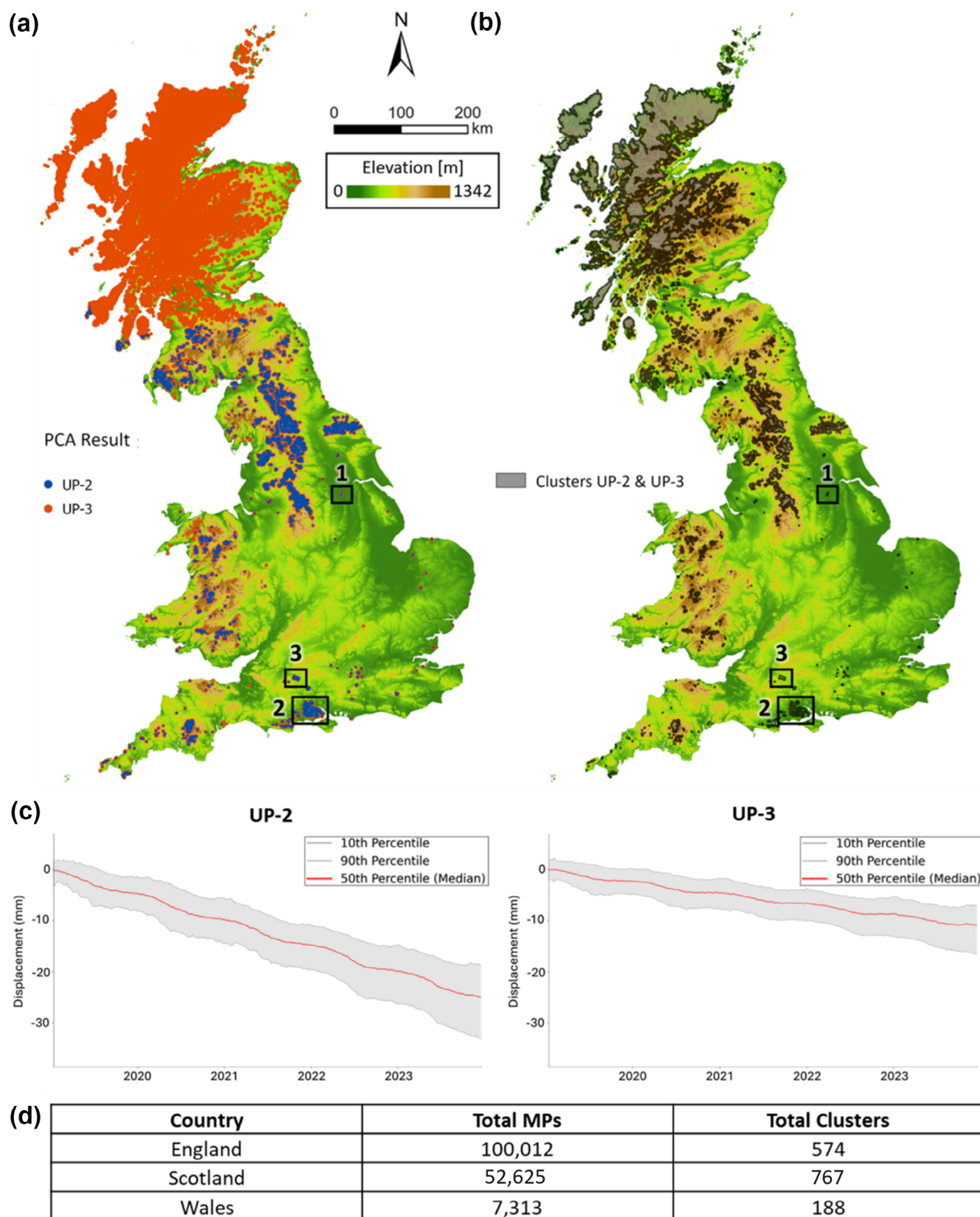


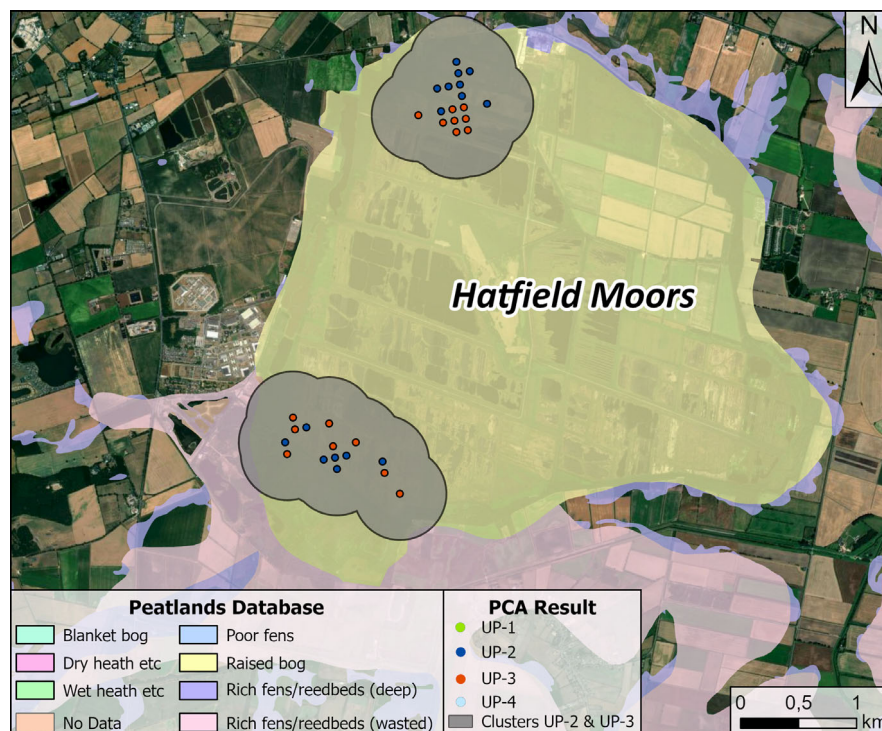
FIGURE 7 Spatial distribution of the detected MPs (a) and PBAs (b). The boxes highlight three focus areas: (1) Hatfield Moors peat bog, (2) New Forest peatlands and (3) a newly identified PBA not classified as peatland in the national land cover database. At the bottom, the time series characterising the selected UP-2 and UP-3 classes (c) and the total MPs and PBAs per country (d).

4.2 | New Forest—Dry heath landscape

The New Forest is one of the largest and most ecologically significant landscapes in Western Europe, covering approximately 148 km². It

represents a rare example of a functioning mosaic ecosystem where heathland, grassland, mires and pasture woodland habitats coexist, largely maintained by traditional pastoral practices (Jeffries et al., 2003). The peatlands within the New Forest consist of lowland

FIGURE 8 Spatial distribution of the identified MPs and PBAs in the Hatfield Moors area. The background shows the GB peatland database (Morton et al., 2024).



raised bogs and lowland heath, forming part of an interconnected network of wetland habitats that are highly dependent on local hydrological systems (New Forest National Park, 2025). The New Forest has received multiple conservation designations due to its ecological importance, including Site of Special Scientific Interest (SSSI), Special Area of Conservation (SAC), Special Protection Area (SPA) and National Park (NP) status (New Forest National Park, 2025). Agriculture has long been the basis of the rural economy and way of life in the more fertile areas surrounding the heathlands, valley mires and pasture woodlands, collectively known as the Open Forest. Much of this fertile land was historically enclosed as private farmland, and farming remains the predominant land use within the NP (New Forest National Park, 2025). When soils become waterlogged, organic matter ceases to decompose and instead accumulates as peat. As the peat layer builds up, bog and mire vegetation begin to take hold. In the New Forest portion, most mires are found in valleys, particularly in the southern part of the natural park (Clarke & Allen, 1986).

The results obtained in the New Forest area show a strong correspondence between the regions identified through the InSAR analysis and those classified as peatlands in the GB land cover database (Figure 10). A total of 4652 MPs with peat-like displacement patterns are detected, forming 15 distinct clusters. Notably, the GB land cover database classifies some of these areas as dry heath peatlands (Morton et al., 2024). The detected PBAs are consistent with known peatland distribution, further validating the effectiveness of the approach in detecting characteristic displacement trends associated with peatland environments.

The mean vertical InSAR time series shows a clear subsidence trend with a slight seasonal pattern (red line) (Figure 11a). In contrast, the moisture index values show no significant seasonality (green line). This is confirmed by the cross-correlation result between InSAR and the moisture index (green line in Figure 11b), indicating a low correlation between the two datasets. The rainfall data (blue bars) show a seasonal component that appears to be related to the InSAR data,

albeit slightly delayed. The analysis becomes particularly interesting when examining maximum and minimum temperature data. A strong seasonal pattern is clearly visible, closely matching the ground displacement time series. The cross-correlation analysis (red line in Figure 11b) further supports this observation, showing a near-perfect inverse correlation. In fact, when the ground surface subsides, temperatures tend to be higher, whereas when the ground surface rises, temperatures tend to be lower.

4.3 | Unclassified PBA

The proposed method also allows the identification of several areas with peat-like displacement behaviour that are not classified as peatlands in the GB land cover database (Morton et al., 2024). In that sense, an area with a high density of MPs showing peat-like displacement behaviour is identified in the north of Tilshead, Salisbury (Figure 12). This area is classified as a sparsely vegetated landscape in the GB land cover database. The clustering analysis reveals a continuous area containing a total of 673 MPs with characteristic peat-like displacement behaviour. The spatial distribution and consistency of these MPs suggest the presence of underlying peat-like surface conditions in the area.

The mean vertical InSAR time series shows a clear subsidence trend with a pronounced seasonal pattern (red line) (Figure 13a). In contrast, the moisture index values display minimal seasonality (green line), which is confirmed by the cross-correlation analysis between the two datasets (green line in Figure 13b). It shows a low relationship between ground displacement time series and moisture index values. Rainfall data (light blue bars) show a seasonal component that does not appear to be related to the InSAR time series. On the contrary, the maximum and minimum temperature data show a strong seasonal pattern that closely matches the ground displacement time series. The cross-correlation analysis (red line in Figure 13b) further confirms this result, showing a near-perfect inverse correlation between the two datasets.

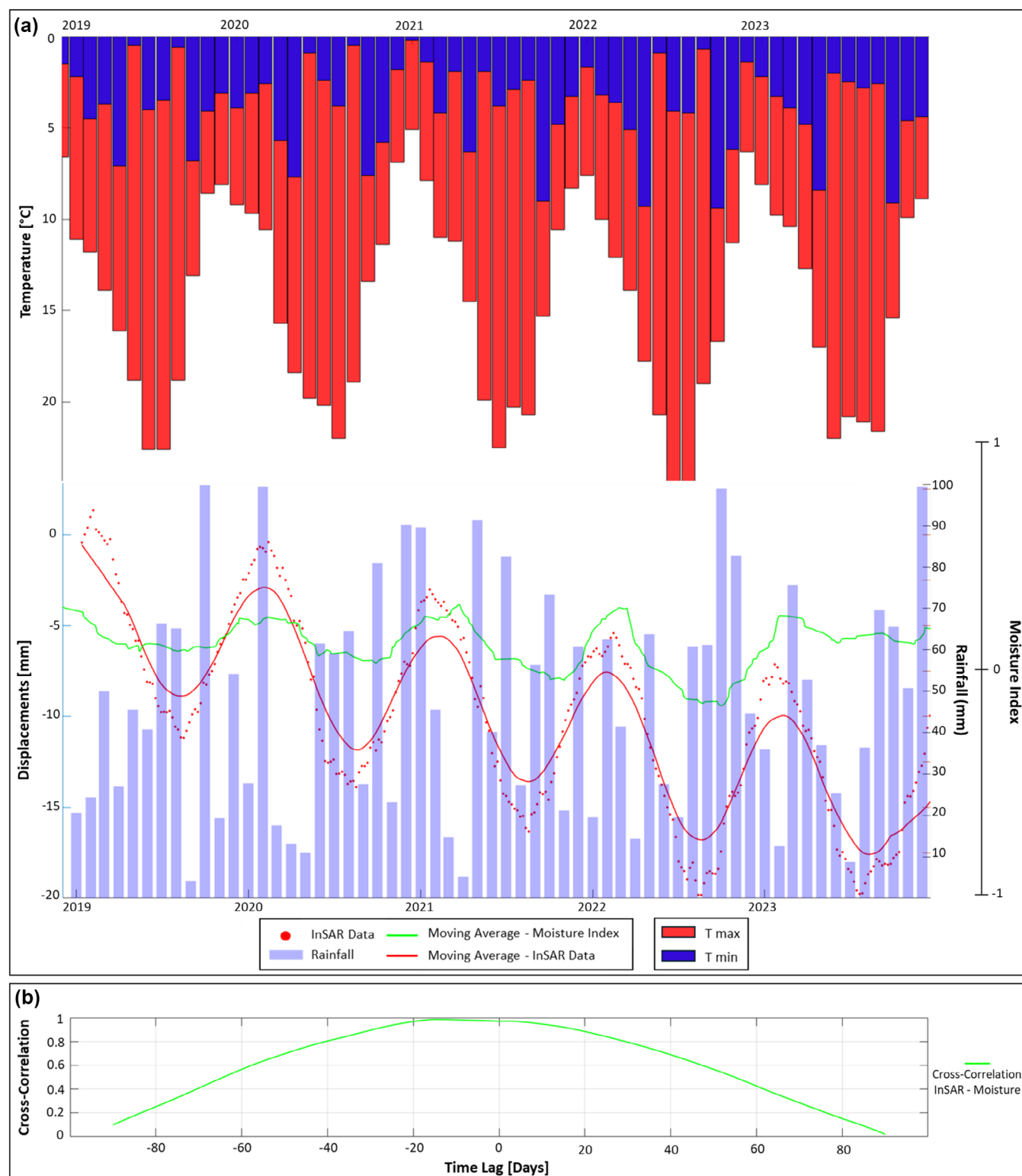


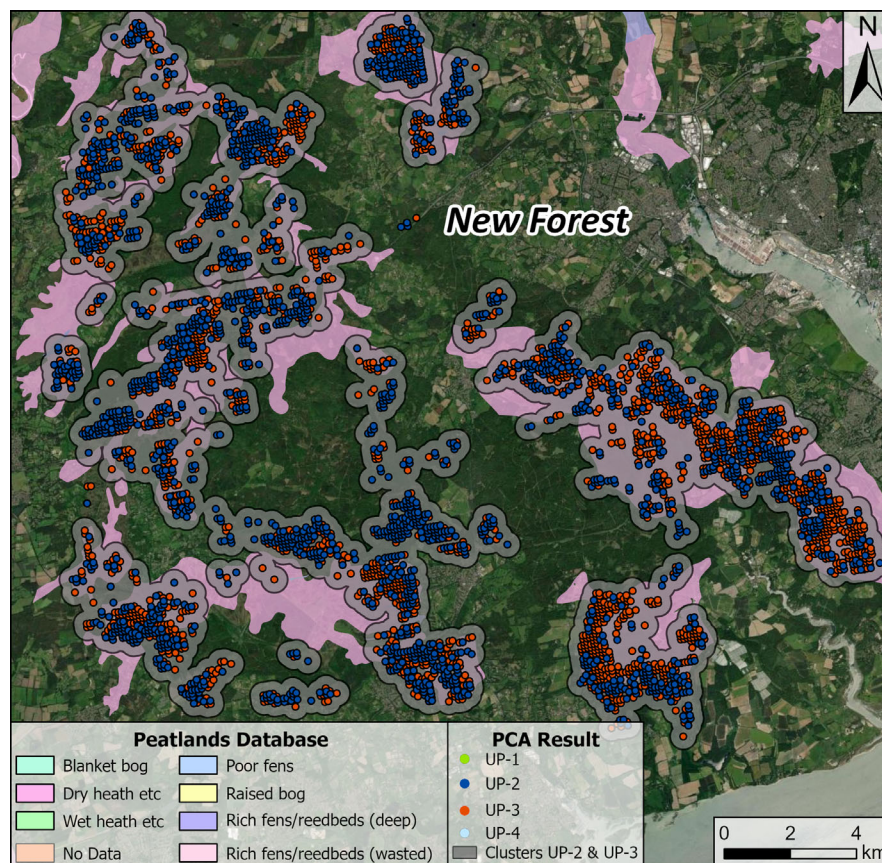
FIGURE 9 Cross-correlation analysis for the Hatfield Moors area. Temporal evolution of maximum and minimum temperatures, rainfall, moisture index and vertical ground displacement (a). Cross-correlation result between InSAR time series and soil moisture (b).

5 | DISCUSSION

Maintaining peatlands in good ecological condition is essential for preserving their water retention capacity and ecosystem services in a changing climate. The analysis of ground displacement data from the EGMS Level 3 Ortho vertical product (EEA, 2024) provides valuable insight into peatland dynamics in GB. Most peatlands exhibit negative surface displacement velocities from January 2019 to December

2023, indicating subsidence effects. This trend is consistent with potential water loss and peat erosion and may be associated with changes in land use and other anthropogenic pressures, highlighting ongoing peatland degradation processes. Another indicator of peatland condition is the degree of seasonality in surface motion, a bog-breathing phenomenon widely recognised as a proxy for peatland hydrological functioning. While Hatfield Moors shows a clear seasonal pattern related to peat bog breathing and restoration

FIGURE 10 Spatial distribution of the identified MPs and PBAs in the New Forest area. The background shows the GB peatland database (Morton et al., 2024).



effort (Humberhead Peatland, 2023), New Forest displays only slight seasonality and a pronounced subsidence effect. This behaviour suggests a greater degree of peatland degradation, probably because of peat erosion due to changes in land use and human activities. Such processes are particularly evident in the New Forest area and confirmed by the land cover classification of the CLC2018 dataset (New Forest National Park, 2025). In the third case study, the InSAR analysis shows an evident subsidence effect with a clear seasonal pattern. This suggests that, although some peat degradation processes may be occurring, the peat deposits are likely to retain sufficient thickness and hydrological integrity to sustain the characteristic seasonal surface displacement associated with the bog-breathing phenomenon.

Mapping the spatial distribution of peatlands has become a central focus of recent research (e.g., O'Leary et al., 2022, 2025). Accurate peatland datasets have significant applications at the international level, including greenhouse gas emission inventory reporting and soil organic carbon stock accounting (O'Leary et al., 2025). Traditional peatland mapping techniques primarily rely on optical imagery and land cover classifications, which often underestimate the detection of peatlands due to their complex and variable surface characteristics (O'Leary et al., 2022). This limitation highlights the need for integrating complementary methodologies, such as InSAR-based analysis, to enhance peatland detection and update existing inventories. The proposed approach represents a significant advancement in the identification of PBAs that are not classified as peatlands in land cover datasets (e.g., CLC and GB Land Cover Map). The results demonstrate the effectiveness of the proposed data-driven approach in improving peatland detection through InSAR analysis. The vertical ground displacement patterns reveal areas with subsidence trends and seasonal patterns typically associated with peat environments in GB. This

suggests that even though some areas are classified differently in the CLC2018 database, InSAR data can help to support their classification. The results highlight the potential to update peatland mapping and, in some cases, reconsider land cover classifications for refining peatland distribution and improving land management strategies.

The detected PBAs are compared with the CLC2018 dataset, revealing that several polygons not classified as peatlands are characterised by clusters of MPs showing peat-like behaviour (Figure 14a). The proposed approach identifies approximately 50% of the mapped peatland clusters, corresponding to 3450 out of 6916 CLC2018 clusters. In particular, 1541 of the 2076 peat bog polygons classified in CLC2018 spatially overlap with the detected PBAs. Conversely, approximately 31.5% of the identified PBAs (482 out of 1529) fall outside existing land cover inventories, potentially indicating previously unmapped peatland areas or locations where peat-like dynamics are not captured by optical classifications. To further characterise the land cover context of these PBAs, their distribution across CLC2018 classes is analysed. This comparison further shows that in addition to the 'peat bogs' category (Class 412), which contains 785 detected PBAs (Figure 14b), and the 'moors and heathland' category (Class 322), which contains 262 PBAs, other land cover classes also exhibit significant peat-like characteristics. Specifically, within the 'forest and seminatural areas' group, 175 PBAs are detected in the 'natural grassland' category (Class 321) and 82 PBAs within the 'coniferous forest' category (Class 312). Furthermore, within the 'agricultural areas' group, the 'pastures' category (Class 231) contains 115 PBAs, suggesting that certain managed landscapes may also share peat-like characteristics. Other classes, such as 'transitional woodland shrub' (Class 324) and 'sparsely vegetated areas' (Class 333), also have a significant number of PBAs, with 56 and 23 clusters,

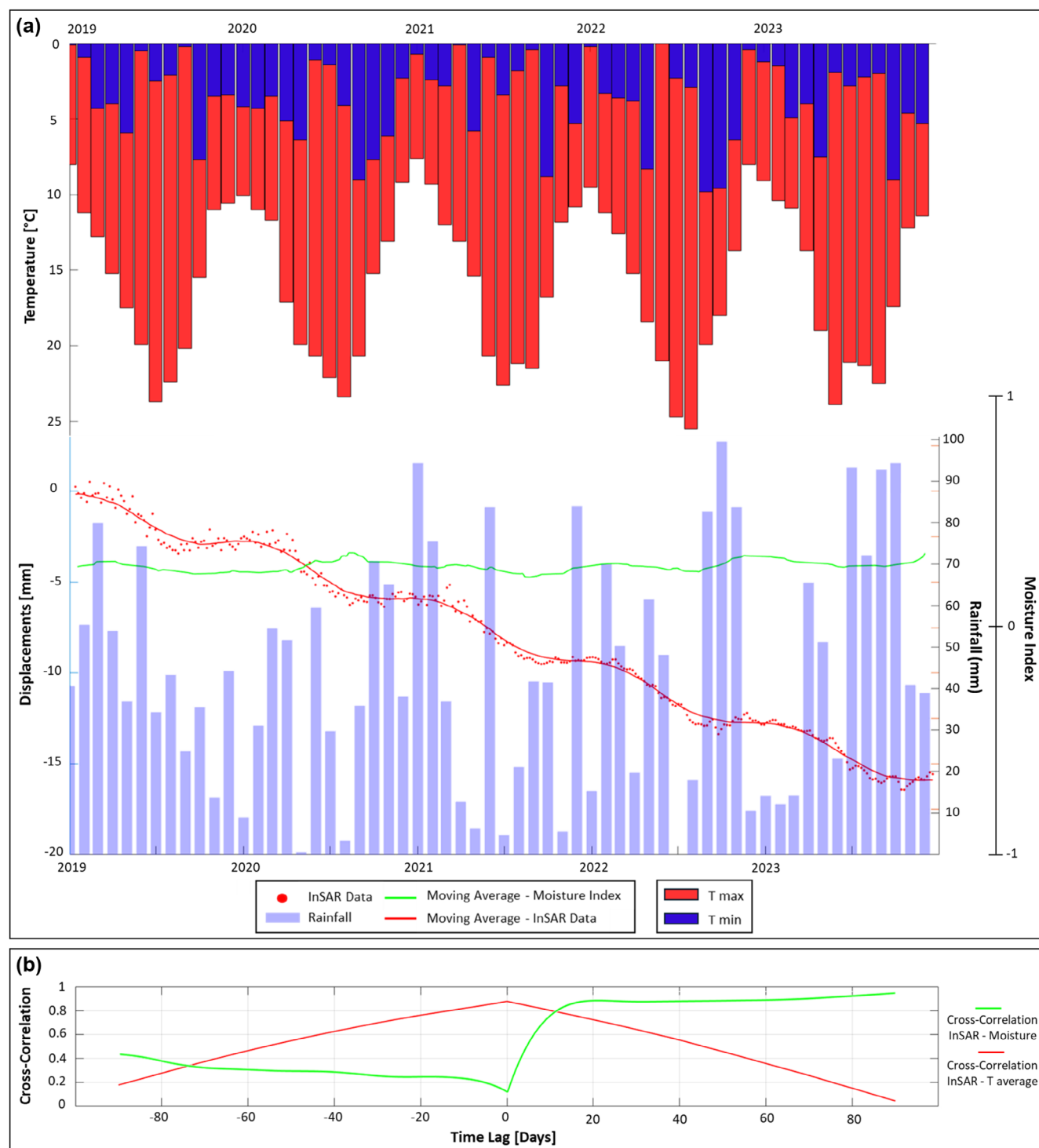


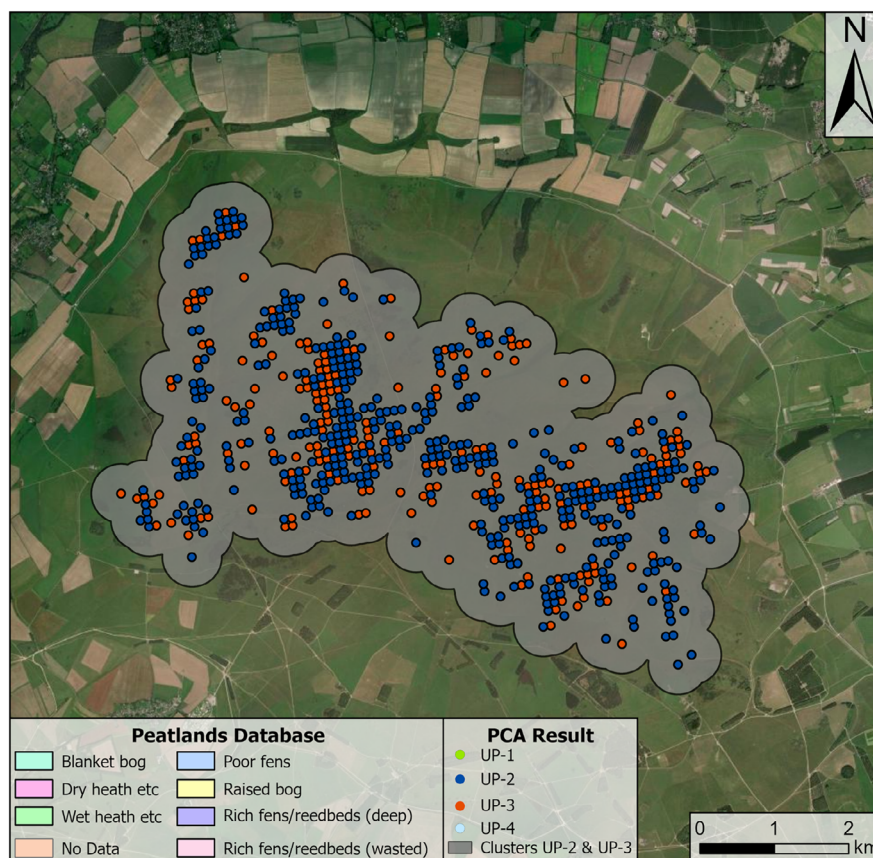
FIGURE 11 Cross-correlation analysis for the New Forest area. Temporal evolution of maximum and minimum temperatures, rainfall, moisture index and vertical ground displacement at the top (a). Cross-correlation results between InSAR time series and soil moisture (green line) and between InSAR and average temperature data (red line) at the bottom (b).

respectively. The consistency of the analysis is supported by the observation that the two CLC2018 categories most closely associated with peat environments, ‘peat bogs’ and ‘moors and heathland’, account for many of the detected PBAs, validating the methodology.

Different types of peatlands respond to the same environmental factors in diverse ways (IUCN, 2011). Peat bogs rely solely on precipitation as their main water source, making their surface dynamics highly sensitive to seasonal changes in soil moisture (Scotland’s Nature Agency, 2023). As a result, peat bogs are the most easily detected by

InSAR analysis due to their distinct seasonal response. The InSAR time series for peat bogs typically show larger amplitude variations. This reflects the swelling and shrinking of the peat layer in response to changing moisture levels. A clear example of this behaviour is observed in the Hatfield Moors study area, where the InSAR time series shows a strong seasonal pattern closely correlated to fluctuations in the moisture index. This pronounced seasonal signal reflects the dynamic surface displacement associated with the bog-breathing phenomenon. Furthermore, cross-correlation analysis supports this observation,

FIGURE 12 Spatial distribution of the identified MPs and PBA in the area north of Tilshead.



showing a significant correlation between ground displacement and NDMI. In contrast, fens and transitional mires are influenced by both groundwater and surface run-off, resulting in more complex and variable ground motion patterns (e.g., Guo et al., 2017; Mahdianpari et al., 2020; Xu et al., 2018). The InSAR time series for the New Forest area shows limited correlation with the NDMI, suggesting that seasonal surface displacement is not primarily driven by soil moisture variations. The low correlation with the NDMI may be partly explained by the presence of dense vegetation, typical of mire-dominated peatland landscapes, particularly rich in *Sphagnum* mosses, which may interfere with the ability of optical sensors to accurately detect soil moisture levels (Abdelmajeed & Juszczak, 2024). On the other hand, the strong correlation with temperature suggests that climate conditions play a key role in controlling surface displacement in this dry heath environment. Higher temperatures may increase evapotranspiration and surface water evaporation, leading to variations in water content conditions and associated changes in peat volume.

Satellite InSAR data have the potential to provide insights into seasonal surface displacement patterns related to peatland dynamics, such as uplift and subsidence driven by moisture, rainfall or temperature fluctuations. The proposed methodology exploits this capability not to directly map peatland extents, but to identify PBAs, defined as regions characterised by ground displacement dynamics that are consistent with peatland processes. The approach is intended to complement existing peatland inventories, which are traditionally based on optical remote sensing and land cover classifications, by providing an additional process-based perspective derived from surface displacement time series. The integration of InSAR-derived PBAs with optical, radiometric and field-based datasets has the potential to significantly improve peatland identification, update existing maps exclusively

made by optical data and, in some cases, highlight areas where land cover classifications may require revision. This approach is particularly advantageous given the open-source and user-friendly nature of the EGMS dataset, as the semi-automated workflow enables high reproducibility and suitability for large-scale and repeated analyses. Once identified, PBAs can provide a robust basis for targeted *in situ* investigations and for integration within broader peatland mapping and monitoring frameworks. Despite these strengths, several limitations must be acknowledged. InSAR coverage in rural and densely vegetated environments can be spatially discontinuous, as the availability of coherent MPs depends on the presence of stable radar targets on the surface. Consequently, peatland areas may be only partially detected, and the method does not allow a precise delineation of peatland boundaries (Wilson, 2025). Noise, decorrelation effects and heterogeneous MP distributions further limit the capability of InSAR to provide detailed spatial mapping. An additional limitation concerns the potential omission of severely degraded or thin peat deposits. These systems may have lost their seasonality while still undergoing slow subsidence and could therefore be underrepresented within the PCA-based classification framework. Furthermore, the interpretation of seasonal signals should be made with caution, as similar seasonal patterns may also arise in non-peatland environments influenced by climatic variability. Therefore, the proposed methodology should not be interpreted as a standalone peatland mapping tool, but rather as a complementary approach for identifying PBAs and improving peatland detection by integrating it with other remote sensing and environmental datasets. In addition, the multi-step data selection and processing workflow may introduce uncertainty into the final results, requiring an explicit evaluation of its cumulative effects to assess the robustness of the proposed approach. Uncertainty was assessed

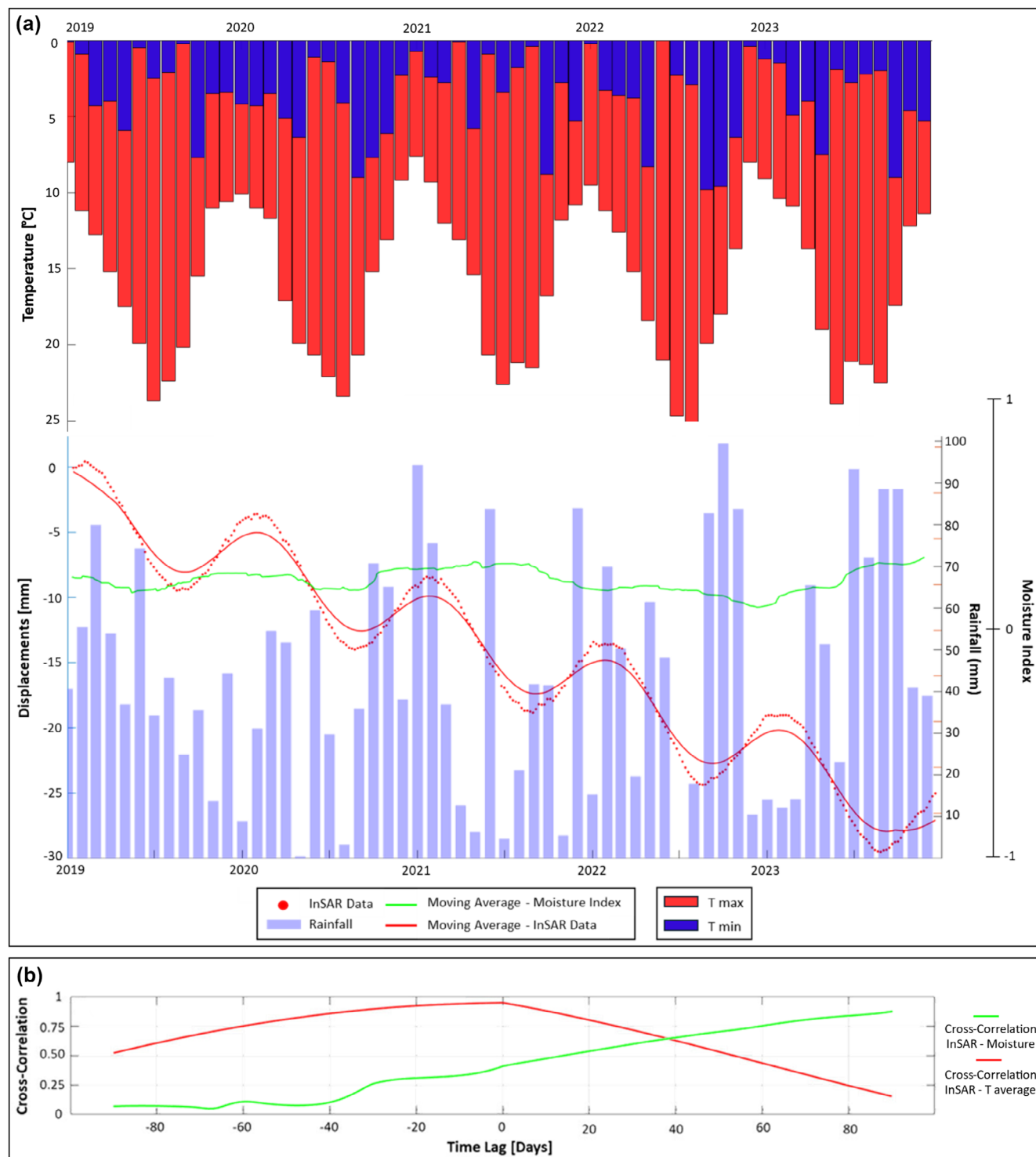


FIGURE 13 Cross-correlation analysis for the Tilshead area. Temporal evolution of maximum and minimum temperatures, rainfall, moisture index and vertical ground displacement at the top (a). Cross-correlation results between InSAR time series and soil moisture (green line) and between InSAR time series and average temperature data (red line) at the bottom (b).

through a filtering sensitivity analysis, quantifying the effects of the main processing steps on the final dataset. The progressive reduction in the number of MPs throughout the workflow provides an indirect measure of uncertainty associated with data selection criteria and clustering choices. Starting from 16 292 844 MPs, the initial land cover filtering (removing urban areas) reduced the dataset to 14 432 186 MPs (88.6% of the original dataset). The subsequent PCA-based time-series classification and *k*-means clustering resulted in a substantial reduction to 1 241 168 MPs (8.6% of the

previous step and 7.6% of the initial dataset) that agree with the sum of PCA2 and PCA3 previously described. Finally, spatial clustering using DBSCAN further refined the results, yielding 1 065 542 MPs (85.9% of the previous step, corresponding to 6.5% of the initial dataset), grouped into 1529 spatially coherent PBAs (Table 1). This analysis highlights the PCA and *k*-means classification as the most influential step in terms of data reduction and uncertainty propagation.

Previous studies on peatland identification have largely prioritised optical remote sensing approaches, with limited use of open-access

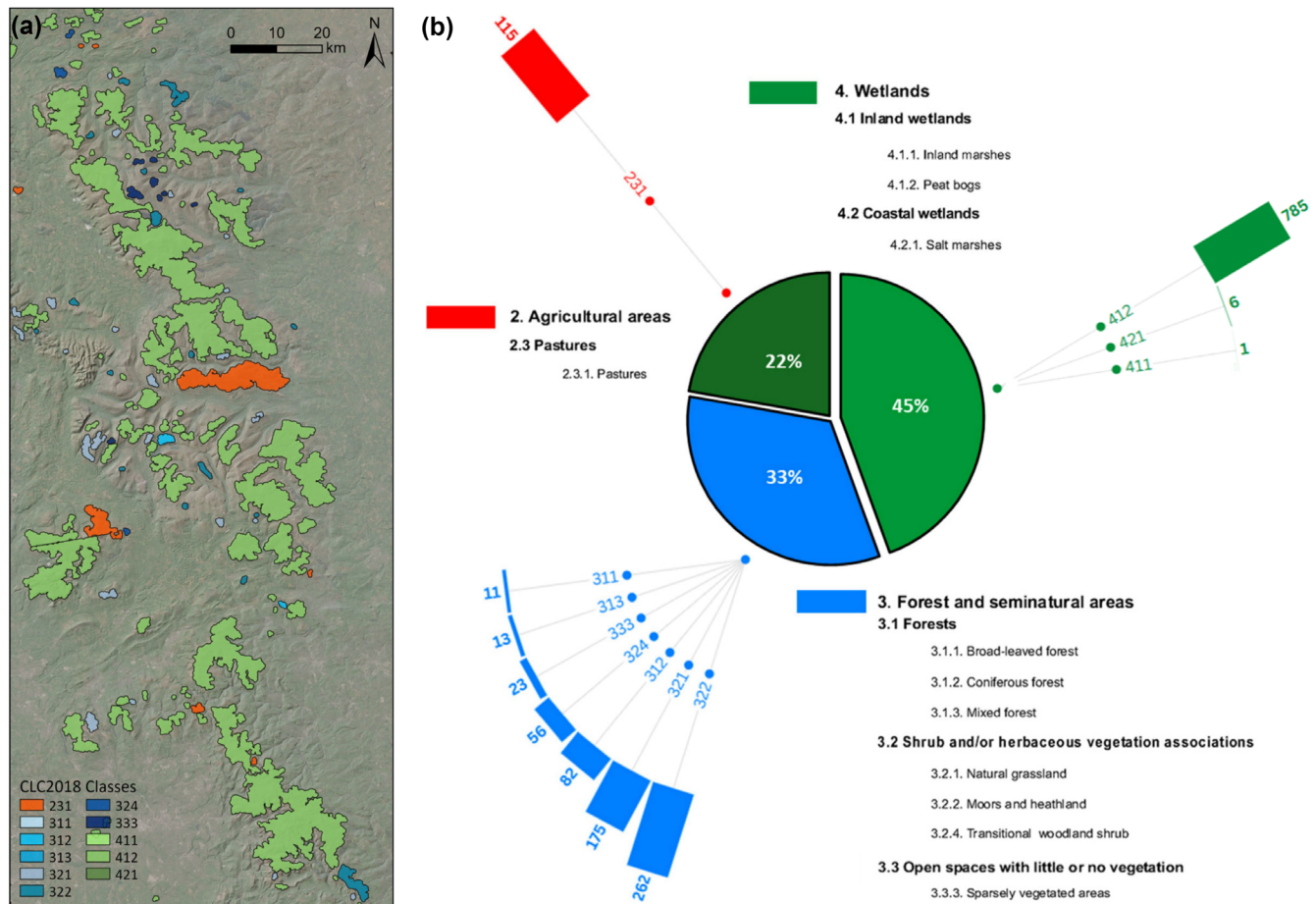


FIGURE 14 Spatial distribution of PBAs against different land cover classes based on the CLC2018 classification (the black contour indicates the new areas identified as PBAs), focusing on the North Pennines National Landscape (a) and statistical analysis of the PBA identification in GB (b).

TABLE 1 Progressive reduction of MPs throughout the processing workflow and associated detection metrics.

Data filtering steps	MPs	% compared to the previous step	% compared to the beginning
Raw MPs	16 292 844	-	100%
After CLC filtering (CLC Class 1: Artificial surfaces)	14 432 186	88.6%	88.6%
After PCA analysis (PC2 and PC3 selected)	1 241 168	8.6%	7.6%
After DBSCAN (400 m and 5 MPs)	1 065 542	85.9%	6.5%

Note: The table summarises the effects of data filtering, PCA analysis and DBSCAN spatial clustering on the final identification of PBAs, providing an indirect assessment of uncertainty propagation.

Abbreviations: CLC, CORINE Land Cover; DBSCAN, density-based spatial clustering of applications with noise; MPs, measurement points; PBAs, peat-like behaviour areas.

InSAR data. For instance, Gilet et al. (2024) developed new approaches for peatland mapping using multiple input sources, including the CLC2018 dataset derived from Sentinel-2 optical data and soil survey maps. Similarly, airborne radiometric data have been used for digital soil mapping of peatlands in Northern Ireland (O'Leary et al., 2025). However, InSAR data have primarily been used for monitoring the degradation status and assessing the restoration of peatland environments (Fibbi et al., 2024; Wilson, 2025).

Extending this approach from a national to a continental scale introduces additional challenges. Peatlands exhibit highly variable hydrological and ecological dynamics depending on their geographical location, climatic conditions and environmental context. The behaviour of peatlands at different latitudes is strongly influenced by

climatic factors such as temperature and precipitation. For instance, peatlands in boreal regions are typically affected by snowmelt and prolonged winter conditions, whereas tropical peatlands are influenced by intense rainfall patterns and higher temperatures (Le Geay et al., 2024), often compounded by anthropogenic pressures (e.g., Gibson et al., 2009; Holden et al., 2004). Drainage, agricultural conversion, burning and peat extraction can substantially alter the hydrological balance of peat soils (e.g., Carlson et al., 2013; Clay et al., 2012; Yallop & Clutterbuck, 2009). In addition, at larger scales, the consistency and reliability of the analysis can be affected by variations in MP density and coherence across regions with different vegetation cover, soil types and topography. Consequently, the identification of specific peatland behaviours through a uniform

InSAR-based approach applied at a continental scale, across diverse climatic zones and land-use regimes, remains challenging. These limitations reflect both the intrinsic heterogeneity of peatland dynamics and the computational constraints associated with processing large volumes of InSAR data with uneven MP distributions. Future developments of this work will focus on extending the proposed methodology to other European countries participating in the Copernicus EGMS programme, using the consistent and reproducible workflow presented in this work. The resulting PBAs will be progressively integrated into the ArcGIS Online web application (<http://bit.ly/4uihDND>), enabling the creation of an evolving, pan-European database of PBAs. This platform will support comparative analyses across different regions, facilitate data sharing and provide an accessible tool for exploring peatland dynamics at multiple spatial scales. Integrating InSAR-derived PBA data with complementary remote sensing products, such as optical images, hyperspectral and radiometric data, as well as *in situ* observations and climatic records, will be essential to account for regional variability and strengthen the robustness and interpretation of the results at a continental scale.

In this context, the detection of approximately 50% of the peatland clusters mapped in CLC2018 should be interpreted as a coherent and meaningful outcome rather than a limitation of the approach. The proposed methodology is not designed to provide an exhaustive map of peatland extents but to identify PBAs defined by characteristic seasonal ground deformation dynamics detectable by InSAR. Consequently, only peatland areas exhibiting sufficient coherence and a measurable displacement signal are expected to be detected. Peatlands lacking stable radar targets, affected by dense vegetation, or characterised by weak or non-seasonal deformation are intrinsically less detectable by InSAR. Therefore, the observed detection rate reflects the sensitivity of the technique to dynamic peatland processes rather than a direct measure of omission error and highlights the complementary role of InSAR-based PBAs with respect to traditional optical inventories.

6 | CONCLUSIONS

The present work advances peatland identification by introducing an InSAR time-series approach focused on the detection of PBAs. The proposed methodology provides insights into peatland surface dynamics that cannot be captured through monitoring programmes based solely on visual observation. The results demonstrate the potential of InSAR ground motion data to identify peat-like displacement behaviour, effectively complementing traditional optical-based land cover classifications. By highlighting areas characterised by peat-specific surface dynamics, the proposed approach supports the updating of peatland inventories and can contribute to more targeted restoration and management strategies. The vertical displacement information provided by the EGMS Level 3 Ortho product offers a novel perspective on peatland condition and distribution without requiring specialised InSAR processing expertise or high data production costs. This makes the methodology particularly suitable for large-scale environmental monitoring, where consistent and harmonised datasets are essential for comparing peatland behaviour across regions. Integrating EGMS data into broader monitoring frameworks

therefore represents an opportunity to improve peatland assessment when combined with field observations and other remote sensing products.

The results also improve the understanding of peatland temporal dynamics. The detection of clear seasonal displacement patterns highlights the sensitivity of peatland systems to hydrological variability and environmental forcing, reinforcing the importance of monitoring both temporal and spatial changes. In this context, InSAR time series represent a valuable tool for assessing peatland responses to climate variability, land-use pressures and restoration activities.

Future work will focus on extending this framework beyond GB towards continental-scale applications across Europe. Expanding the spatial coverage will allow more systematic comparisons of peatland dynamics under different climatic, geomorphological and management conditions, potentially improving the identification of regional differences in peatland behaviour and degradation status. Achieving this goal will require the integration of multi-source environmental datasets and harmonised European products to enhance both the robustness and transferability of the methodology. In this context, the present study contributes to the development of a more consistent, scalable and process-oriented approach for peatland monitoring and identification across regional and national scales, supporting future Europe-wide applications.

AUTHOR CONTRIBUTIONS

G.F. wrote the first version of the manuscript. G.F. and F.P. developed the analysis software. M.D.S. supervised the writing, reviewed and improved the manuscript, and supervised the project. G.F., F.P. and C.M. interpreted the results. All authors read and commented on the final version of the manuscript.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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