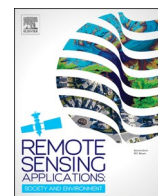




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Assessing peat surface motion using Interferometric Synthetic Aperture Radar (InSAR) in the Great Fen area of Cambridgeshire, UK

Abhishek Patil ^a, Abdou Khouakhi ^{a,*}, Nicholas Girkin ^b, Ian Holman ^a^a Faculty of Engineering and Applied Sciences, Cranfield University, College Rd, Wharley End, Bedford, MK43 0AL, UK^b School of Biosciences, University of Nottingham, Sutton Bonington, LE12 5RD, UK

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ABSTRACT

Peatland degradation is a critical global climate issue, releasing millions of tonnes of CO₂ annually due to drainage and changes in land use. As countries strive to meet net-zero targets, restoring degraded peatlands has become a priority for carbon sequestration and biodiversity conservation. However, monitoring peatland recovery remains a challenge, especially for large-scale restoration projects. This research is driven by the need for low-cost validation of peatland re-wetting schemes, enabling robust monitoring of peat physical condition and hydrological recovery, with implications for carbon accounting and agriculture's contribution to net-zero targets. This paper addresses this gap by applying satellite remote sensing data from Interferometric Synthetic Aperture Radar (InSAR) to track peat surface motion in Cambridgeshire's Great Fen, one of the UK's largest lowland peatland restoration initiatives. Sentinel-1 InSAR data (2015–2025) were used to quantify ground motion and derive deformation-based proxies for peat carbon flux. Our analysis revealed distinct subsidence patterns for undrained, early-restored, and later-restored farms, enabling first-order, deformation-based carbon flux estimation under common parameter assumptions. Early-restored farms experienced subsidence rates of up to 1.17 cm/year and deformation-associated carbon flux proxies of 14.50 tons CO₂/ha/year, compared to 1.40 cm/year and 17.37 tons CO₂/ha/year in later-restored sites. National Nature Reserves (Holme Fen and Woodwalton), under long-term conservation management, recorded the lowest subsidence (~0.48 cm/year) and lowest deformation-associated carbon loss proxy (5.98 tons CO₂/ha/year), consistent with higher peat moisture conditions relative to restored farmland. These estimates, interpreted as relative indicators rather than direct measurements of net ecosystem carbon balance, demonstrate InSAR's utility for tracking peatland condition and relative peat carbon vulnerability across restoration timelines. Seasonal fluctuations aligned with soil moisture and precipitation anomalies, indicating a strong hydrological control on peat surface motion. Together, these findings show that InSAR provides a high-resolution, cost-effective tool for continuous monitoring of peatland physical dynamics, supporting comparative assessment of restoration outcomes and climate-relevant land management decisions.

* Corresponding author.

E-mail address: a.khouakhi@cranfield.ac.uk (A. Khouakhi).<https://doi.org/10.1016/j.rsase.2026.101919>

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1. Introduction

Peatlands are unique wetland ecosystems characterised by the accumulation of deceased organic matter. They form when the production of plant litter exceeds the rate of peat decomposition, typically in environments with regular or constant water saturation. Although they occupy only ~3 % of the Earth's land surface, peatlands store about one-third of global soil carbon (approximately 600 Gt C), making them a disproportionately important component of the terrestrial carbon cycle (Page and Baird, 2016; Loisel et al., 2021). Lowland peatlands are classified into two functional types: i) fens which are fed by mineral-rich surface or groundwater, and ii) raised bogs which rely almost exclusively on rainwater and are therefore nutrient-poor. Both systems build deep organic soils and rank among the most carbon-dense terrestrial ecosystems. When in good condition, peatlands provide a suite of ecosystem services: they store large amounts of carbon over long timescales, regulate water quantity and quality, moderate flood and drought risk, and support specialist biodiversity (Alshammari et al., 2018). However, many lowland peats have been drained for agriculture, leading to shrinkage, compression and decomposition (biochemical oxidation) of the peat, as well as increasing their vulnerability to wind erosion. The degradation of peatlands poses significant threats to these valuable ecosystems, resulting in substantial costs to society. Degraded peats decrease water quality, create a fire hazard, and release stored carbon dioxide into the atmosphere. Due to extensive habitat modification and drainage aimed at facilitating agriculture and peat extraction, these areas have transformed from natural carbon sinks to significant carbon emitters. Consequently, they have emerged as one of the leading contributors to greenhouse gas (GHG) emissions within the UK's land-use sector (Evans et al., 2017). Quantifying peatland condition and directing restoration are therefore global climate-mitigation priorities.

Peatland surfaces are dynamic rather than static. Alongside long-term peat accumulation and the natural processes of compression and organic matter decomposition, they also undergo irreversible subsidence due to drainage, as well as reversible elastic deformation of the peat matrix caused by short-term changes in water and gas content (Alshammari et al., 2020). These mass fluctuations are driven by daily, seasonal and long-term environmental factors, including evapotranspiration, rainfall, atmospheric pressure variations, land drainage, temperature changes, decay, and loading. Each of these processes is linked to the condition of the peat, which in turn affects the ecosystem services that peatlands provide (Alshammari et al., 2020). Hence, investigating peatland surface motion and separating irreversible subsidence from elastic deformation becomes crucial for evaluating the overall well-being of these peatlands and the effectiveness of restoration efforts. Peatland can be monitored using both remote sensing and in situ methods. In-situ approaches produce high-quality data but are limited to specific locations inside an area of interest, can be difficult to install and maintain (especially in remote areas), and will not capture large-scale spatial and temporal changes in peat motion behaviour. In contrast, remote sensing methods offer a more practical and cost-effective approach to identifying and monitoring vast regions affected by land deformation. In particular, satellite-based methods enable researchers to assess the behaviour and extent of land deformation on a larger scale, contributing to a better understanding of their dynamics (Urgilez Vinuesa et al., 2022) and the potential to monitor peatland restoration effectiveness, land-based carbon markets etc.

For instance, Large et al. (2025), applied InSAR across ~680,000 ha of Scottish peatlands, demonstrating its effectiveness for monitoring surface motion and providing spatially continuous measurements that complement sparse in-situ surveys. Among the suite of established InSAR processing algorithms, the Small Baseline Subset (SBAS) technique has gained popularity for detecting slow, spatially extensive ground motions (Li et al., 2022) such as occurs in peatlands. SBAS typically yields higher coherence than Permanent Scatterer InSAR (PSI) where vegetation is present (Li et al., 2022). Compared with conventional differential InSAR, SBAS discards decorrelating pixels and relies on many scenes to improve precision. For example, Zhang et al. (2025) demonstrated the use of SBAS-InSAR for urban subsidence monitoring in Chongqing, further proving the applicability and precision of this technique in monitoring deformation in both urban and agricultural areas.

While many studies have established the value of InSAR for tracking land deformation (e.g., Berardino et al., 2002; Crosetto et al., 2016; Osmanoğlu et al., 2016; Kou et al., 2025), farm-scale quantification of deformation in lowland peatlands and its translation into carbon-flux proxies and explicit links to restoration practice remains scarce. Comparative analyses across InSAR ascending/descending geometries or different observation counts are also uncommon, and multi-decadal validation against ground surveys is rarely attempted. While Large et al. (2025) and Mitchell et al., 2025 demonstrate landscape-scale peatland monitoring in Scotland, important gaps remain, including: (i) farm-scale assessment of restoration impacts in lowland fens, (ii) integration of long-term ground datasets for validation, and (iii) quantitative tests of how restoration timing maps onto measurable surface-motion changes. Methodologically, SBAS-InSAR has proven capable of resolving staged deformation in other contexts (e.g., Yang et al., 2024, for landslides), highlighting its suitability for detecting restoration-related changes through time in this study.

This paper evaluates the potential of SBAS-InSAR to detect and quantify surface motion in lowland peatlands and assesses its reliability against independent ground-based survey data. We analyse peat surface deformation across multiple spatial scales (pixel, farm, and sub-region), examine the influence of satellite viewing geometry and interferogram density on measurement precision, and characterise seasonal deformation in relation to soil moisture and rainfall. Using the Great Fen restoration project in eastern England as a case study, we demonstrate how InSAR provides cost-effective, spatially continuous monitoring of peatland physical dynamics from

farm to landscape scales. We further derive first-order, deformation-based proxies for peat carbon flux to support comparative assessment of restoration outcomes and inform sustainable land management.

2. Material and methods

2.1. Study area

The East Anglian Fens contain a considerable portion of the remaining lowland peat in England, as shown in Fig. 1a Ongoing drainage since the 17th century of increasing intensity has created a substantial area of fertile farmland, a key agricultural region within the UK, in which most land is dedicated to high-quality horticultural and arable cultivation. However, these drainage efforts have also resulted in widespread and continuous peat degradation (Evans et al., 2017).

The Great Fen Project is a 50-year restoration initiative aimed at reconnecting the remaining fen habitats of Woodwalton Fen and Holme Fen National Nature Reserve (Fig. 1b) through restoration of the surrounding agricultural peatland. Recognised as one of Europe's most significant restoration projects (Wildlife Trust BCN, n.d.), the Great Fen Project began acquiring farms in 2002 to expand the reserve and initiate phased field restoration, which started in 2005. The study area includes the protected Woodwalton and Holme Fens as well as nearby farmland undergoing restoration (Fig. 1b). The restoration areas are divided into two regions based on the timing of restoration efforts - Region A, comprised of Holme Lode, Tower, Froghall and Ironhouse Farms, in which peatland restoration did not commence until 2012 (with some sites remaining untreated till 2014); and Region B comprised of Ladyseat, Old Decoy, New Decoy, Corney and Chalderbeach Farms, in which restoration commenced in 2009 and successfully transformed the landscape into productive wet meadows (Jasper et al., 2022). The diverse landscape provides an ideal setting for investigating and analysing peat surface motion with InSAR techniques, with this division allowing comparison of peat motion between areas at different restoration stages.

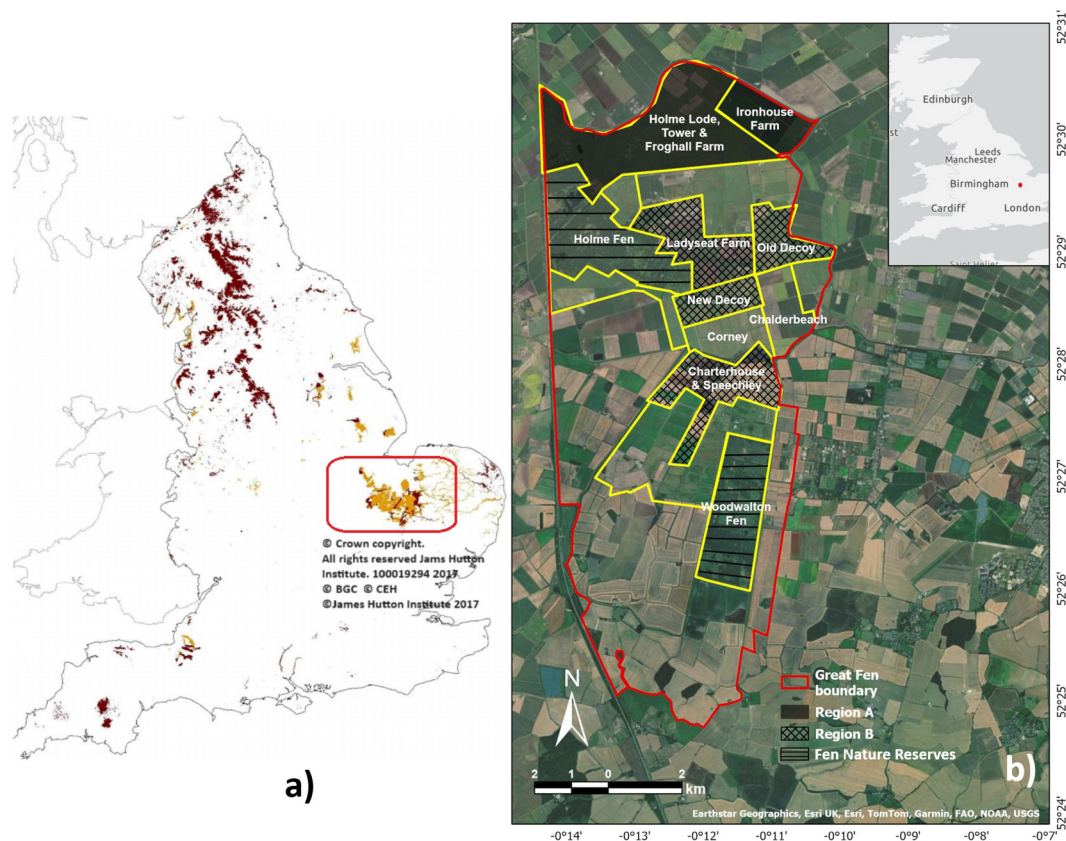


Fig. 1. (a): Distribution of peatlands across England (Natural England, 2010). Deep peats shown in brown, wasted peats in orange. The red box highlights the East Anglian Fens study area, where the majority of wasted peat is concentrated, particularly in the Cambridgeshire region. (b): Area covered by the Great Fen Project area (red boundary). Yellow outline covers a study area for validation and CO₂ estimation, farms within the early restored (Region B) and late-restored (Region A) areas, and the Holme Fen and Woodwalton Fen National Nature Reserves. The basemap is a composite of imagery from the World Imagery basemap (ESRI, 2024).

Table 1
Sentinel-1 SAR acquisitions used in this study (SLC data).

Data Set	Flight Direction	Beam Mode	Path	Frame	Polarisation	Dates
Sentinel 1 A & B*	Ascending	IW	132	168	VV + VH	March 2015 - April 2025
Sentinel 1 A & B*	Descending	IW	81	417 & 418	VV + VH	May 2015 - April 2025

2.2. InSAR data and pre-processing

To analyse peat surface motion, we used SAR data from the Sentinel-1 mission (2015–2025). Its frequent acquisition intervals i.e. every 6 days until 2020 and every 12 days thereafter following the loss of S1B ([European Space Agency, n.d.](#)) support robust time-series analysis and deformation monitoring. [Table 1](#) details the Sentinel-1A/B (S1) Single Look Complex (SLC) satellite data used in this study. Acquired in Interferometric Wide (IW) swath mode on both ascending (track 132) and descending (track 81) passes, data were retrieved via the Alaska Satellite Facility (ASF) Data Search Vortex platform. First, we downloaded and processed interferograms independently for the ascending and descending Sentinel-1 tracks. These separate interferograms datasets used in producing velocity maps in [Figs. 4a–5a](#) (ascending) and [4b–5b](#) (descending) each using its own stable, high-coherence reference pixel. Next, we downloaded and merged the ascending and descending interferogram stacks into a single combined dataset by co-registering both geometries to a common reference frame. This merged processing yielded the combined velocity map shown in [Figs. 4c–5c](#).

SAR is an active remote sensing technique that transmits microwave pulses and records the returned signal to characterise surface properties. Interferometric SAR (InSAR) exploits phase differences between repeated SAR acquisitions to measure changes in the sensor–target distance over time. The interferometric phase (ϕ) comprises contributions from topography, earth curvature, surface displacement, atmospheric delays, and noise, and can be expressed as:

$$\phi = \phi_{\text{DEM}} + \phi_{\text{flat}} + \Phi_{\text{disp}} + \phi_{\text{atm}} + \phi_{\text{noise}} \quad \text{Equation (1)}$$

Differential InSAR isolates surface deformation by removing the topographic and flat-earth components, yielding

$$\Phi_{\text{disp}} + \phi_{\text{atm}} + \phi_{\text{noise}} = \phi - (\phi_{\text{DEM}} - \phi_{\text{flat}}) \quad \text{Equation (2)}$$

with appropriate processing, Sentinel-1 InSAR can resolve centimetre-scale surface deformation. Measurement accuracy is enhanced by using interferograms with short temporal and perpendicular baselines, which minimise decorrelation and noise ([Fielding et al., 1998](#); [Alaska Satellite Facility ASF, 2021](#)). Interferogram stacks were processed using the Jet Propulsion Laboratory's InSAR Scientific Computing Environment (ISCE). A 30-m Shuttle Radar Topography Mission (SRTM) DEM was used for geocoding and removal of topographic phase contributions. Interferograms were multi-looked using a 20×4 (range $\times$ azimuth) configuration and filtered using a power spectral filter (value = 0.5), following ASF HyP3 recommendations for Sentinel-1 IW mode data. This configuration yields an effective spatial resolution of ~ 160 m and provides substantial speckle noise reduction, which is particularly important for peatland environments where coherence is inherently low due to dense vegetation and fluctuating moisture conditions ([Braun and Veci, 2021](#)). The 20×4 multilook configuration was combined with conservative SBAS thresholds of 40 m perpendicular baseline and 12 days temporal separation to ensure robust phase stability. While alternative configurations (e.g. 10×2 multilooking with relaxed baseline thresholds) generated a larger number of interferograms, they exhibited lower coherence and increased noise, resulting in less reliable deformation estimates. The adopted configuration therefore represents a balanced trade-off between spatial resolution and phase quality, suitable for farm-to regional-scale peatland subsidence analysis (see [Figures S-8 to S-13](#)). A total of 672 Sentinel-1A/B acquisitions (2015–2025) were used to generate 529 interferograms from ascending and descending tracks. Pre-processing was performed using the ASF HyP3 InSAR workflow and included precise orbit application, thermal noise removal, calibration, TOPS co-registration with enhanced spectral diversity, coherence estimation, debursting, terrain correction, and signal-to-noise ratio (SNR) optimisation. Phase quality was further improved using the Goldstein–Werner adaptive phase filter, which suppresses phase noise and enhances fringe visibility, thereby improving the reliability of phase unwrapping and deformation estimates ([Goldstein and Werner, 1998](#); [Alaska Satellite Facility, 2023](#)).

2.3. Methods

2.3.1. Data processing for SBAS time series analysis

To quantify time-dependent peat surface motion, we used the open-access MintPy InSAR time-series software ([Zhang et al., 2019](#)), implemented in Python ([Fig. 2](#)). Time series were constructed using the SBAS approach ([Berardino et al., 2002](#)), weighted by the inverse of phase covariance. SBAS selects interferometric pairs with short temporal and perpendicular baselines to minimise decorrelation and atmospheric noise, enabling robust deformation monitoring ([Berardino et al., 2002](#); [Lanari et al., 2004](#)). In this study, SBAS was applied to Sentinel-1 acquisitions spanning 2015–2025, with interferometric pairs separated by approximately 12 days, allowing temporal variations in peat surface motion to be resolved with high precision ([Alaska Satellite Facility ASF, 2021](#)).

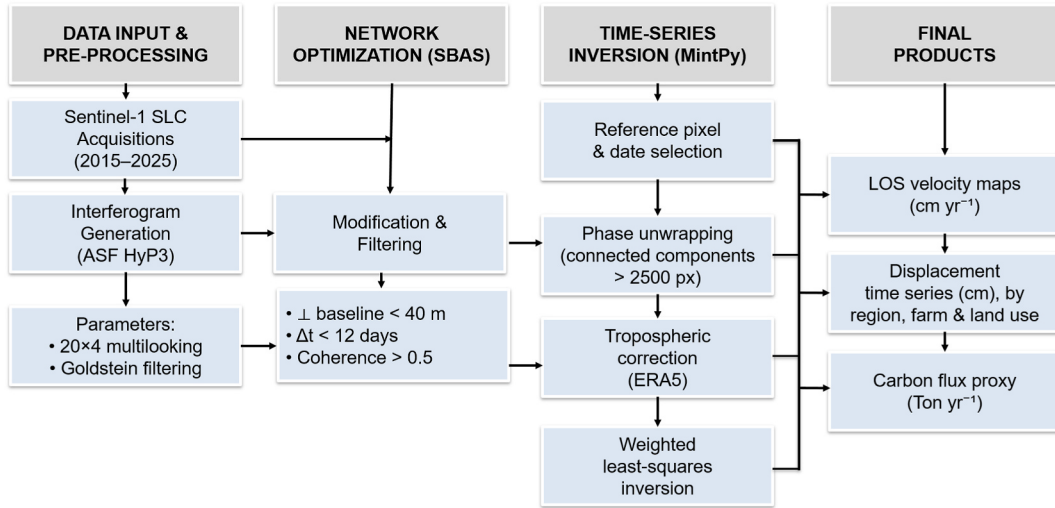


Fig. 2. Overview of the SBAS-InSAR processing workflow implemented in MintPy, from Sentinel-1 data preparation to deformation time-series and derived products.

(a) Interferogram Preprocessing and SBAS Network Optimisation

Interferogram stacks containing unwrapped phase, coherence, and geometric information were loaded into MintPy for SBAS processing. Interferometric pairs were constrained to perpendicular and temporal baselines of 40 m and 12 days, respectively, to maximise phase coherence (Fig. 3). Interferograms exceeding these thresholds were excluded, and an additional coherence-based refinement was applied using a threshold of 0.5 to suppress noisy measurements while retaining sufficient network connectivity. Based on these criteria, 58 interferograms were removed. This network refinement is standard practice in SBAS processing and follows established ASF HyP3 guidelines for ensuring reliable deformation estimates in low-coherence environments (Fielding et al., 1998; Zhang et al., 2019; Alaska Satellite Facility ASF, 2021).

(b). Reference Point

The reference point for InSAR time-series analysis was selected using a coherence-based approach to ensure measurement stability. The processed InSAR data produced a coherence map (146×70 pixels, mean coherence = 0.875), from which we identified one of the most stable pixels by applying a minimum coherence threshold of 0.9, and verifying local stability within a 3×3 -pixel window. (Supplementary Figure S-1). In Fig. 5, all three line-of-sight (LOS) velocity maps record values near zero at the reference point (black dot $0^{\circ}13'53''\text{W}$, $52^{\circ}26'24''\text{N}$). Coherence at this point is very high (≈ 0.9) with no displacement. The processed InSAR time series data also confirms that the chosen reference point is stable from 2015 to 25 (Figure S-6). Google Earth imagery from 2008, 2014, 2020, and 2025 confirms that this road beside the railway has remained unchanged, satisfying InSAR's optimal reference criteria of prioritising stability, coherence, and land cover, thereby minimising phase unwrapping errors and enhancing the reliability of deformation estimates.

(c). Plotting the Interferogram Modified Network

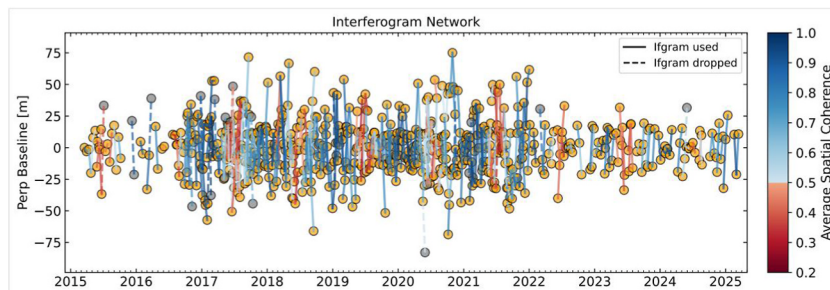


Fig. 3. The interferogram network is displayed in time-baseline space and colour-coded by the average spatial coherence of the interferograms. Dashed lines indicate interferogram pairs excluded for exceeding the perpendicular baseline threshold of 40 m. Reddish lines denote pairs dropped due to falling below the spatial coherence threshold of 0.5. Interferograms marked with dashed or reddish lines did not meet either criterion.

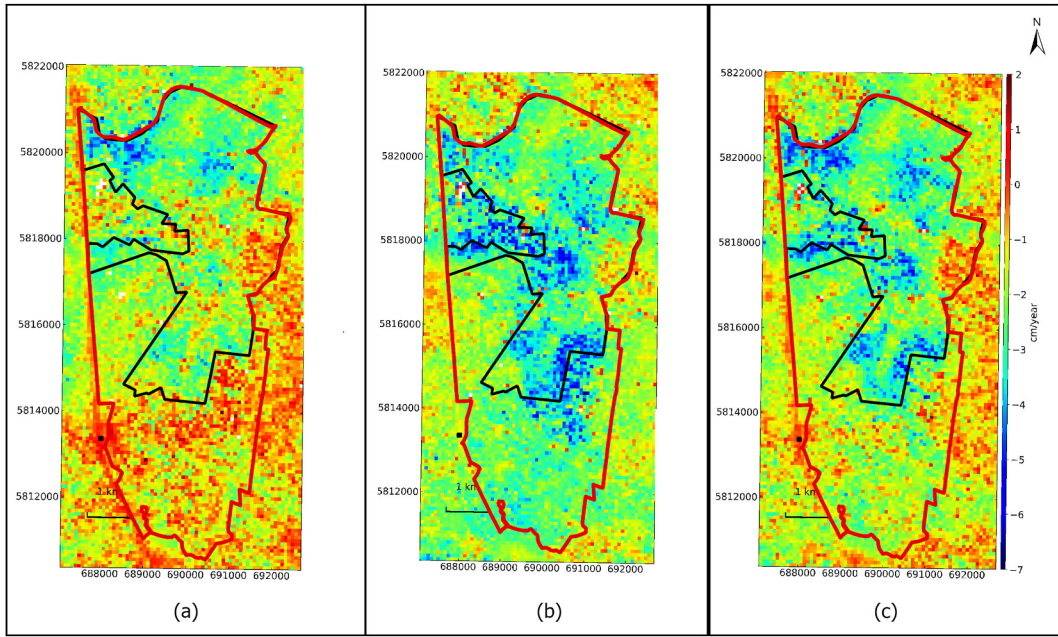


Fig. 4. Average Phase Velocity Map (2016-2025) for the Great Fen, derived from the Ascending Path, Descending Path, and Combined Satellite Datasets (left to right) shown prior to SBAS network optimisation and coherence-based filtering. The red outline marks the Great Fen boundary, the black outline indicates the study (farm) area, and the black point represents the reference location.

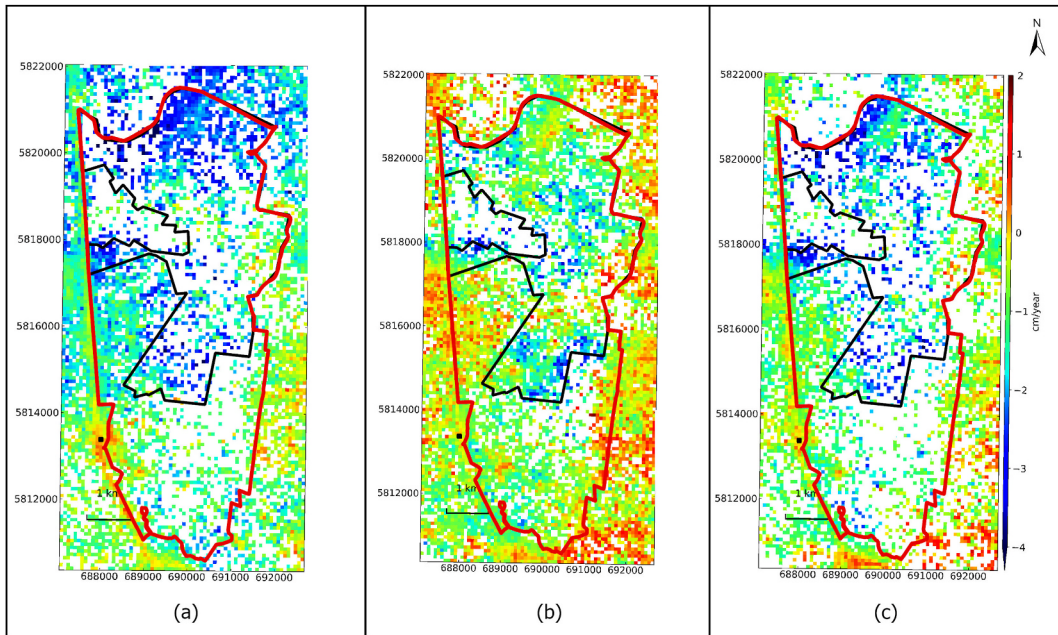


Fig. 5. LOS Displacement (Processed Velocity Timeseries Map, 2016-2025) for the Great Fen from (left) Ascending Path, (middle) Descending Path, & (right) Combined Satellite Datasets for Great Fen. Negative values (cool colours) indicate subsidence, while positive values (warm colours) indicate uplift. White (no colour) represent areas where the InSAR signal was unreliable due to low coherence often caused by vegetation, water bodies, or other surface change, and were excluded from analysis. Compared to the raw phase map in Fig. 4, which includes noise and uncorrected artefacts, these maps show filtered, geophysically meaningful deformation rates. At the reference point (black dot $0^{\circ}13'53''\text{W}$, $52^{\circ}26'24''\text{N}$), all three LOS velocity maps recorded values near zero.

After baseline and coherence filtering, the remaining interferogram network was inverted into a deformation time series using a weighted least-squares (WLS) approach, with weights defined as the inverse of the phase covariance (Tough et al., 1995; Guarnieri and Tebaldini, 2008). The resulting interferogram network was visualised in temporal and perpendicular baseline space (Fig. 3). Due to limited satellite acquisitions for a consistent path and frame between mid-2015 and mid-2016, the network is sparse in the early period. To ensure continuity and robustness of the time-series analysis, subsequent processing was restricted to data acquired from mid-2016 onwards. This resulted in 505 interferograms generated from 633 Sentinel-1 acquisitions across ascending and descending tracks.

2.3.2. Error analysis (separating signal from noise)

After modification of the interferogram network, inversion was performed to generate displacement time series and long-term surface velocity estimates. Measurement accuracy depends on the quality of the inversion and the effective separation of true ground displacement from atmospheric and noise-related phase components. Tropospheric delays were corrected within the MintPy workflow using the PyAPS3 package, which applies ERA5 atmospheric reanalysis data to model and remove stratified atmospheric phase delays in the satellite line of sight. These corrections were applied prior to time-series inversion to reduce atmospheric contamination of deformation signals.

Following inversion, MintPy metrics were used to assess pixel reliability and residual noise. Spatial coherence was used to evaluate phase consistency across neighbouring pixels (Figure S-1), while temporal coherence quantified the stability of the phase through time. A coherence-based mask was applied to retain only stable pixels for deformation analysis. Phase unwrapping was further constrained by removing small, disconnected components (threshold = 2500 pixels) likely associated with noise or artefacts. Velocity uncertainty was quantified from the standard deviation of the linear regression applied to the displacement time series (Figure S-11), providing an estimate of confidence in the derived deformation rates.

2.3.3. Validation and temporal analysis of Peatland dynamics

(a). Seasonal Surface Deformation Analysis

To evaluate short-term (seasonal) surface dynamics, we analysed the temporal InSAR displacement signal for cyclical patterns corresponding to seasonal hydrological changes. The InSAR-derived displacement time series was detrended to isolate seasonal components and then compared against two independent hydrological indicators: (1) the three-month Standardised Precipitation Index (SPI-3) for the Great Ouse catchment from the UKCEH Water Resources Portal, and (2) soil moisture data from the COSMOS-UK Fincham site (~12 km from the study area), including volumetric water content at 5 cm and 50 cm depths. Both datasets were standardised and aligned temporally with the InSAR time series to assess the consistency between seasonal ground movement and moisture dynamics, thus providing additional validation of the InSAR signal.

(b). Long-Term Displacement and Restoration Impact Assessment

To validate InSAR-derived displacement measurements, we compared them with ground-based peat-depth surveys from the 1980s Lowland Peat Survey (Burton and Hodgson, 1987) and more recent field measurements reported by Jasper et al. (2022) and Girkin et al. (2022). These datasets, originally collected to assess carbon stocks and historical peat loss, provide independent evidence of long-term peat subsidence patterns. Peat-depth measurements from the 1980s survey and the 2021–2022 field campaign were interpolated to a common spatial grid using Ordinary Kriging with a consistent variogram model in ArcGIS Pro. The resulting peat-depth rasters were differenced to estimate mean annual subsidence over the 38-year period (1987–2025), which was then compared with InSAR-derived deformation rates (2015–2025) to assess consistency and ongoing peat degradation.

Time-series analysis was first conducted across the Great Fen boundary to examine spatial variation in surface motion in relation to restoration timing (Fig. 1b). In addition, InSAR-derived deformation was compared across three areas with contrasting land-use and management histories: Holme Fen and Woodwalton Fen, which represent long-standing wetland reserves under conservation management with relatively high and stable water tables, and previously intensively drained farmland restored from 2009 (Region B) and 2012–2014 (Region A) (Fig. 1b).

Based on land-use history, we hypothesised that subsidence would be lowest in the National Nature Reserves under long-term wet conservation management, followed by earlier-restored farms in Region B, and highest in later-restored farms in Region A. To test this, regional surface motion was quantified by spatially averaging LOS displacement values across all pixels within each area. The resulting averaged time series were used to examine temporal patterns of deformation and assess how restoration timing and land management influence peat surface dynamics.

2.3.4. Estimation of deformation-based carbon flux

Deformation-associated peat carbon flux was estimated using Equation (3), which relates changes in accumulated peat volume to peat carbon mass (Hoyt et al., 2020; Khodaei et al., 2023):

$$C_{em/ab} = A \times D_v \times BD \times C_{org} \quad \text{Equation 3}$$

where $C_{em/ab}$ is the annual deformation-associated carbon flux (kg C yr^{-1}), A is the peatland area (m^2), D_v is the mean surface

deformation rate derived from the InSAR time series (m yr^{-1}), BD is the dry bulk density of peat (kg m^{-3}), and C_{org} is the organic carbon content of dry peat (dimensionless mass fraction).

InSAR-derived surface deformation integrates multiple processes, including reversible hydroelastic deformation driven by water-table fluctuations, mechanical compaction, and irreversible peat oxidation. Only peat oxidation directly represents carbon loss to the atmosphere. Because these contributions cannot be independently resolved using InSAR alone, Equation (3) is applied here as a first-order, deformation-based proxy for potential peat carbon loss, rather than as a direct estimate of net ecosystem carbon balance or CO_2 exchange.

For baseline calculations, we adopted a single representative dry bulk density of 400 kg m^{-3} . The adopted value is justified by both regional literature and site-specific measurements. Similar values have been used in prior carbon assessments of the Fenland region (Milne et al., 2006; Holman, 2009). The Great Fen is characterised as a shallow peatland. The deepest peat in the Great Fen occurs around Holme Fen National Nature Reserve, where peat depth is $< 4 \text{ m}$ and locally reduced to about 2–3 m, whereas across much of the surrounding area the peat is now very shallow or entirely absent (Great Fen Partners, 2010), for which bulk densities substantially higher than blanket bog peat are expected. This value is further supported by laboratory analyses of peat cores collected within the Great Fen restoration area during a 2021–2022 field campaign (Jasper et al., 2022), which are consistent with measurements reported by the Defra SP1210 programme (Evans et al., 2017).

A mean organic carbon content of 31% for UK lowland peat was applied across the study area. This value is derived from Holman (2009), which synthesises analytical measurements of Fenland peat horizons, and is corroborated by Natural England's national assessment of peat carbon stocks (NE257; Natural England, 2010). Contemporary field measurements from the Defra SP1210 Interim Report indicate an organic carbon content of 30.8% for shallow peat in East Anglia (Evans et al., 2017), providing direct regional validation of the 31% assumption. The original basis for this value is traceable to Milne et al. (2006), who analysed organic carbon content across the UK National Soil Inventory and historical soil survey datasets. Together, these sources establish 31% as a regional average for East Anglian lowland fen peat and improve transparency and reproducibility of parameter selection (Section 2.4.4). While this approach does not capture fine-scale spatial variability in peat properties, it provides internally consistent assumptions suitable for regional-scale comparison of deformation-associated carbon flux between land-use and restoration classes. Negative values of D_v indicate subsidence and positive values indicate surface uplift; resulting flux estimates are therefore interpreted in a relative sense, reflecting deformation-associated carbon loss or retention.

To assess sensitivity to uncertainty in peat properties and process attribution, a bounded sensitivity analysis was conducted. Dry bulk density was varied between 250 and 550 kg m^{-3} and organic carbon content between 0.25 and 0.45, spanning literature-reported values for degraded and rewetted lowland peat under contrasting management conditions (Natural England, 2010; Evans et al., 2017). In addition, an oxidation attribution factor (f_{ox}) was introduced to represent the fraction of long-term deformation assumed to correspond to irreversible peat oxidation. The baseline scenario assumes $f_{\text{ox}} = 1$, representing a conservative upper-bound case in which all long-term deformation is attributed to oxidation, while sensitivity bounds explore f_{ox} values between 0.3 and 0.7, consistent with field-based studies showing that oxidation typically accounts for less than half of total subsidence in drained peatlands (Pronger et al., 2014; Liu et al., 2020).

For each land use category, deformation-based carbon fluxes were recalculated under baseline and bounded parameter combinations to generate uncertainty envelopes. These bounds are used to guide interpretation of absolute flux values in Section 3.4, while preserving robust relative comparisons between land-use and restoration classes.

3. Results and discussion

3.1. Raw phase and LOS velocity time series

3.1.1. Average raw phase map

The initial output of the InSAR process is a raw average phase velocity map (Fig. 4), which reflects the cumulative phase differences calculated from multiple acquisitions. This map captures the raw phase differences (i.e., the time delays between transmitted pulses and their echoes) without any filtering or error removal. As a result, the map includes atmospheric and tropospheric delays, topographic effects, and noise, causing the values to be overestimated. Despite these limitations, the map provides a useful preliminary overview of regional characteristics and changes. For example, Fig. 4 shows a relatively higher phase delay in the northern part of the Fen area, which may be due to ground subsidence as well as atmospheric and other error sources.

Overall, the average raw phase velocity time series (2016–2025) across the great Fen region shows a range of values of -4.21 to 5.48 cm/year for ascending passes, -11.13 to 0.35 cm/year for descending passes, and -7.11 to 1.26 cm/year when the data are combined.

3.1.2. Line of sight velocity displacement

Although the peat subsidence caused by agricultural drainage is initially strongly non-linear with time, the long history of drainage in the Fens means that recent ground deformation from various geophysical or anthropogenic processes can be approximated as linear. Here, the rate of recent ground deformation is estimated by calculating the slope of a linear fit to the time-series data. The velocity map is generated from unwrapped interferograms, providing the Line of Sight (LOS) displacement (in centimetres) for each acquisition. These displacement values serve as the basis for calculating vertical velocity by analysing the linear relationship between displacement and time using data from all available images (Umarhadi et al., 2021).

Table 2

Data range of LOS displacement (Processed velocity timeseries map) for Great Fen with ascending, descending, and combined (ascending + Descending) satellite path.

LOS Displacement (Processed Velocity Timeseries Map 2016-25)	Ascending	Descending	Combined
Scale (cm/year)	−5.31 to 1.08	−5.32 to 2.12	−4.46 to 1.74

Fig. 5 displays the LOS displacement results for the Great Fen area based on ascending, descending, and combined datasets, with the scale details provided in Table 2. These results represent the overall displacement rate from 2016 to 2025 after eliminating tropospheric delays and other errors. The difference in pixel coverage between Figs. 4 and 5 reflects the type of data presented. Fig. 4 shows raw phase velocity (temporal average of all unwrapped phases, including noisy pixels), while Fig. 5 presents quality-filtered LOS velocity (SBAS-processed, noise-corrected). This filtering trades pixel density for measurement reliability, a fundamental SBAS characteristic, resulting in fewer but more robust deformation estimates. These ascending datasets exhibit greater displacement away from the sensor compared to the descending datasets, while the combined dataset yields deformation values that fall between the two. Notably, across all three datasets, the northern Fen consistently shows more pronounced displacement away from the sensor than other areas of the Fen.

The reliability of results derived solely from either the ascending or descending path is limited due to the satellite's inherent LOS bias. Sentinel-1, an eastward-looking satellite, records negative values when the surface moves away from the sensor (indicating subsidence or eastward displacement), while positive values signify movement towards the sensor (indicating uplift or westward displacement). This directional effect, combined with the number of processed interferograms, significantly influences the outcomes. The slight discrepancies in magnitude observed in Fig. 5, comparing ascending and descending LOS velocities, may be attributed to minor differences in incidence angles. Although Sentinel-1 satellites have similar incidence angles for ascending and descending passes, they are not identical, typically ranging between 29° and 46° depending on the acquisition mode (European Space Agency, n.d.). These small variations in incidence angles can lead to differences in LOS measurements, even for purely vertical deformation. Additionally, variations in the interferogram pairs selected for the SBAS (Small Baseline Subset) model, as well as the number of pairs used in the analysis, could contribute to these minor inconsistencies. While it is possible to decompose LOS measurements into vertical and horizontal components using both ascending and descending Sentinel-1 data, we did not pursue this step because the LOS velocities from both geometries show consistently identical signs across the study area. As illustrated in Fig. 5, a dominant east–west displacement would produce opposite LOS signs (negative in ascending, positive in descending, or vice versa) (Norwegian Geological Survey, n.d.). The same-sign pattern we observed indicates that horizontal motion is negligible and that the deformation is primarily vertical (subsidence or uplift). This interpretation is further supported by the geological stability of East Anglia, which lies on the Eurasian Plate with no active faults or recent tectonic activity (British Geological Survey, nd; Hancock and Skinner, 2000). Given this evidence, explicit decomposition would not materially alter the results and was therefore deemed unnecessary.

In this context, Fig. 5 represents positive values (depicted in red and orange) as movement towards the sensor (uplift) and negative values (shown in shades of lighter yellow, green, and blue) as movement away from the sensor (subsidence). For further analysis, the combined dataset was prioritised, as it offers a greater number of interferograms. The results indicate LOS displacement rates ranging from −4.46 to 1.74 cm/year over the period 2016 to 2025. In particular, the northern part of the Great Fen shows a higher subsidence rate, with some pixels indicating up to 3 cm/year of subsidence, while some red pixels exhibit uplift of up to 2 cm/year. This uplift is likely influenced by factors such as infrastructure development, soil moisture changes, and restoration efforts, all of which can locally enhance surface elevation.

3.2. Seasonal Surface Deformation Analysis

To examine whether the short-term (sub-annual) signal extracted from the InSAR time-series reflects seasonal swelling and shrinkage of the peat ground surface rather than longer term peat wastage or accumulation, we compared it with two independent indicators of seasonal wetting and drying.

First, a three-month Standardised Precipitation Index (SPI-3) product for the Great Ouse catchment obtained from the UKCEH water resource portal (Barker et al., 2022). The SPI rescales accumulated rainfall anomalies so that values > 0 denote wetter-than-normal conditions, values < 0 drier-than-normal. Second, soil-water content was taken from the Fincham COSMOS-UK site (~12 km north-east of the study area), where a cosmic-ray neutron probe provides daily volumetric water estimates for the upper metre of the soil profile. We used the 5 cm and 50 cm depth layers, converted each to standardised monthly means to make them unitless and directly comparable with SPI.

The regional-mean InSAR displacement was obtained by averaging line-of-sight (LOS) values for all coherent pixels in the entire Fen area. Fig. 6 shows the detrended InSAR displacement time series (blue line) with two independent hydrological series; a catchment-scale SPI-3 and profile soil-moisture anomalies. The upper panel indicates displacement with the 50 cm moisture layer, the lower panel with the 5 cm layer; grey bands mark the dry season (May–September).

A consistent seasonal rhythm is clear. The ground surface rises during the wet half of each year and subsides as the profile dries. The ascent through the exceptionally wet winter of 2019–2020 exceeds +0.6 cm and is reflected by strong positive anomalies in 50 cm moisture and in SPI-3. In contrast, the severe droughts of 2018 and 2022 show negative SPI-3 bars, depleted 50 cm moisture and a corresponding fall of about 0.6 cm in the displacement curve. The timing, however, is not uniform. In 2019–2020 the moisture

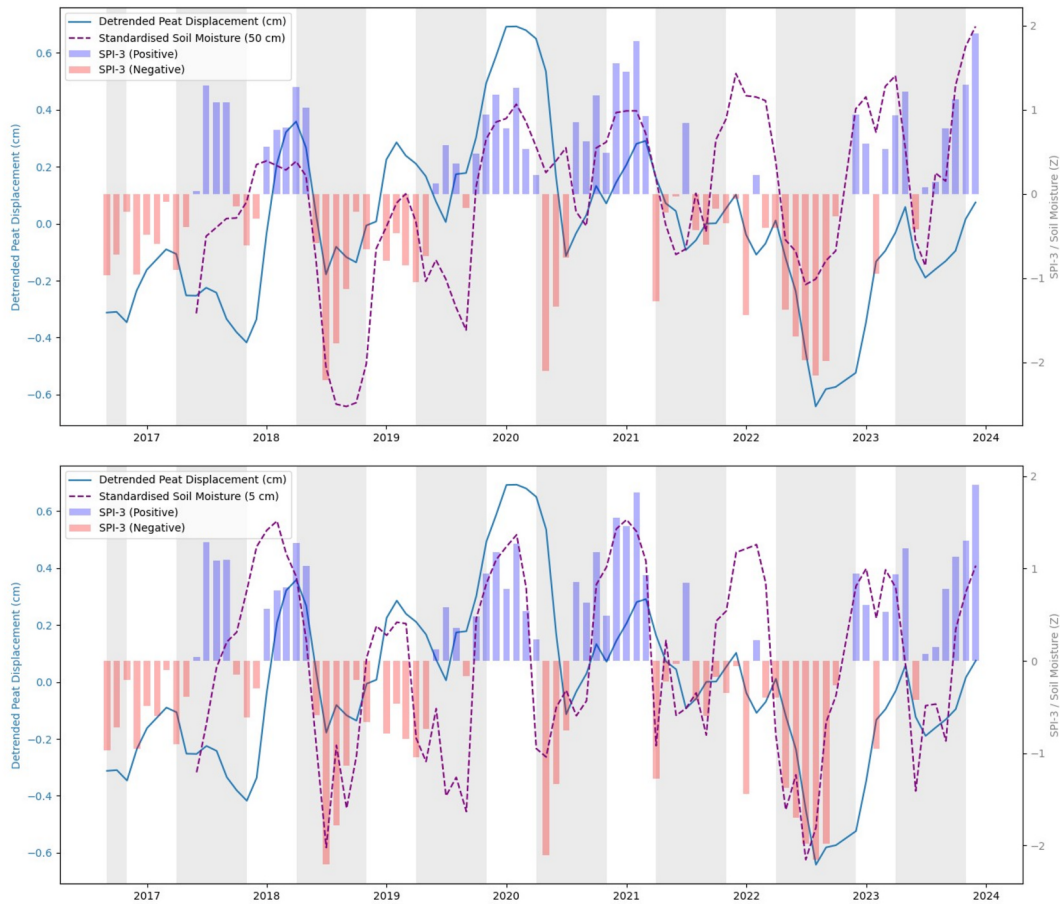


Fig. 6. Seasonal co-variations between detrended InSAR ground-surface displacement and independent hydrological indicators (2016 – 2024). **Upper panel:** displacement (blue line), 50 cm soil-moisture anomaly (purple dashed line, right axis) and SPI-3 bars (blue = wetter than normal, red = drier than normal, left axis). **Lower panel:** same displacement curve compared with the 5 cm soil-moisture anomaly. Grey vertical bands denote the dry season (May–September).

anomaly turns positive a few weeks before the displacement maximum, whereas during the rapid onset of drought in spring 2018 SPI-3 and displacement plunge almost simultaneously. Such year-to-year variability is expected because infiltration rates, evapotranspiration and antecedent water levels all modulate how quickly rainfall anomalies propagate to the peat matrix.

The shallow 5 cm seem to oscillate rapidly in response to individual rain events and evapotranspirative drying that are not reflected immediately in the displacement series. This poor match suggest that seasonal expansion and contraction of the peat body are controlled mainly by intermediate-depth moisture rather than by transient surface wetting. This depth-dependent response likely reflects the hydroelastic properties of the peat matrix: surface moisture fluctuations cause only transient loading, whereas intermediate-depth (50 cm) moisture changes drive more sustained swelling and shrinkage through capillary tension variations and load redistribution in the peat structure (e.g., Price and Schlottzhauer, 1999). The 50 cm depth approximately corresponds to the capillary fringe and active rooting zone in our study area, where hydraulic properties exert dominant control on bulk deformation.

Overall, the depth-dependent agreement between InSAR displacement and soil water, and the broadly synchronous variations with SPI-3 and soil moisture, indicate that the SBAS time-series is capturing hydrologically driven surface loading and unloading associated with changes in near-surface moisture and water-table dynamics rather than artefact of atmospheric delay. This provides confidence to the interpretation of longer-term subsidence patterns (see section 3.3.).

3.3. Spatial and temporal patterns of Long-Term Displacement

3.3.1. Great Fen and its sub-regions

Fig. 7 presents the time series of InSAR-based deformation results from 2016 to 2025 for the Great Fen, and for spatially averaged pixel values across three equal divisions of the Great fen area (north centre and south of the Fen area). Overall, the Great Fen region shows an average subsidence rate of 1.24 cm/year (Fig. 7b). Superimposed on these long-term trends are short-term fluctuations, due to seasonal variations in soil moisture, water table and atmospheric effects (Fig. 6).

Fig. 7c indicates that the northern region experienced the highest average subsidence (approximately 1.51 cm/year), followed by the central region (1.31 cm/year), while the southern region exhibits the lowest subsidence rates of 0.84 cm/year. These variations underline the spatial heterogeneity of peatland subsidence within the Great Fen area.

In 2021 and 2022, Girkin et al. (2022), conducted an evaluation of peat depth and properties in the Great Fen Project area incorporating measurements dating back to the 1980s. As a first step, we compared the spatial patterns of interpolated peat loss (Girkin et al., 2022) and InSAR-derived deformation map (Fig. 8). This visual inspection highlighted consistent zones of elevated peat loss and

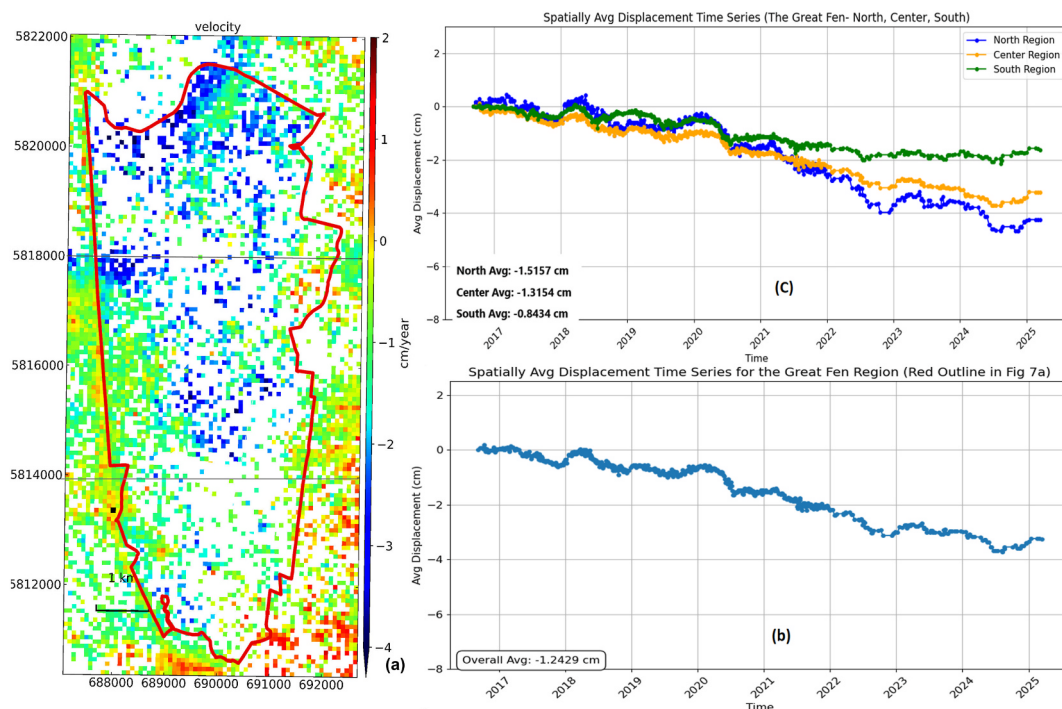


Fig. 7. (a) InSAR based Line of Sight Deformation map of the Great Fen Area (outlined in red). (b) Spatially averaged displacement timeseries for the entire Great Fen Area, (c) Spatially averaged displacement timeseries for 3 equal divisions: North, Centre, and South of fig. 7a).

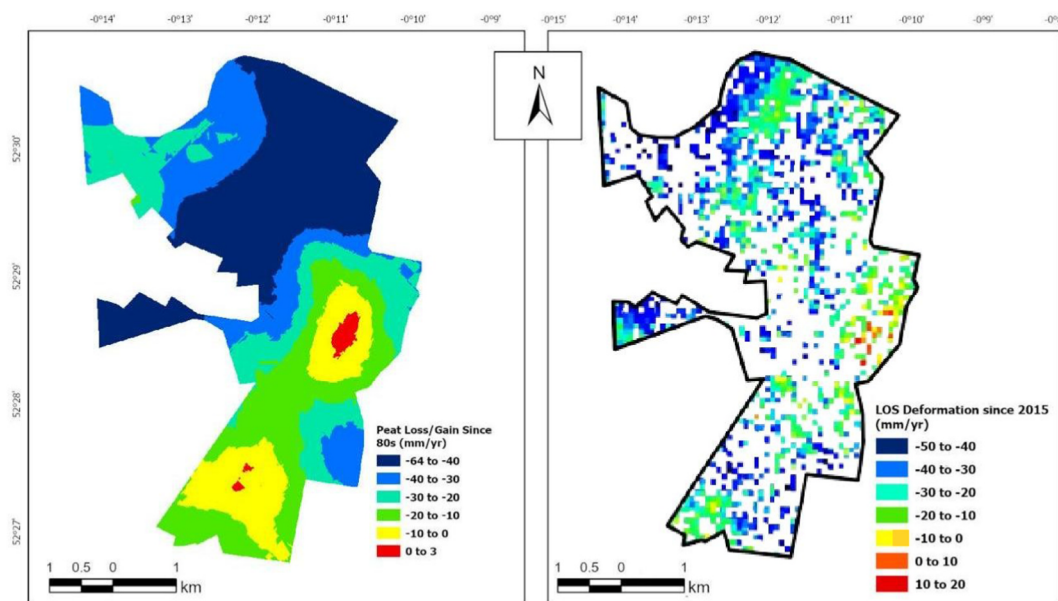


Fig. 8. Great Fen Peat Changes. Left: Interpolated peat loss/gain (mm/yr) from the 1980s to 2022 (Girkin et al., 2022; Jasper et al., 2022). Right: InSAR based LOS deformation (mm/yr) from 2016 to 2025.

subsidence, particularly in the northern sector with relatively lower loss in the centre-east. We then extracted the mean rates of peat surface change from SAR Sentinel-1 data (2015–2024) for each farm polygon within the study area. These values were then compared against the long-term average peat loss rates derived from traditional ground surveys conducted between the 1980s and 2021. To explore the relationship between the two independent datasets, we plotted the mean SAR-based rates against the survey-based rates for each farm. This allowed us to assess whether farms experiencing higher or lower long-term peat loss also show corresponding patterns in recent SAR observations. The results show that, while the magnitudes differ (with survey rates generally more negative, reflecting longer-term averages), the spatial pattern of peat loss is consistent between the two methods. Farms identified as more stable in the surveys (e.g., Chalderbeach) also show relatively low SAR-derived loss rates, whereas farms with high historical loss (e.g., Ladyseat, Holme Lode) similarly exhibit stronger subsidence in the SAR data (Figure S-7).

Overall, the higher mean peat loss rate of 1.80 ± 0.65 cm per year for the Great Fen area compared to our InSAR based average subsidence rate of 1.24 cm per year is to be expected due to their longer period in which there was more peat to degrade and probably lower drain water levels. Girkin et al. (2022) focused on peat loss, while this InSAR based study examines the surface displacement.

3.3.2. Assessing the effects of restoration on Peatland dynamics across regions

The InSAR analysis revealed distinct spatial and temporal patterns of ground displacement across the study regions from 2016 to 2025 (Fig. 9). Region B, which includes early restoration areas such as Ladyseat Farm, Old Decoy, New Decoy, Corney, and Chalderbeach Farm, shows an average subsidence of 1.17 cm/yr. Region A, encompassing later restored farms which are Holme Lode Farm, Tower and Froghall Farm, and Ironhouse Farm, exhibits the highest average subsidence rate at 1.40 cm/yr. In contrast, Holme Fen and Woodwalton Fen, two National Nature Reserves in the Great Fen area that have remained under long-term wet conservation management exhibited the lowest subsidence rates of 0.48 cm/year among all sites as shown in Fig. 9b. Individually, Holme Fen showed an average subsidence of 0.54 cm/year, while Woodwalton Fen demonstrated even lower subsidence at 0.41 cm/year.

The InSAR time series (Fig. 9) captures both long-term trends and short-term fluctuations, likely driven by re-wetting schemes, seasonal variations in soil moisture and atmospheric disturbances, providing a comprehensive view of peatland dynamics.

3.4. Deformation-based carbon flux estimates

Deformation-associated carbon fluxes were estimated using Equation (3) and the parameter assumptions defined in Section 2.4.4. Resulting values represent first-order, deformation-based proxies for potential peat carbon loss and do not constitute direct measurements of net ecosystem CO₂ exchange.

Using the baseline parameter set (dry bulk density = 400 kg m^{-3} , organic carbon content = 31%, oxidation attribution factor $f_{ox} = 1$), Table 3 summarises deformation-based carbon flux proxies for each land-use category. Farms in Region A (later-restored sites), which exhibited the highest mean subsidence rate (1.40 cm yr^{-1}), show the largest deformation-associated carbon loss proxy,

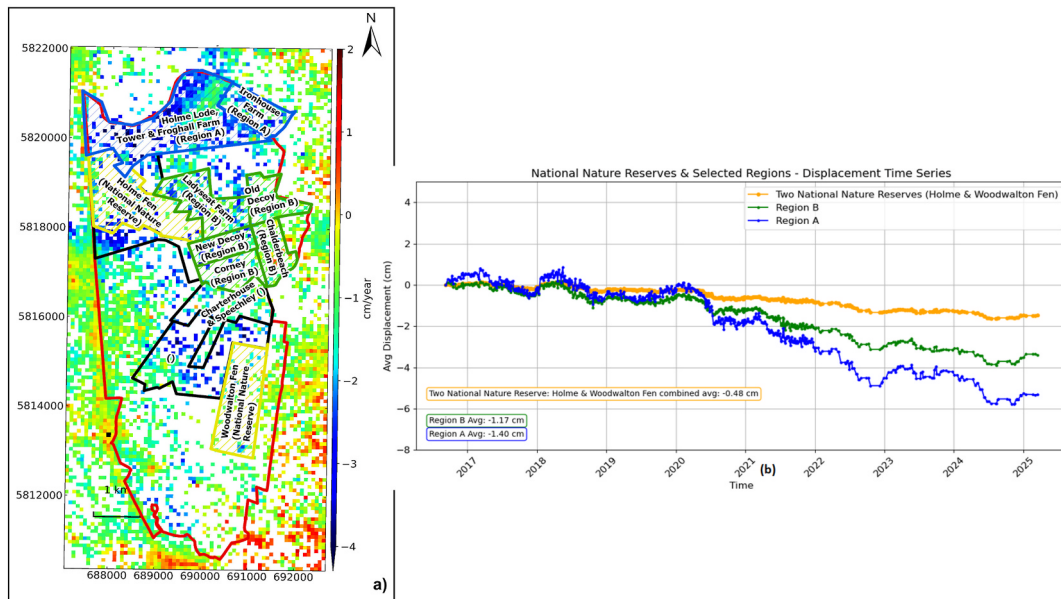


Fig. 9. (a) Line of Sight Deformation at farms in the Great Fen study area. (b) Spatially averaged displacement time series (cm) for Two National nature Reserve: Holme Fen & Woodwalton Fen, Region B (Green Outline -Early restoration) encompassing Ladyseat Farm, Old Decoy, New Decoy, Corney, and Chalderbeach Farm, and Region A (Blue Outline -Late restoration) which includes Holme Lode Farm, Tower and Froghall Farm, and Ironhouse Farm.

Table 3

Baseline deformation-based carbon flux proxy derived from InSAR surface deformation using Equation (3) and the baseline parameter set ($BD = 400 \text{ kg m}^{-3}$, $C_{org} = 31\%$, $f_{ox} = 1$). Values represent first-order proxies for potential peat carbon loss and are shown for comparative purposes across land-use and restoration classes.

Region	Farms	Deformation (cm yr ⁻¹)	CO ₂ Flux (Ton yr ⁻¹)	Tons CO ₂ /ha/year
Region A	Holme Lode Farm, Tower and Froghall Farm, and Ironhouse Farm	-1.40	-8917.08	-17.37
Region B	Ladyseat Farm, Old Decoy, New Decoy, Corney, and Chalderbeach Farm	-1.17	-7246.74	-14.50
Two National Nature Reserve	Woodwalton Fen, Holme Fen	-0.48	-2791.23	-5.98

equivalent to $17.37 \text{ t CO}_2 \text{ ha}^{-1} \text{ yr}^{-1}$. Region B farms (earlier restoration), with a lower mean subsidence rate of 1.17 cm yr^{-1} , show correspondingly lower values around $14.50 \text{ t CO}_2 \text{ ha}^{-1} \text{ yr}^{-1}$. The two National Nature Reserves (Holme Fen and Woodwalton Fen), under long-term conservation management under long-term wetland conservation management, exhibit the lowest deformation-associated carbon flux proxy, averaging $5.98 \text{ t CO}_2 \text{ ha}^{-1} \text{ yr}^{-1}$.

Sensitivity analysis demonstrates that absolute flux values are strongly dependent on assumptions regarding peat bulk density, organic carbon content, and the fraction of deformation attributed to irreversible peat oxidation. When parameters are varied within the bounded ranges defined in Section 2.4.4 ($BD = 250\text{--}550 \text{ kg m}^{-3}$, $C_{org} = 0.25\text{--}0.45$, $f_{ox} = 0.3\text{--}0.7$), deformation-based carbon flux estimates span approximately an order of magnitude (Fig. 10). Despite this uncertainty in absolute magnitude, the relative ranking of land-use categories is preserved across all plausible parameter combinations, with two National Nature Reserves consistently exhibiting the lowest deformation-associated carbon loss proxy, followed by earlier-restored farms (Region B) and then later-restored farms (Region A). While our analysis appropriately acknowledges uncertainty in absolute carbon flux values, the fundamental conclusions regarding the effectiveness of restoration timing in reducing peat deformation are not compromised by this parameter uncertainty.

These results indicate that InSAR-derived surface deformation provides a spatially explicit indicator of relative peat carbon vulnerability and mitigation associated with drainage history and restoration timing. However, the deformation-based flux estimates presented here do not account for other major components of peatland carbon balance, including autotrophic and heterotrophic respiration (Rankin et al., 2022), methane emissions under rewetted conditions (Leifeld and Menichetti, 2020), or dissolved organic carbon export (Clark et al., 2008). Consequently, they should be interpreted as comparative indicators of deformation-associated carbon loss rather than definitive measures of carbon sequestration or net ecosystem carbon balance.

3.5. Limitations and future recommendations

3.5.1. Key intrinsic limitations

C-band Sentinel-1 data has limited penetration through vegetation. The radar signals are either absorbed or reflected from varying depths within the canopy, resulting in decorrelated signals particularly in densely vegetated peatland areas. This can lead to signal attenuation in the active vegetation layer, though some penetration into the upper few centimetres of peat substrate still occurs. While in this study, these limitations were mitigated through the use of the SBAS approach combined with conservative temporal and perpendicular baseline thresholds and coherence filtering, future studies could integrate L-band SAR data (e.g., ALOS-2 PALSAR-2), which exhibits deeper canopy penetration and improved coherence in vegetated areas (Rosenqvist et al., 2003). Additionally, vegetated areas typically exhibit lower coherence due to potential growth or movement of vegetation between different acquisitions. This

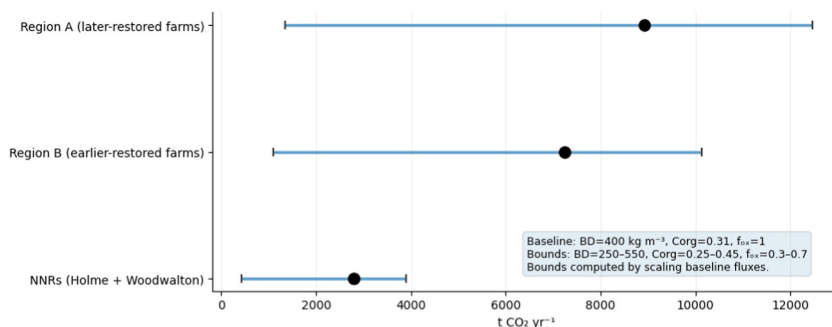


Fig. 10. Sensitivity bounds around baseline deformation-based carbon flux proxies for each land-use category. Bars show baseline estimates derived using $BD = 400 \text{ kg m}^{-3}$, $C_{org} = 31\%$, and $f_{ox} = 1$. Error bars indicate lower and upper bounds obtained by varying peat bulk density ($250\text{--}550 \text{ kg m}^{-3}$), organic carbon content ($0.25\text{--}0.45$), and oxidation attribution factor ($f_{ox} = 0.3\text{--}0.7$), as defined in Section 2.4.4. Absolute values vary widely, but relative differences between land-use classes are preserved across all scenarios.

decorrelation is mainly caused by changes in scattering characteristics of ground objects during satellite revisit periods. This leads to a reduced number of coherent pixels available for time-series analysis. While SBAS relies only on consistently coherent pixels, ISBAS approach can mitigate this limitation by including intermittently coherent pixels, thereby improving spatial coverage in vegetated or dynamic landscapes (Sowter et al., 2013).

3.5.2. Key extrinsic limitations

Limited temporal overlap between InSAR (2016–2025) and ground surveys (1980s–2022) introduces uncertainty. Moreover, the datasets measure different quantities; surveys capture changes in peat depth, whereas InSAR measures surface deformation, so a direct, one-to-one comparison of magnitudes is not expected. Our comparison is therefore interpretive and focuses on spatial correspondence and relative patterns, not exact numerical agreement.

Applying constant peat bulk density and organic carbon values oversimplifies variability across land uses. Specifically, we used uniform values for peat bulk density and organic carbon content across all land types. While this approach allows for a consistent, first-order comparison, it may not fully reflect the differences between intact peat in nature reserves and degraded, compacted peat in agricultural areas. In reality, agricultural peatlands often have higher bulk density and potentially lower organic carbon content due to oxidation and mineralisation. Therefore, the absolute flux values should be interpreted cautiously, as they are driven mainly by the variation in deformation rates (Dv) rather than site-specific peat properties.

Equation (3) assumes that deformation-driven CO₂ emissions are the dominant pathway of carbon loss. However, this approach does not account for other important fluxes. Autotrophic respiration from roots and microbial associations, for instance, can contribute 47–62% of total ecosystem respiration in bog environments (Rankin et al., 2022), meaning that deformation-based methods may overestimate peat-derived CO₂ loss in areas with high vegetation activity. Rewetting may also enhance CH₄ emissions under anaerobic conditions, although long-term assessments suggest that CO₂ reductions generally outweigh CH₄ increases (IUCN UK Peatland Programme, 2024). In addition, dissolved organic carbon (DOC) export via drainage represents a substantial and hydrologically controlled loss pathway, particularly in drained peatlands (Worrall et al., 2011). Taken together, these limitations suggest that focusing solely on deformation may lead to overestimation of CO₂ loss in vegetated systems while underestimating total carbon loss in settings where DOC and CH₄ fluxes are substantial. For future work, integrating site-specific soil data would refine these flux estimates and strengthen their applicability in carbon accounting frameworks.

Our subsidence rates for restored farms (1.17–1.40 cm/year) align with values reported for temperate drained peatlands in similar climatic zones (Khodaei et al., 2023; Hoyt et al., 2020), while our National Nature Reserves (0.48 cm/year) approach near-natural conditions, suggesting that restoration measures are reducing peat loss rates.

4. Conclusion

Our study has demonstrated the effectiveness of InSAR for monitoring lowland peatland dynamics, using the case study in the Great Fen area of Cambridgeshire between 2016 and 2025. By integrating Sentinel-1 satellite imagery, and applying SBAS time-series analysis in MintPy, we obtained detailed displacement maps revealing clear differences in subsidence patterns linked to land management and restoration. Two national nature reserves, Holme Fen and Woodwalton Fen, under long-term wetland conservation management, demonstrated the lowest subsidence rates, followed by farms under early restoration (Region B, restored in 2009) displayed lower subsidence compared to later-restored farms (Regions A, restored in 2012 and 2014), indicating that timely interventions can reduce emissions and potentially enhance carbon sink potential. This emphasises the critical window for restoration interventions to mitigate land degradation and climate feedbacks. InSAR data effectively captured seasonal peatland surface dynamics, closely linked to subsurface hydrological conditions, especially soil moisture at 50 cm depth, highlighting its potential as a key indicator of peatland water balance. The depth-dependent correlation between detrended InSAR displacement and soil water, along with the consistent temporal patterns observed with SPI-3 and soil moisture, suggests that the SBAS time series effectively captures hydrological loading and unloading of the ground surface. These findings reinforce the credibility of the observed long-term subsidence trends. The alignment of these InSAR-derived findings with ground-based measurements further validates the reliability of satellite-based approaches. Beyond demonstrating that InSAR can accurately detect peatland subsidence, this research also used measured deformation rates to generate first-order carbon flux estimates, highlighting the broader implications of peatland restoration for climate change mitigation. Moreover, our work highlights InSAR's potential as a high-resolution (temporal and spatial) and cost-effective tool to support national inventory reporting, validating peatland code restoration sites or quantifying the public benefits of agri-environmental payments to support higher water table in lowland peats. In the Fenland context where conventional agricultural drainage drives continued peat loss, routine, wall-to-wall InSAR can pinpoint ongoing hotspots of degradation, verify gains from more sustainable farming (e.g., raised water tables, wet grasslands, paludiculture), and provide spatially explicit evidence to prioritise and demonstrate conservation outcomes from farm to reserve.

Looking ahead, future work should prioritise: (1) integrating L-band SAR (ALOS-2 PALSAR-2, NISAR) to improve coherence in vegetated areas; (2) implementing ISBAS to capture intermittently coherent pixels; (3) coupling InSAR-derived subsidence with in-situ measurements of bulk density, Corg, and water table depth to refine carbon flux estimates; (4) extending the approach to other UK lowland peatlands to support national inventory reporting and peatland code validation; and (5) investigating the relationship between subsidence rates and specific restoration practices (e.g., water table management, vegetation establishment). These steps will refine our understanding of peatland processes and improve long-term restoration strategies. Ultimately, the proven concordance between InSAR results and ground-based observations confirms the value of InSAR for continuous, large-scale peatland monitoring, allowing for timely interventions and more effective management of carbon-rich ecosystems.

CRediT authorship contribution statement

Abhishek Patil: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Abdou Khouakhi:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Methodology, Investigation, Conceptualization. **Nicholas Girkin:** Writing – review & editing. **Ian Holman:** Writing – review & editing.

Ethical statement

This study did not involve human participants, animal subjects, or any personal or sensitive data requiring ethical approval. All remote sensing and environmental datasets used (e.g., Sentinel-1 SAR imagery, COSMOS-UK soil moisture data, SPI indices) are publicly available and were accessed in accordance with the data usage policies of the respective providers. The research complied with all relevant institutional and national guidelines for conducting environmental studies. No conflicts of interest are declared by the authors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.rsase.2026.101919>.

Data availability

The interferometric synthetic aperture radar (InSAR) data used in this study were obtained from the Alaska Satellite Facility (ASF) Distributed Active Archive Center (DAAC) via the VERTEX data portal (<https://search.asf.alaska.edu>). The interferograms were processed using ASF's OpenScienceLab platform (<https://opensciencelab.asf.alaska.edu>). All datasets used are freely available to registered users and can be accessed by referencing the corresponding Sentinel-1 mission products.

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Patil, Abhishek; Khouakhi, Abdou; Girkin, Nicholas T.; Holman, Ian P.

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