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No. 674

Copernicus User Uptake Work Package 6: Support for Applications

Monitoring change in peatland condition using analysis-ready Sentinel data

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Forest Research

NATURAL ENGLAND

Llywodraeth Cymru
Welsh Government

Summary

Working with partners from Forest Research, Natural England, and Welsh Government, this project demonstrates how Very High Resolution (VHR) images, such as aerial photography from manned aircrafts and drones, and Sentinel-2 imagery can be used to map change in aspects of peatland condition over time. Monitoring condition so far has mainly relied upon experts in the field, whereas this project aimed to explore how Earth observation is able to provide a cost-effective means for targeting ground interventions. Specifically, through mapping changes in the areas of bare unvegetated peat, an indicator of habitats in poor condition, we can highlight areas in decline to target these for further intervention, as well as monitor how effective restoration measures have been over time. This helps to provide evidence for meeting peatland restoration goals, a key target for a number of crucial policy areas, such as climate change, soil health, and biodiversity.

The project focussed on four sites, including both upland and lowland peatlands, across England, Scotland and Wales. Fine scale maps of bare peat were created by calculating indices from the aerial photography, such as Normalised Difference Vegetation Index and Normalised Difference Wetness Index and using threshold values to separate the bare peat pixels from the rest of the imagery. These maps were then used to inform regression models to predict the amount of bare peat cover, using a time-series of Sentinel-2 imagery from 2015 to 2020. Resulting maps of the predicted percentage cover of bare peat per 10m pixel were then compared between years to assess where change had occurred.

The results were compared to ground observations, VHR and drone imagery, and expert knowledge from site teams. Overall, this approach was highly effective for some sites, with annual predicted bare peat cover and change maps successfully highlighting areas with large amounts of bare peat. For most of the sites, predicted bare peat maps showed good agreement with site expert knowledge and demonstrated where changes were occurring in the landscape due to restoration measures or further degradation from erosion. Inaccuracies were found where models were trained on particularly anomalous climate conditions, leading to overprediction of bare peat in extrapolated years. Training the models using data from multiple years helped to alleviate this and provided more accurate predictions as opposed to training data acquired from a single year. Seasonality also had a key impact on developing both the fine-scale maps and time-series maps, with summer imagery providing the best conditions for distinguishing between vegetated and non-vegetated peat. The maps of changes in peatland condition throughout the time series demonstrate notable differences between sites, illustrating the impacts of restoration operations and water management at the sites, which could be further explored. Further ground validation and further development of the initial detection using VHR data is required to increase confidence in the predicted cover values.

This study has demonstrated how we can build regression models informed by VHR to infer peatland condition in Sentinel-2 imagery. By applying this method over time series data, we can dynamically explore how exposed peat is changing across the landscape. Practitioners managing the sites praised the usefulness of the method and the value tools such as this can have in quantifying the amount of bare peat through time and informing actions taken on the ground. There feedback also highlighted some uncertainties which would need to be addressed in order to operationalise such an approach, which are explained further in this report. These maps can help to provide operational teams with the tools to target restoration efforts and assess the effectiveness of such interventions, leading to more effective, sustainable land management practices.

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1 Introduction

Peatlands are a UK Priority Habitat important for supporting endangered and threatened species, regulating greenhouse gases and mitigating flood risk. Over 80% of UK peatlands are in a degraded state due to anthropogenic activities, including land conversion, drainage, extraction and burning (Bain *et al*. 2011). Peatland restoration has been recognised as a nature-based solution which can aid in tackling biodiversity decline and climate change. In order to achieve the UK Government's targets for Net Zero greenhouse gas emissions by 2050, the Committee on Climate change (2020) has recommended restoring at least 50% of upland peat and 25% of lowland peatland. As part of this drive, the UK government has invested £640 million as part of the Nature for Climate Fund to "protect, restore and expand" peatbogs and woodlands as well as a further £25 million though the Nature Recovery Network Fund (IUCN UK Peatland Programme 2020). Restoration goals also feature heavily in policies, both UK-wide and for the devolved governments. In Scotland there has been a £20 million investment in peatland restoration this year to support a major programme of work under the Peatland Action restoration project (SNH 2015; IUCN UK Peatland Programme 2020). In England, restoration is embedded in the 25-year Environment Plan with £10m funding dedicated to peat restoration projects (Defra 2018). In Wales, there are schemes such as the Welsh Peatlands project under the Sustainable Management Scheme and in Northern Ireland, there is engagement through pilot restoration projects and the development of a Northern Ireland Peatland strategy (Welsh Government 2018; McGuckin 2019).

Restoring these vital habitats requires evidence on the current condition of peatlands, in order to spatially prioritise and target where interventions are required. The presence of bare unvegetated peat soils is a visible indicator of habitats in poor condition, demonstrating the depletion of the quality and quantity of the peat soils (SNH 2020). In poor condition, carbon is emitted from the peat soils either directly or via erosion, hence the importance of targeting these areas for revegetation in order to contribute to net zero emissions targets. Identification of these landscape features has previously relied upon ground surveys; however, remote sensing offers a cost-effective means of large-scale assessment. Monitoring peatlands using earth observation data provides a means to quickly and dynamically assess changes in habitat condition over time. Several studies have highlighted the use of satellite data such as Sentinel-2 and MODIS to classify the extent of bare peat in the landscape (Artz *et al*. 2019; Blake & Frake 2020). However, smaller patches of bare peat can often be missed in the satellite imagery at lower resolutions, which collectively can make up a substantial area across the landscape, particularly through the impacts of gullying and erosion. Earth observation data recorded at a much higher resolution, for instance captured through aerial photography or drone imagery, may help to bridge this gap and provide precise locations of bare peat at the site level. Being able to detect both large expanses and small patches of bare peat would help landowners to target priority areas for restoration, and to assess their effectiveness, leading to better, more sustainable land management decisions.

JNCC has been partnering with 48 organisations across European countries as part of the Caroline Herschel Framework Partnership Agreement on Copernicus User Uptake, to demonstrate the applications of satellite data from the European Union's Copernicus Programme operated by ESA (JNCC 2020). Under this work package, JNCC has worked with partners from Forest Research, Natural England and Welsh Government to explore the use of earth observation data to map changes in peatland condition in sites across the UK. This focussed on four study sites across England, Scotland and Wales (Figure 1), including both upland and lowland peatland habitats. Building on previous methodologies developed by Williamson *et al*. (2018) and Trippier *et al*. (2020), the project used aerial photography to create fine-scale bare peat maps. These maps were then used to parameterise regression models to predict the amount of bare peat cover per 10m pixel, using variable derived from Sentinel-2 optical imagery, as well as climatic and topographic data. Sentinel-2 time series were also used to explore how the predicted bare peat cover changed over time. The methodology used for mapping at these two scales and the results from the four study sites are described in the following sections. This project aimed to evaluate how well this methodology performed across a range of UK sites and understand how best to operationalise such an approach to monitor condition and inform on the effectiveness of restoration measures.

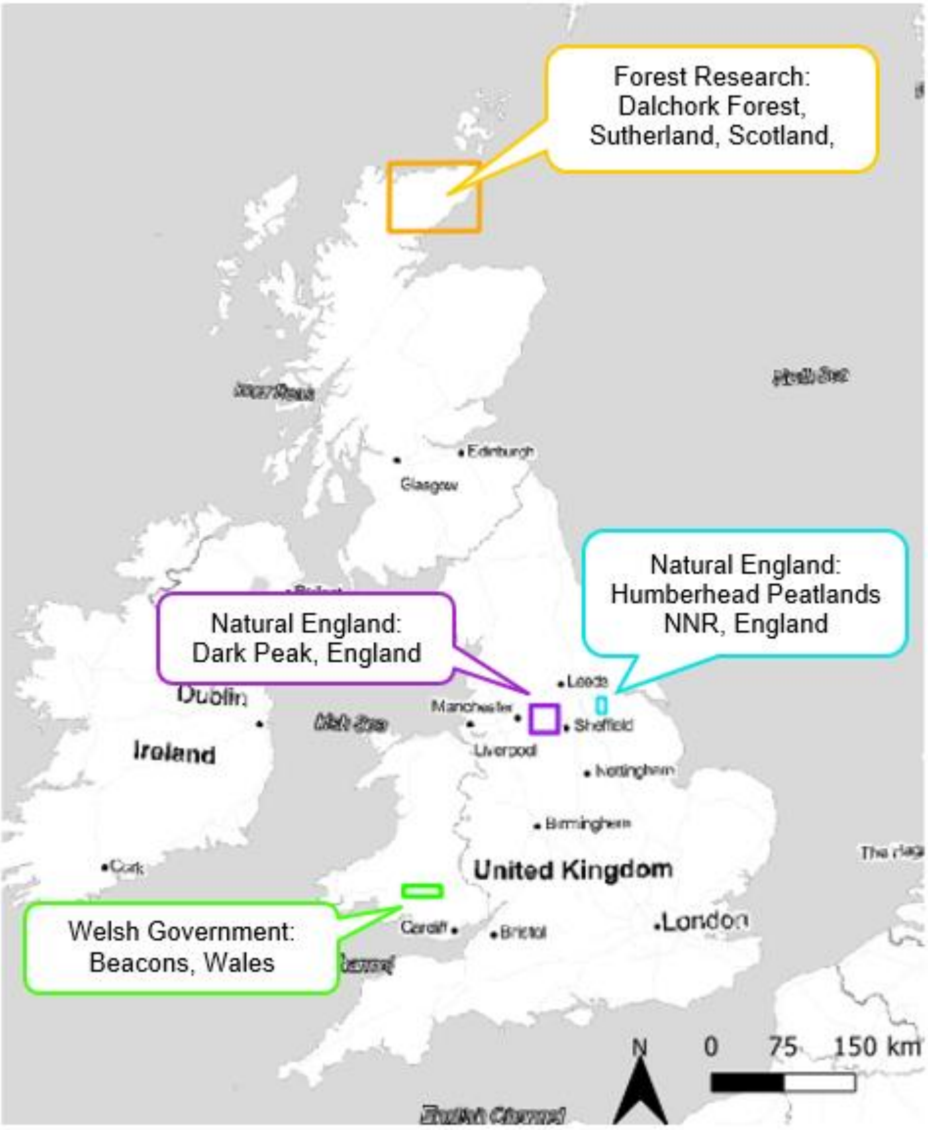


Figure 1: A map of the study sites. Map tiles by Stamen Designs (stamen.com) C-BY 3.0. Contains © OpenStreetMap contributors data.

2 Methodology

2.1 Fine-scale mapping

To create the fine-scale maps, VHR imagery for each site was obtained from the Aerial Photography GB (APGB) service (Bluesky International 2019); RGB images at 25cm and Colour InfraRed aerial photography (CIR) at 50cm spatial resolution. The service captures imagery every 3-5 years during the April to November period. Data were obtained for all available dates between 2015 and 2020, shown in Appendix 1.

Four sites across England, Scotland and Wales, shown in Figure 1, were selected based upon the presence of a variety of peat soils in both good and poor condition, being of local interest for condition monitoring, and the availability of validation data. All site boundaries were georeferenced to British National Grid (ESPG:27700), and visual comparisons and basic manipulation were conducted in QGIS v. 3.4.5-Madeira (QGIS Development Team 2020). The site boundaries for the Brecon Beacons were provided by Welsh Government derived from Soils of Wales - Series Map. Derived from Soils Data © Cranfield University (NSRI) and for the Controller of HMSO (2020).

Data processing and transformation was conducted in R version 3.6.1 (R Core Team 2019), with GDAL functionality integrated through the 'gdalUtils' package (Asher Greenberg & Mattiuzzi 2018). Figure 2 shows an infographic of the workflow.

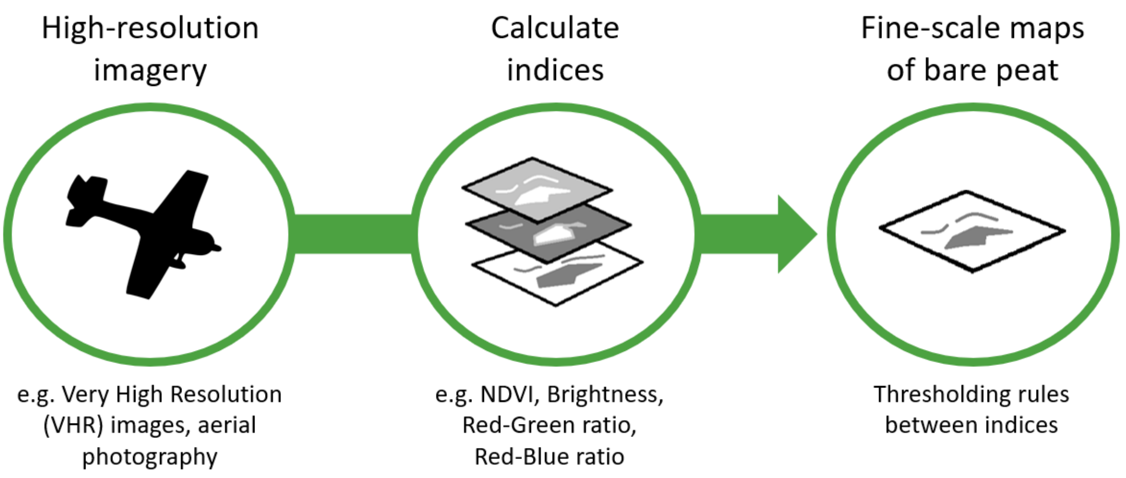


Figure 2: Infographic of the workflow for producing the fine-scale maps of bare peat.

For each site, the near-infrared band from the CIR imagery was resampled using bilinear interpolation to 25cm resolution, to match the spatial resolution of the RGB imagery. Visual assessments identified tiles within each site where areas of bare peat were clearly visible. These combined images with the Red-Green-Blue and near-infrared bands were uploaded into the JNCC 'PeatPal' R Shiny application, which is designed to help develop rules for detecting features using indices values (Figure 3). For making the data more manageable at the higher resolution and less computationally demanding, each tile was split into sub-tiles for processing within the application. Combinations of the four imagery bands (Red, Green, Blue, Near-infrared bands) were used to calculate spectral and vegetation indices. These included Normalised Difference Vegetation Index (NDVI), Normalised Difference Wetness Index (NDWI), Brightness, Red/Green (RG) ratio, Red/Blue (RB) ratio, and Green Leaf Index (GLI). The indices calculations are shown in Appendix 2, referenced from IDB Project (2019). Minimum and maximum threshold values for the indices were explored to establish a rule for separating the bare peat pixels from the rest of the image, including vegetated peat but also bare rock, water and other land cover types. Threshold rules were first established for the representative tiles, and then a consensus rule was applied across all the imagery tiles for a site. The results were then visually assessed in QGIS, with those displaying inaccuracies reassessed using PeatPal, with the rule tweaked for the individual image. For the Dark Peak site, the fine-scale map was obtained from the JNCC pilot study by Trippier *et al.* (2020), which covered 80% of the site.

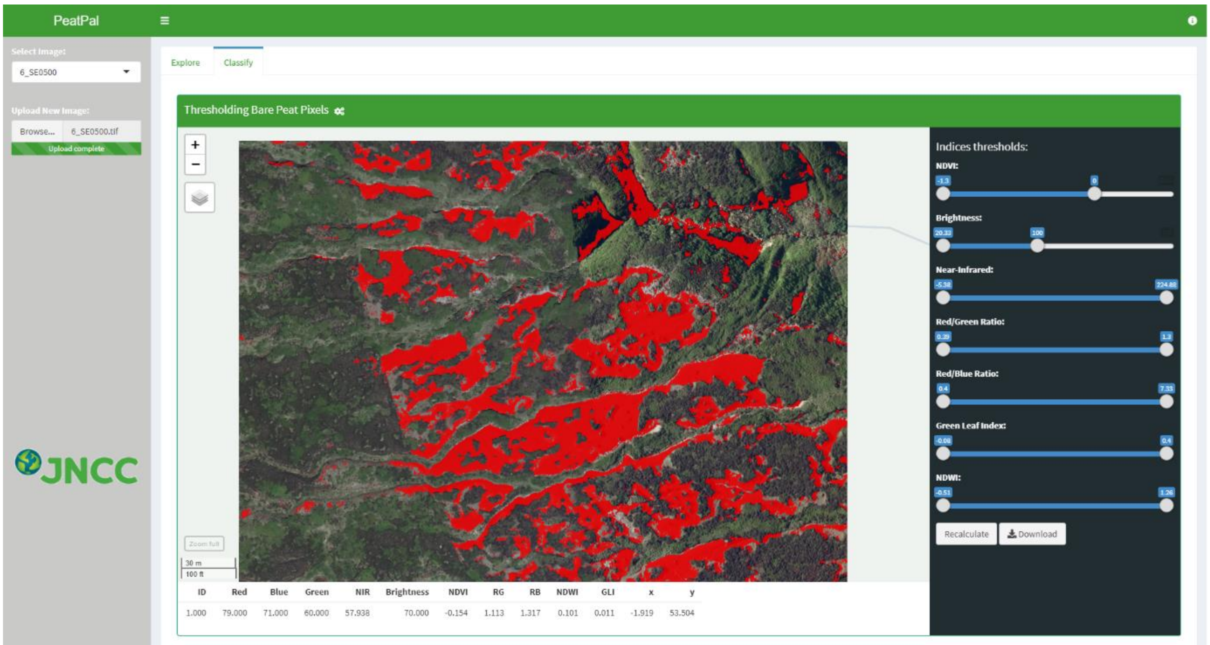


Figure 3: PeatPal R Shiny Application.

Once the bare peat pixels were identified, the tiles were reclassified into a binary classification: 1 for bare peat pixels, and 0 where bare peat was absent. This was then aggregated to a percentage bare peat per 10m pixel by dividing the number of 25cm cells containing bare peat to the total number of 25cm cells per 10m pixel. An infographic illustrating the transformation process is shown below in Figure 4.These were then mosaicked together based on the closest capture dates of the Sentinel-2 imagery (Appendix 3 – Sentinel Imagery dates). This process created fine-scale maps of bare peat at the 25cm spatial resolution and as a percentage cover of bare peat per site per date at the 10m spatial resolution.

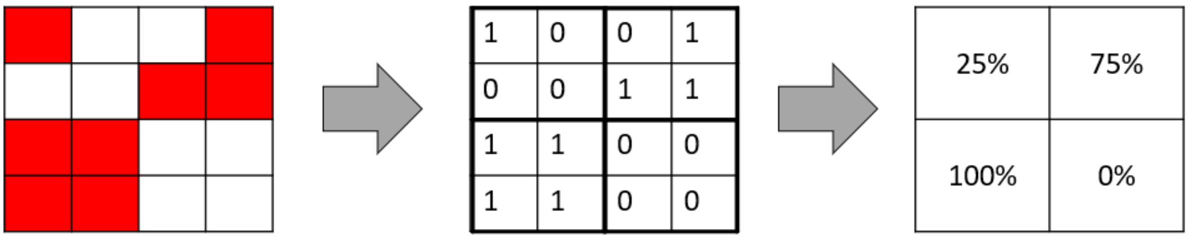


Figure 4: An illustration of the transformation of identified bare peat cells into a percentage cover value.

Validation of the fine scale maps was limited due to available ground data for the imagery dates. Vegetation survey data were available for the Dark Peak site provided by Natural England as part of the Space2Eye Lens Partnership with Manchester Metropolitan University, Moors for the Future, Bowland AONB and United Utilities Partnership used as training data in the development of the State of the Bog model applied across Bowland, West and South Pennines including the Dark Peak (Field *et al.* 2020). The observations from 2018 included a classification of vegetative states including a ‘bare peat’ state as well as an estimate of total percentage cover of bare peat at 2m resolution. These were used to assess the accuracy of the fine-scale map by conducting a statistical comparison with the observed points, noting the difference in scale would likely impact upon the results.

2.2 Time-series modelling

Sentinel-2 is a multispectral high-resolution imaging mission that is part of the European Union’s Copernicus Programme operated by ESA (2020). The optical data obtained for each of the site were standard Sentinel-2 Analysis Ready Data (ARD) products. The 20m image bands were sharpened to 10m through the application of linear regression models, to produce a final output with 10 x 10m multispectral bands, described in Appendix 2. The 60m bands are used for atmospheric aerosol processes and therefore removed from the final product. The final ARD displays a topographically corrected surface reflectance product with cloud and topography masks. Climatic and topographic variables were also obtained for the analysis. This included a Digital Terrain Model (DTM) at 10m spatial resolution collated from Environment Agency’s Integrated Height Model (IHM) using Lidar data (Bluesky International Ltd/Getmapping PLC). From this, a slope layer was calculated using ‘gdalUtils’ package using the Zevenbergen Thorne algorithm (Asher Greenberg & Mattiuzzi 2018). Summer total precipitation and minimum, maximum and average summer temperatures were obtained from the Met Office (2019), using their HadUK gridded 1km monthly product available through CEDA’s archive. All variable layers were resampled to 10m spatial resolution to match that of the Sentinel-2 imagery.

Figure 5 depicts the methodology applied for the time series modelling. Vegetation indices of Brightness, Normalised Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Red-Green ratio, Green Leaf Index (GLI) and the Normalized Burn Ratio (NBR) were calculated for each of the Sentinel-2 imagery dates. These indices along with the machine learning algorithm selected were chosen based on conclusions drawn from the pilot study (Trippier *et al.* 2020). Imagery dates are noted in Appendix 2, and indices were calculated using the equations described in Appendix 2. For each date, the derived Sentinel-2 indices layers were then combined into a rasterstack with the near infrared band, slope layer and climate layers for the relevant year in the time series. Training points derived from the fine-scale maps were used to extract data from the rasterstacks to produce the training dataset with which to train the regression models. These were extracted from the rasterstacks with the closest Sentinel-2 imagery date to the APGB data acquisitions dates.

The datasets were used to train a random forest regression model, built using the ‘caret’ R package (Kuhn *et al.* 2020). Each model was run 10 times, with each run resampling the training data by random stratified sampling across five percentage cover categories (0, 0-25%, 25-50%. 50-75%, 75-100%). A target number of 10,000 points were sampled with 2000 points attempted per category. Where 2000 points were not available for a category, all available category points were sampled. For the Brecon Beacon site, training data was only created for approximately 4% of the site where there were areas of particularly interest, with relatively few training points available compared with the other sites. Therefore, for this site only a total of 5000 training points were sampled. For all of the sites, the model parameters were tuned by repeated 5-fold cross validation resampling and 25% of the data were held back for model evaluation. The models were evaluated with the Root Mean Square Error (RMSE) and R-squared statistics. The best performing models were used to predict percentage cover values across the time series rasterstacks. Lastly, the predicted maps were averaged across the 10 modelled runs to produce a mean prediction per site per year. This helped to reduce sampling bias.

Changes in the amount of predicted bare peat cover between years were assessed by calculating the differences between year predictions, using the equation:

Change in bare peat cover (%) = end date prediction (%) – start date prediction (%)
To explore the predicted results, data were loaded into an R Shiny application to let users interact with the modelled predictions of bare peat for each site and view comparisons of change between years. This was made available via shinyapps.io (RStudio & PBC 2020): https://jncc.shinyapps.io/BarePeatMapper/ .

Different validation strategies were adopted for the sites, with their effectiveness and reliability depending on the availability of ground observations, and drone and VHR imagery. For the Scottish site, oblique drone imagery from various points observing restoration measures were provided between 2018 and 2019. These were assessed qualitatively with the predicted maps to explore the amount of bare peat pre- and post- restoration operations. Types of restoration operations carried out on the site were also provided as polygons. For each polygon, the total percentage cover of bare peat was calculated from the predicted maps and compared to see how these had changed during the time period from the end date of the management measures.

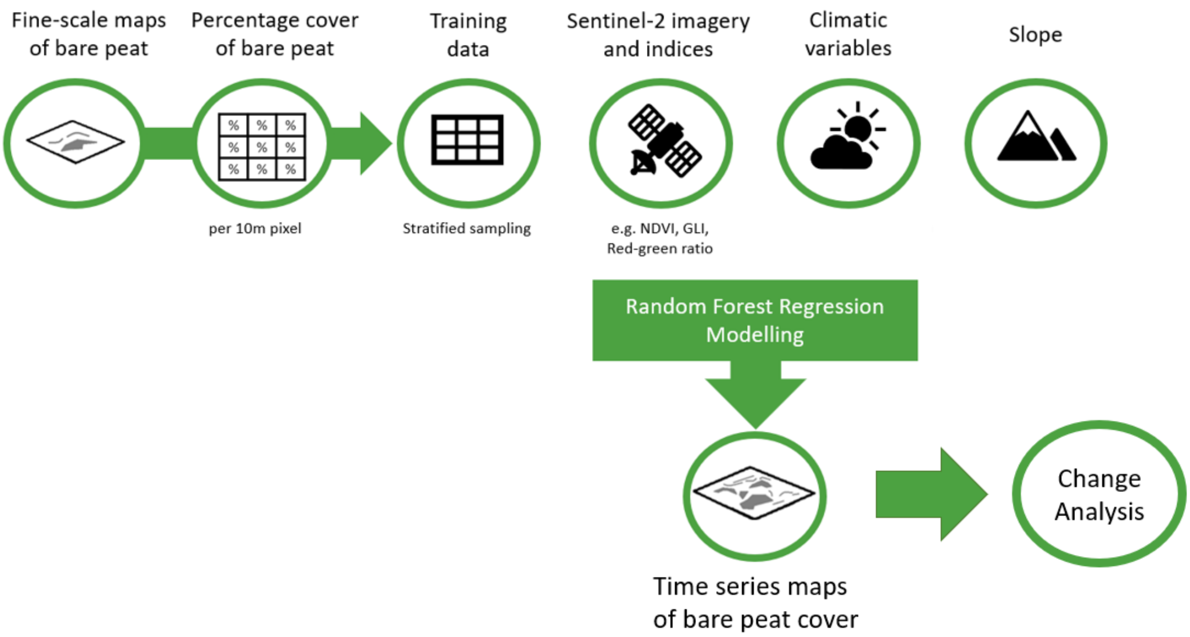


Figure 5: An infographic of the processing steps in the time series modelling of bare peat cover.

For the two English sites, various ground data observations and vegetation survey data were supplied to validate the predicted maps. A Desktop Validation Study was developed to gather local site advisor and specialist knowledge of management activity and areas of bare peat to assess each pilot site. An interactive Web App was set up using ESRI ArcGIS Online (AGOL) for viewing the Sentinel-2 imagery and the predicted bare peat model outputs together with a Bare Peat Validation Assessment spreadsheet to collate these observations and management activity developed to assess these sites. Polygons of known bare peat were digitised by site experts for making comparisons with the predicted maps, then their local knowledge of the site and opinions on the accuracy of the predictions was captured using the assessment spreadsheet. To validate the Humberhead maps further, ground observations from 2014 and 2015 were provided for part of the site as polygons with estimates of bare peat cover with differing levels of film coverings of water, as this is a very dynamic site that seasonally floods. (Kohler 2020). For the Dark Peak site, survey data derived from the “State of the Bog” vegetation survey were provided as 2m x 2m quadrat data. This included datasets from NE condition and NVC surveys, Moors for the Future and an extensive dataset from Carlos Benson all carried out in 2018 (MMU 2020).

For the Welsh site, no appropriate ground truthing data were available for validation, so limited validation was trialled using an alternative source of VHR data. Imagery from Planet's Dove satellites was obtained from multiple swathes for the time series dates, with 4-bands (Red, Green, Blue and Near-Infrared) captured by PS2 and PS2.SD instruments at 3 metres spatial resolution (Planet Team 2017). NDVI was calculated from these images and used to sampled points by taking 100 randomly stratified points: 50 points where NDVI value was below 0.5, and 50 points above 0.6. These thresholds were chosen based upon visual comparisons of the NDVI layer against the Planet imagery. These points were then visually assessed against the Planet imagery, manually noting if bare peat appeared to be present or absent. These points were then extracted from the corresponding time series map, with predictions converted into a presence of bare peat where cover values were over 10% or absence where they were under 10%. The accuracy of the predictions was then established using a confusion matrix to compare the observed and predicted results, with predictions judged to be correct where bare peat was present and NDVI was less than 0.5, or where bare was absent and NDVI was greater than 0.6.. Further validation points of the locations of bare peat were also provided from 2019, digitised by a peatland ecologist familiar with the site using aerial photography. These were compared to the predicted map from 2019, converting these to a presence and absence based on a threshold cover value of 10%.

3 Results

3.1 Dalchork Forest, Sutherland

3.1.1 Fine-scale mapping

Appendix 4 – Fine Scale maps of bare peat cover – contains the fine scale maps developed for all the sites showing the percentage cover of bare peat at 10m spatial resolution. The Dalchork Forest site included a mixture of both natural unplanted land and heavily managed conifer plantations, now clear felled and containing bare ground covered by decaying vegetation, such as pine needles and brash. To reduce model complexity, these two regions were mapped separately, with each identifying the different features, shown in Figure 6.

The indices of brightness, NDVI, NDWI and RG ratio were used to detect both features, with GLI additionally used to aid in the bare peat separation in the unplanted regions. The bare peat was separated with a maximum NDVI value of 0.2, with higher values demonstrated with the bare peat identification having an average maximum threshold of 0.14 ± 0.10, in comparison to 0.07 ± 0.08 used to identify the pine-needle covered bare peat. The brightness thresholds had a greater range of values for extracting the pine-needle covered bare peat, with an average minimum limit of 109.23 ± 14.68 and maximum limit of 169.00 ± 3.65, compared to the bare peat in the unplanted areas where the average maximum limit used was 117.80 ± 10.86. This reflected the wider variety of material detected in the planted regions and the changing appearance of brash and conifer leaves as they decay in the landscape. The minimum limits for RG were similar for both regions and the average maximum limits for NDWI was slightly higher in the planted regions (0.14 ± 0.07) than the unplanted regions (0.09 ± 0.02). This may result from a greater amount of surface water being held between layers of the stacked vegetation. The greater NDWI threshold may also reflect the condition of the soils in the different regions and microtopographic levels which may be present, for instance in the ploughed managed grounds a variety of different levels and depths could result in a greater accumulation of pooling water and dead vegetated material.

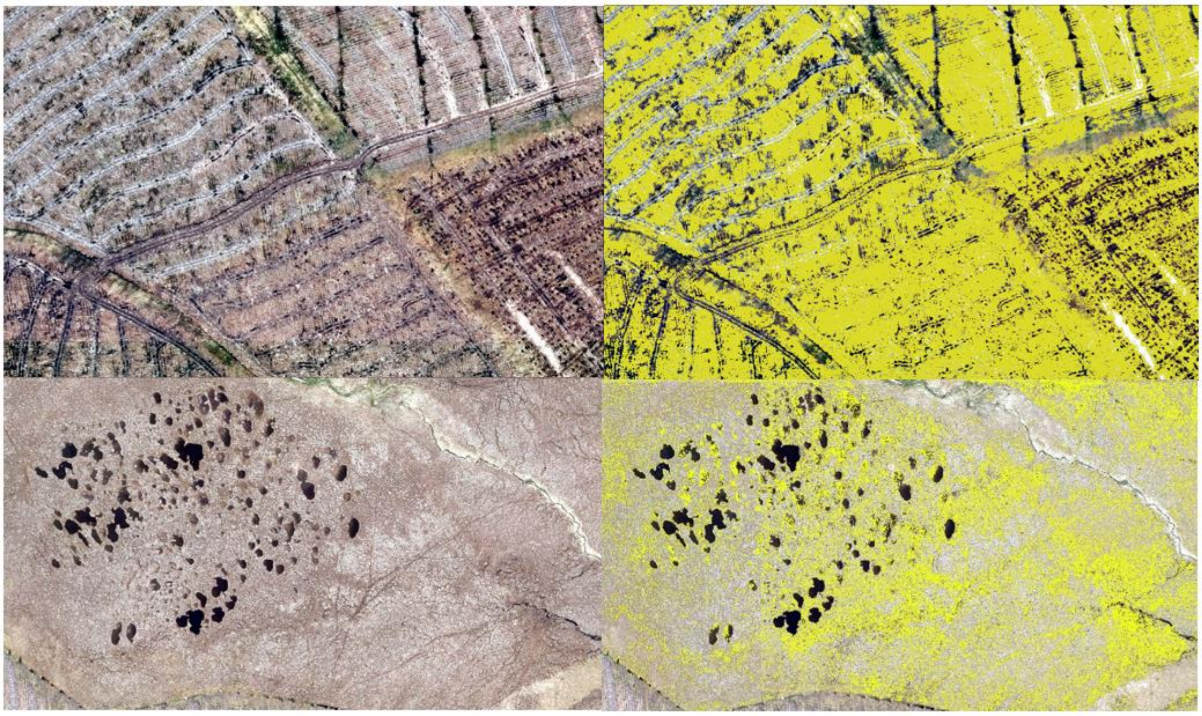
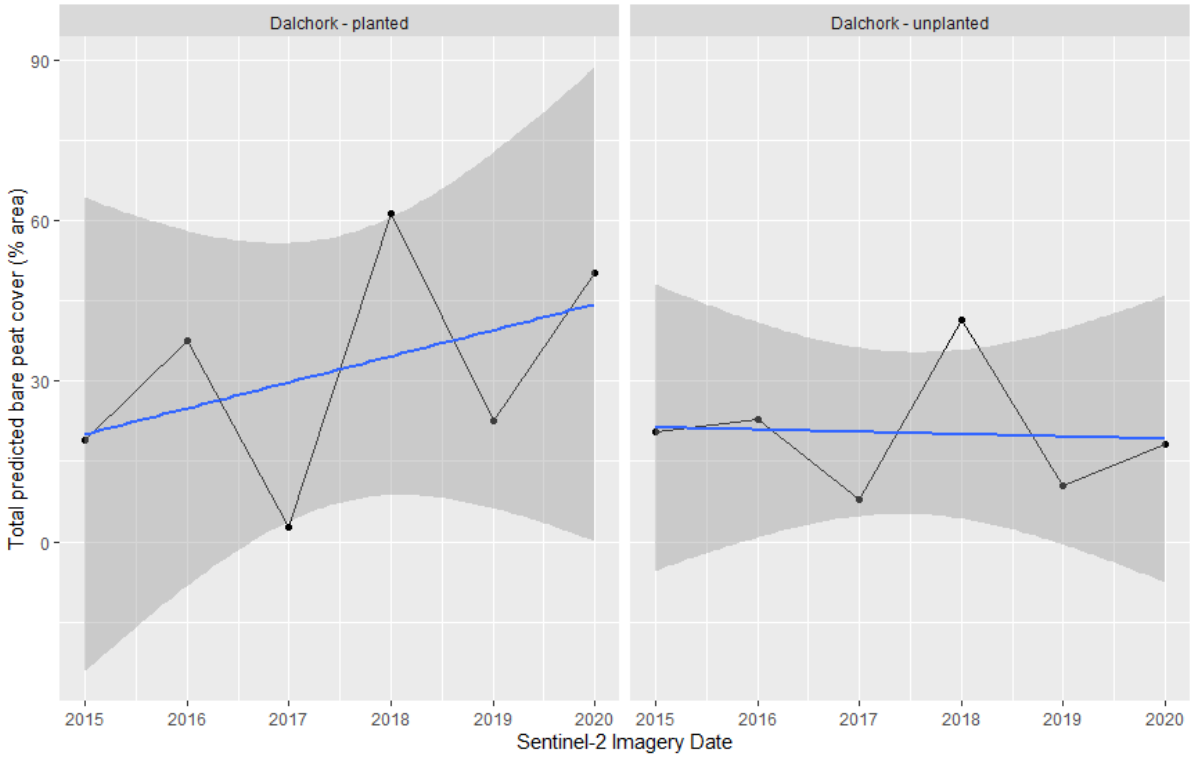


Figure 6: Examples of the planted (above) and unplanted (below) regions of the Dalchork Forest site and the features which were identified in the APGB imagery from 2016 (Bluesky International 2019).

3.1.2 Time-series modelling

The time series analysis demonstrated an overall predicted decrease in bare peat cover between 2015 and 2020 for the unplanted areas of the site, described in Figure 7. The predicted maps of bare peat per year are displayed in Figure 8. The model was trained on one year of APGB data from May/June 2016 and produced a mean RMSE of 0.12 and R^2 value of 0.85.



Sentinel-2 Imagery Date	Total predicted bare peat cover (km^2)	Total predicted cover of pine-needle covered bare peat (% planted area)	Total predicted bare peat (km^2)	Total predicted bare peat cover (% unplanted area)
2015-09-29	2.66	18.98	1.93	20.48
2016-06-05	5.26	37.52	2.16	22.97
2017-09-23	0.37	2.61	0.74	7.86
2018-06-30	8.61	61.37	3.91	41.51
2019-08-26	3.16	22.52	0.98	10.42
2020-05-07	7.04	50.19	1.72	18.29

Figure 7: Summary statistics for the predicted cover of bare peat in the planted regions and the predicted pine-needle covered bare peat in the planted regions of the Dalchork Forest site. The black line shows the observed totals described in the table below, and the blue line shows a linear trend across the time period with a confidence band in grey.

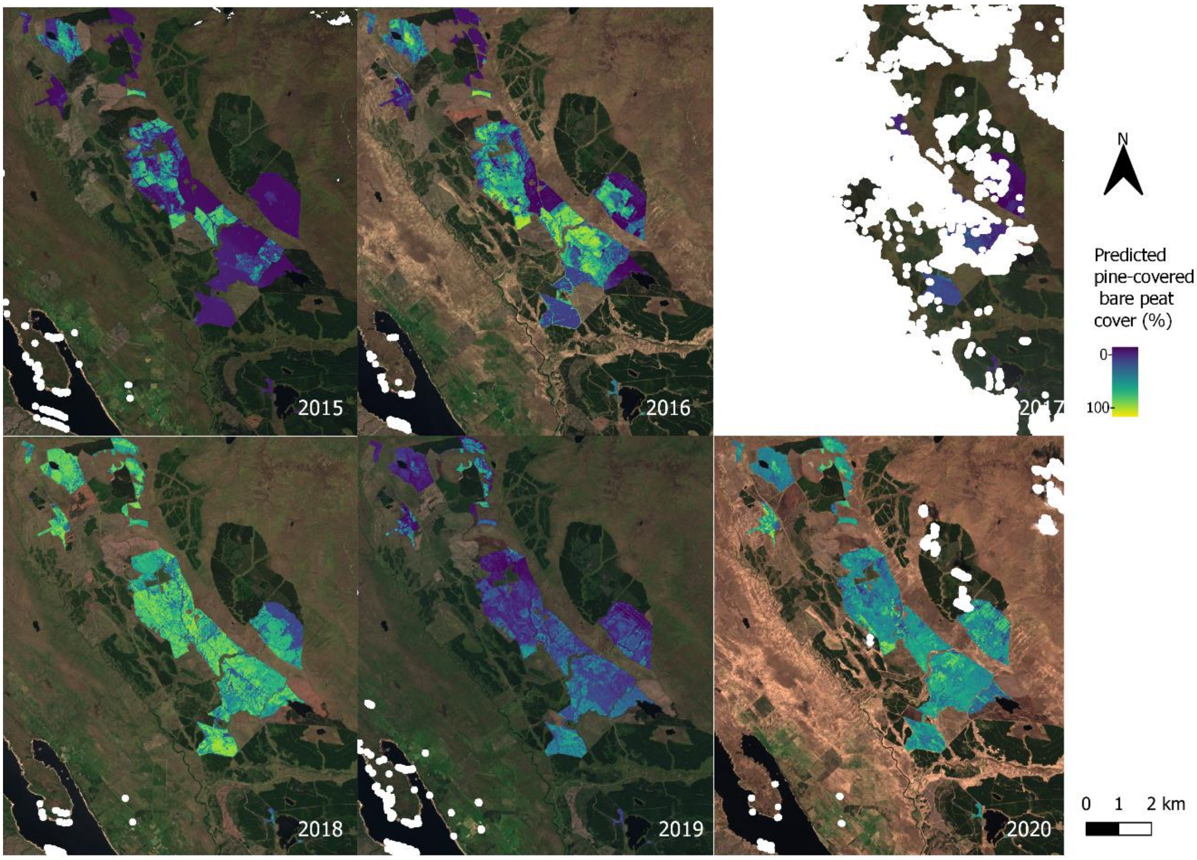


Figure 8: The predicted cover of bare peat in the unplanted regions of the Dalchork Forest site for the time period 2015-2020, plotted against the Sentinel-2 imagery.

The pine-needle covered bare peat model in the planted regions was similarly trained on the one year of data from May/June 2016, producing a slightly lower accuracy with a mean RMSE of 0.14 and R^2 value of 0.77. This could have been due to the greater variation in the features used to train the models, which is also apparent from NDVI displaying the greatest importance to the model in splitting the data. This indicates that the productivity of active vegetation is a much more important factor in deriving these features compared to the bare peat, where image brightness and near infrared band plays a much greater role. Figure 9 shows the results from each year in the time series predicting the areas of pine needle covered bare peat.

The predictions show drastic differences in the amount of bare peat that is covered in layers of pine needles throughout the time series, echoing the changing management that has been applied within the site. From the summary statistics in Figure 7, we can see vast differences between the 2018- 2019 periods despite both having imagery from a similar time of year, with areas of bare peat covered in pine needles predicted to cover 61.37% of the modelled area in 2018 and only 22.52% in 2019.

The limited summer availability of cloud-free Sentinel-2 imagery for both models, meant the time series imagery often fell outside of the June to August period. 2017 had particularly poor visibility and the closest available image for the site was from late September containing vast amounts of cloud cover, which led to low predicted cover totals at both planted and unplanted regions. In contrast, the predictions for the planted and unplanted regions in 2018 are double the average amount of bare peat for the time period. This higher prediction were likely due higher seasonal temperatures and lower total rainfall observed during the 2018 summer period. The climatic variables showed importance to reducing uncertainty in the predictions, however, were not as important as other predictor variables such as the near infrared band, brightness and Red-Green ratio which consistently came out as the most important. The drastic difference in 2018 conditions can be seen in Figure 10, where the bare peat predictions are plotted against the total summer rainfall and average summer temperatures. The rainfall results for 2018 are significantly lower and fall outside of the range of the rest of the timeseries, indicating an anomalous year which could explain the predictions for this year being greater than expected. The 2018 imagery also showed to be an outlier in its index's signatures, with higher bare peat cover found in pixels containing higher NDVI and lower NDWI values in comparison the other years in the time series. Our results demonstrate overprediction in anomalous years such as that seen in 2018, however raises interesting questions as to how to quantify when you are looking at such a year, requiring long-term climatic data but long-term comparable imagery records in order to determine this.

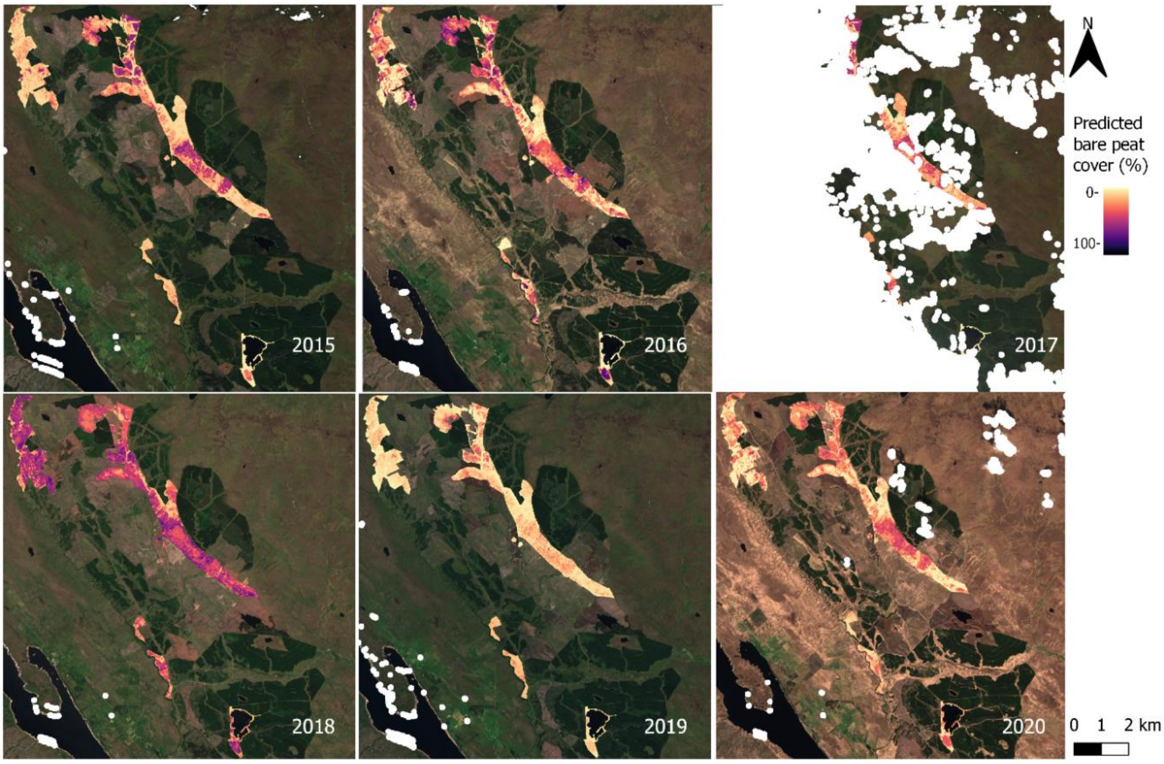


Figure 9: The predicted cover of pine-needle covered bare peat in the planted regions of the Dalchork Forest site for the time period 2015-2020, plotted against the Sentinel-2 imagery.

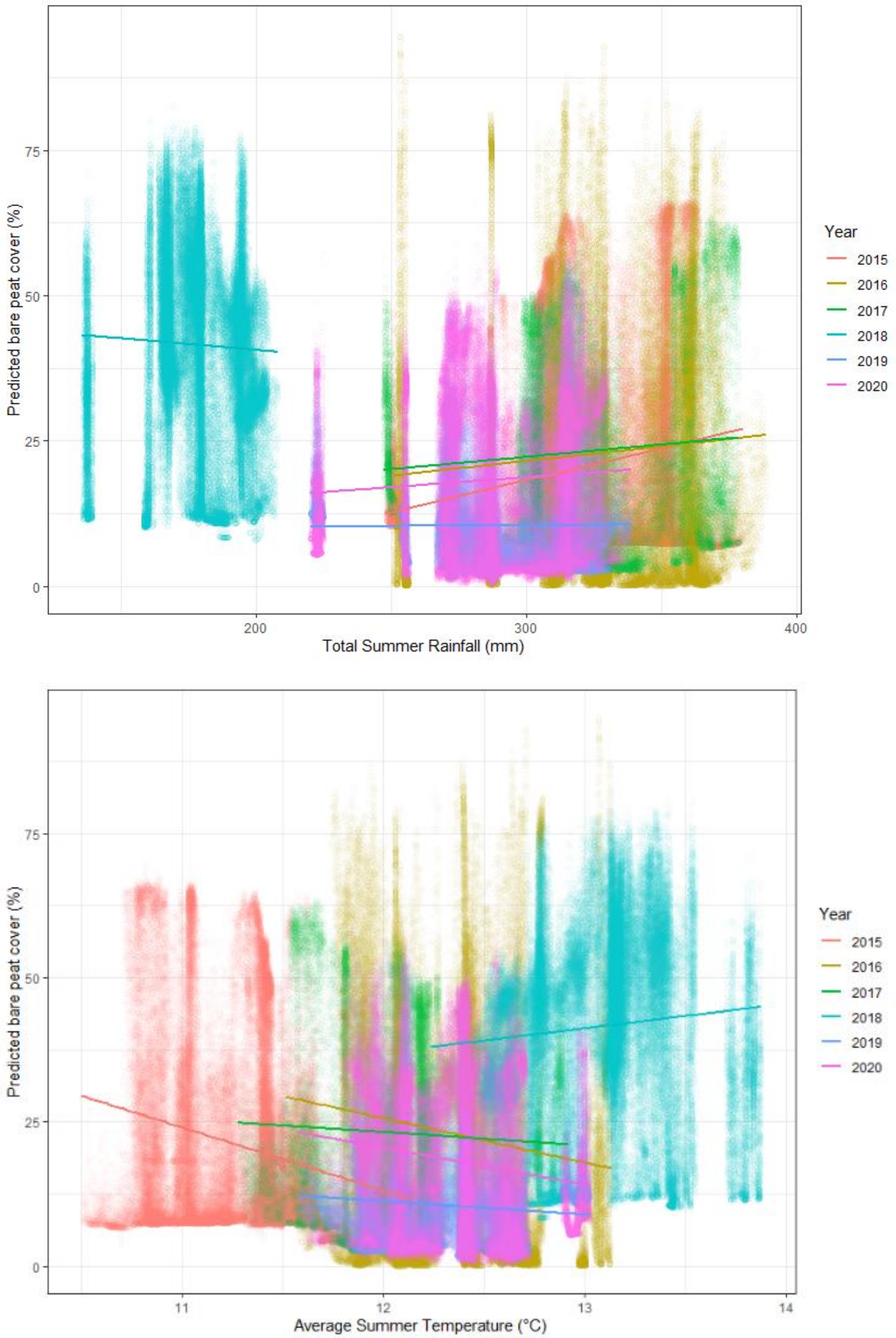


Figure 10: Plots displaying the total summer rainfall recorded per year from the Met Office (2019) HadUK gridded 1km monthly product, plotted against the predicted bare peat covers for the unplanted Dalchork Forest site.

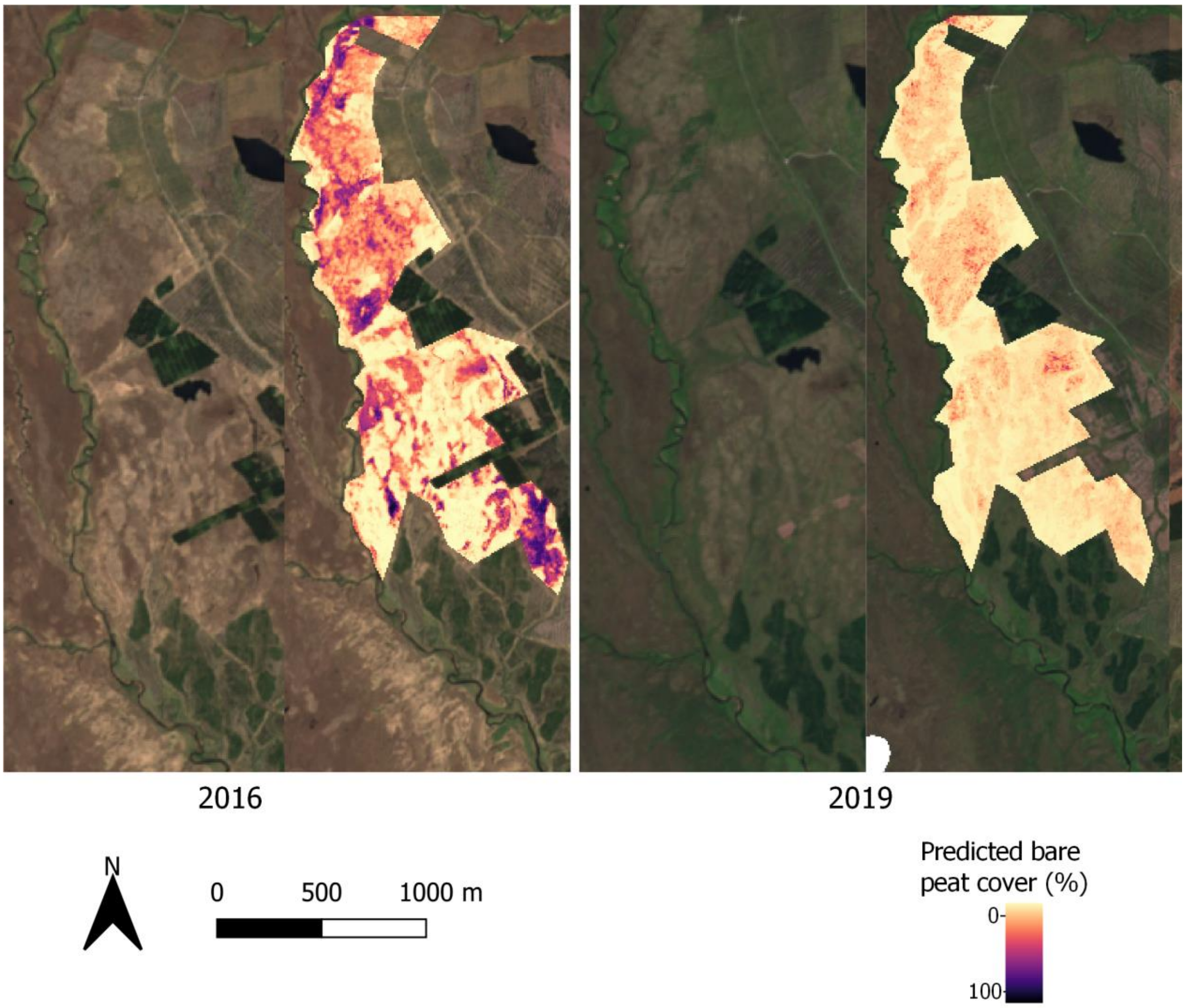


Figure 11: Images displaying the Sentinel-2 imagery for 2016 and 2019 compared with the predicted bare peat cover maps for an unplanted region in the north of the Dalchork Forest site.

Focusing on the unplanted regions, Figure 11 highlights a region in the north of site which experienced a percentage decrease of 61.38% between 2016, when the model was trained, and 2019. The change in condition may be in part due to the differences in seasonality of the imagery, with the 2016 image having been captured on 5 June compared with the 2019 image captured on 26 August, with vegetation appearing a lot greener. However, the Sentinel-2 imagery demonstrates a decrease in bare peat patches, with vegetation having been restored during these time periods and only small patches on bare ground being visible in the 2019 image.

Recovery in 2019 is also evident in the highly managed forested areas of the site. During 2018 to 2019, management interventions such as mulching and ground smoothing were implemented to help restore the peatland to a more natural state. These predicted maps of pine-needle covered bare peat can help to indicate when most felling has occurred within the site and dead vegetation has been piled on the ground. The decreasing cover indicates where growth may be occurring, where the dead vegetation has begun to rot, and it is being replaced in the site by active vegetation. Looking at specific management examples within these areas, Figure 12 demonstrates where ground smoothing has been implemented within the site leading to restoration of the wetland vegetation. The before photo and accompanying maps from 2018 show the impact of the coniferous plantation after harvesting, with clear lines apparent in the landscape from ploughing, cross-drains and brash piled up in strips. In March 2019 the site underwent extensive ground smoothing to turn over the peat soils and encourage vegetative growth, which we can see is beginning to return in the imagery in August. Our predictions demonstrate a decrease in pine-covered bare peat, with low cover values around the areas of new growth, showing how this analysis can be used to help monitor peatland restoration.

Comparisons of the restoration operations at the site demonstrated reductions in the amount of predicted pine-needle covered bare peat during the time period, shown in Figure 13. The change between the predicted results from the last management date and 2019 displayed reductions in pine-needle covered bare peat, suggesting revegetation at the sites. Greater reductions over the three-year period were seen with drain/furrow blocking activities compared with ground smoothing and drain blocking. This may reflect the longer time scale the peatland takes to recover after ground smoothing activities taking longer for sites to recover. Ground smoothing has shown to be effective at raising the water table sufficiently for bog vegetation to recover. The results also show a greater reduction with operations implemented later in the time series with greater recovery seen where sites underwent management in 2017/18 compared with 2016, particularly with drain blocking and furrow blocking activities. Drain blocking has been found to create a short term rise in the water table which may be why we are seeing a greater amount of vegetation recovery with the most recent activities from 2017/18, compared with where drain blocking had been implemented in the previous year (Artz *et al.* 2018). However, this could also be due to the 2018 temperature effect previously mentioned. Activities were also combined into these summarised categories for comparisons across plots, whereas further analysis of the different individual types of intervention and their revegetation rates can help to evidence how successful restoration has been.

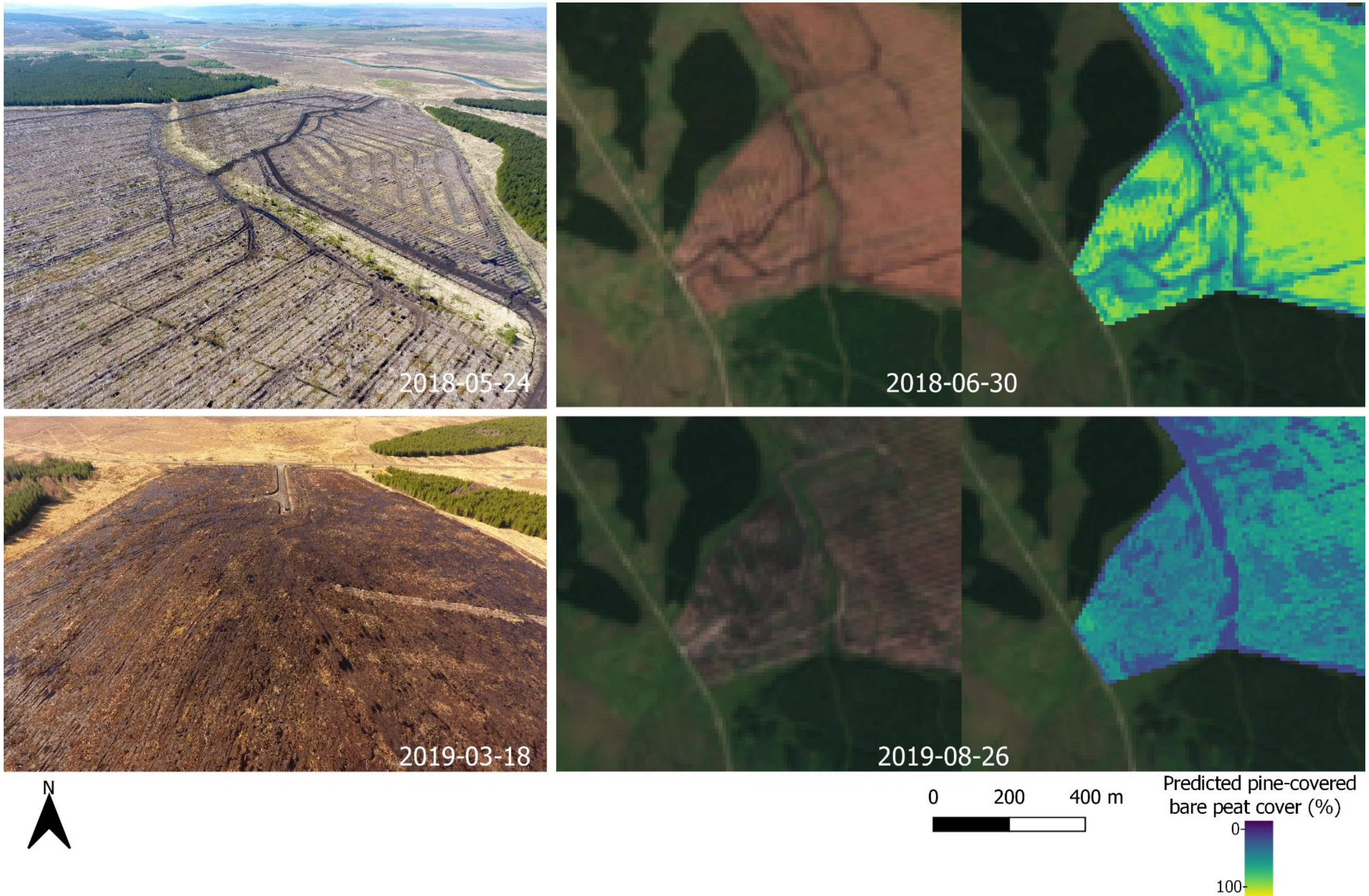


Figure 12: Images showing the impact of peatland recovery measures implemented within the site (NC57401514). Drone imagery (top-left) displays the site before the restoration measures looking northwards, and (bottom-left) after ground-smoothing looking south. The maps to the right display the Sentinel-2 imagery from these years in the time series and predicted cover of pine-covered bare peat (Forestry and Land Scotland (FLS) 2020).

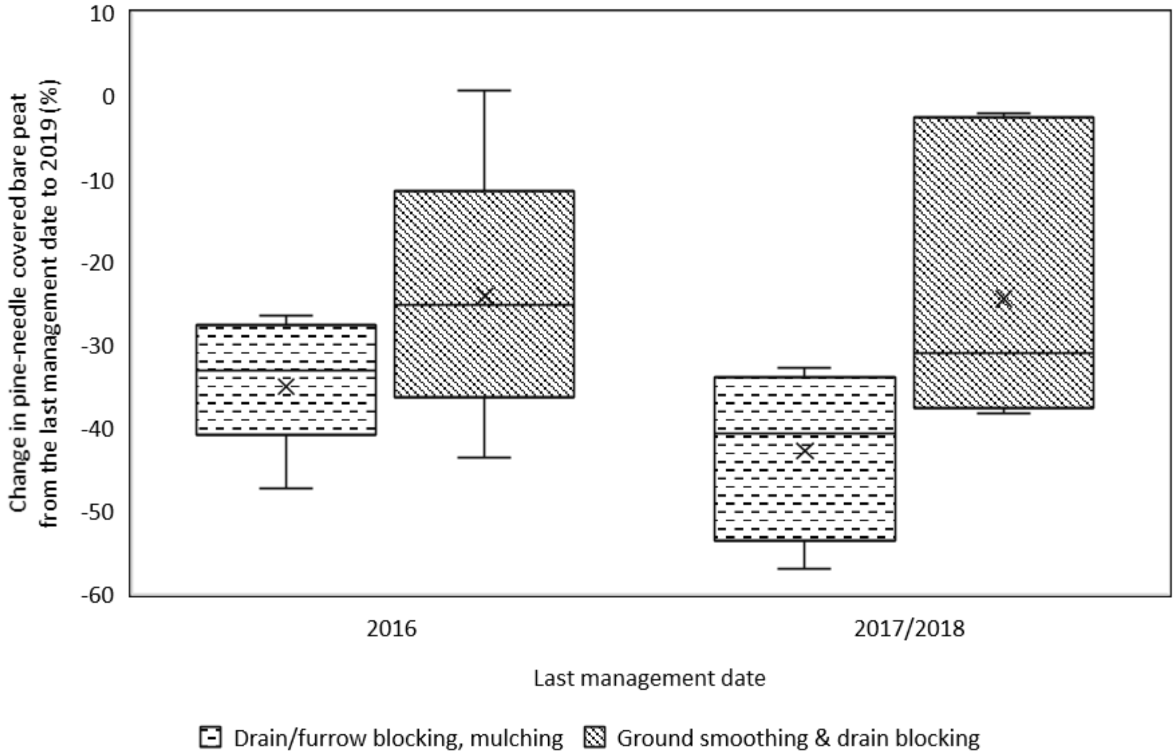


Figure 13: Boxplots displaying the differences in restoration operations seen at the Dalchork Forest site.

3.2 Dark Peak, England

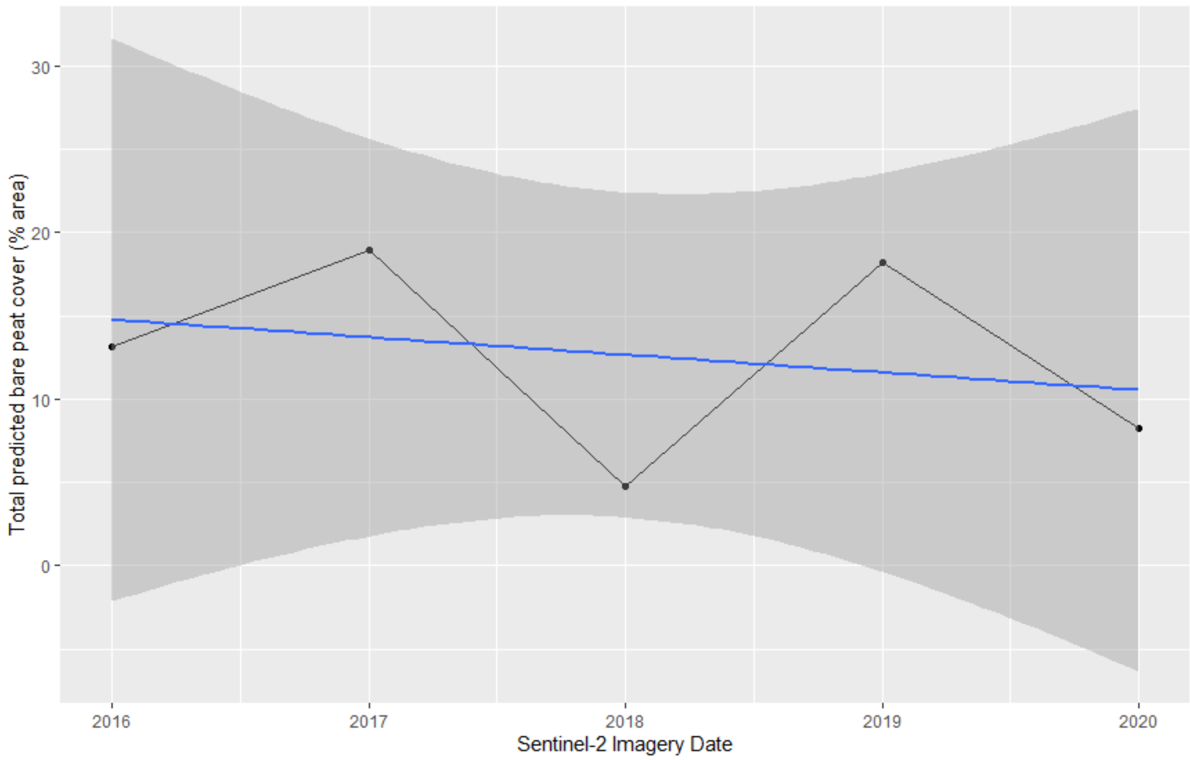
3.2.1 Fine-scale mapping

The fine-scale map developed in the JNCC pilot project (Trippier *et al.* 2020) was used for the Dark Peak site, covering 80.38% of the site. The thresholding rule to derive these points was based upon NDVI being below 0, Brightness below 100, RG below 1 and RB above 1.25. It is worth noting the GLI and NDWI indices were not assessed in the pilot study in this methodology step.

Comparisons of 2m ground observations from 2018 noting the presence and absence of bare peat with our fine scale maps at the 25cm resolution, showing the locations of bare peat before these are converted to a percentage cover, revealed a 97% accuracy. However, this also gave a sensitivity of 0.36 for the positive identification of bare peat. This uncertainty was likely due to the difference in scale, where the ground observations were taken at a scale of 2m, significantly larger than our predictions at the 25cm scale. This highlights issues in collating comparable ground data and the confidence we can have in this comparison as a method of validation. Adequate ground data at the same scale as our predictions are needed in order to accurately validate the fine-scale maps and derived time series maps.

3.2.2 Time-series modelling

The time series results for the Dark Peak showed varying predicted bare peat cover between 2015 and 2020, described in Figures 14 and 15. The model was trained on one year of APGB data from 27 June 2018 covering 80% of the site and produced a mean RMSE of 0.13 and R^2 value of 0.66. Unfortunately, due to cloud cover over the site, no data was available for 2015, and the imagery for 2017 and 2019 fell outside of the summer period. This may explain the drastic differences shown in the predicted results during these years, with over 18% of the site predicted as having bare peat. One reason for this variation may be due to the seasonality of the vegetation present in late-April and late-October, with less pronounced differences between the vegetated and unvegetated peat apparent from the Sentinel imagery.



Sentinel-2 Imagery Date	Total predicted bare peat cover (km^2)	Total predicted bare peat cover (%)
2016-07-19	41.78	13.10
2017-10-29	60.53	18.98
2018-06-29	15.24	4.78
2019-04-22	57.93	18.16
2020-06-25	26.21	8.22

Figure 14: Summary statistics for the predicted cover of bare peat at the Dark Peak site. The black line shows the observed totals described in the table below, and the blue line shows a linear trend across the time period with a confidence band in grey.

Extrapolated years seem to have higher underlying predicted cover values compared with 2018, when the model was trained. This can be seen in the summary statistics as well as the close up view of Kinder Scout in Figure 16. The underlying values for the vegetated regions are higher in the extrapolated years at between 5-15% cover, whereas these areas are closer to 0% in 2018. This may be due to 2018 being a particularly dry and hotter summer anomalous in comparison with other years in the time series. Rainfall was significant in the model for determining the predictions, with only the variables of RG and GLI found to be more important. Training the model on this anomalous year may have caused overprediction in the predictions where values for other years fell outside the range of those used in the training data. The total summer rainfall values for each year () display how much of an outlier 2018 was from the rest of the years of the time series. Using VHR data from multiple years to train the models would help to alleviate this in future, sadly only 2018 data were available for this site. Further investigation comparing with long term imagery and climatic records would help to determine whether you are in this type of year and whether an adjustment factor could be applied to avoid this adverse effect.

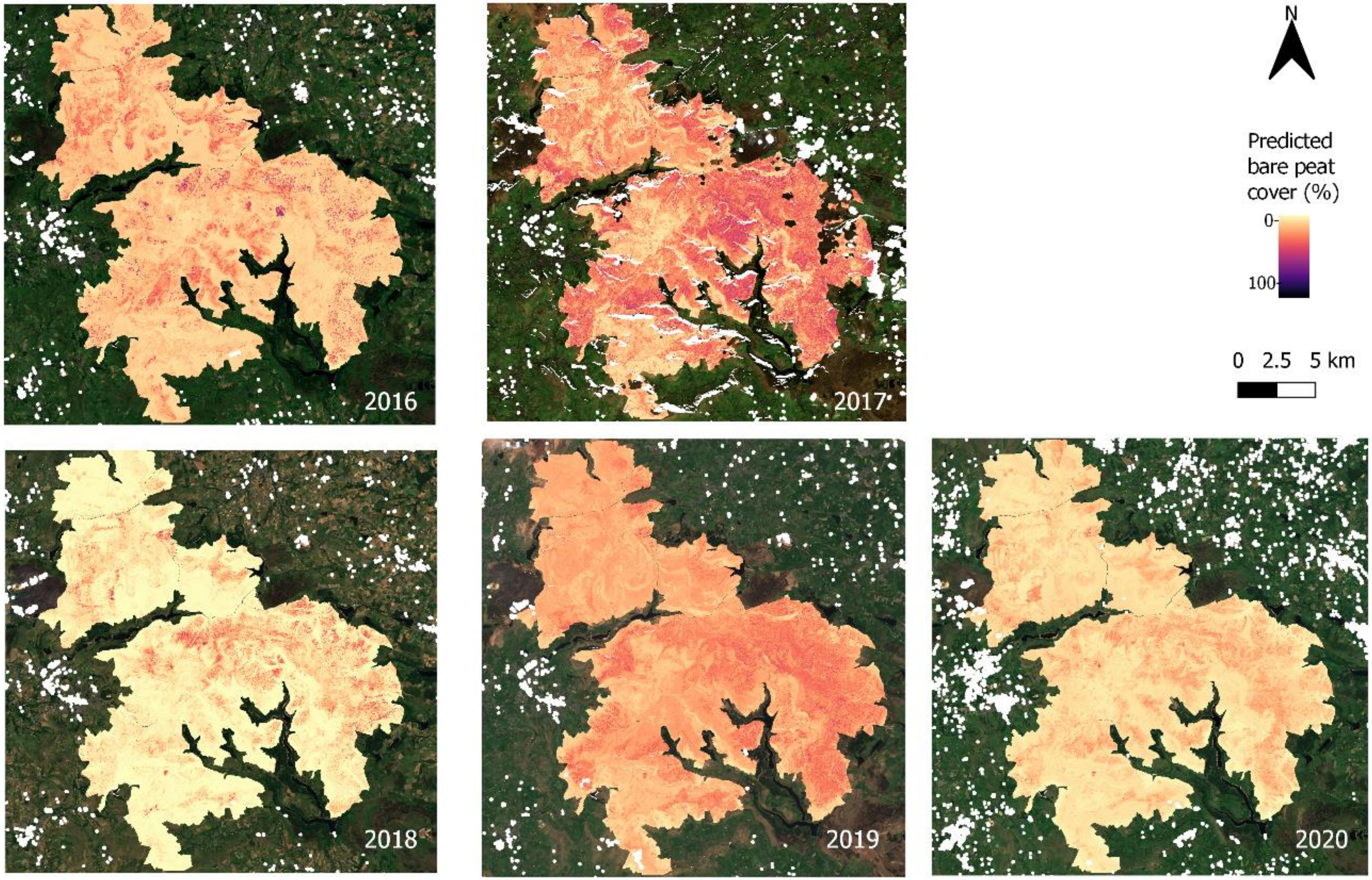


Figure 15: The predicted cover of bare peat at the Dark Peak site for the time period 2016-2020, plotted against the Sentinel-2 imagery.

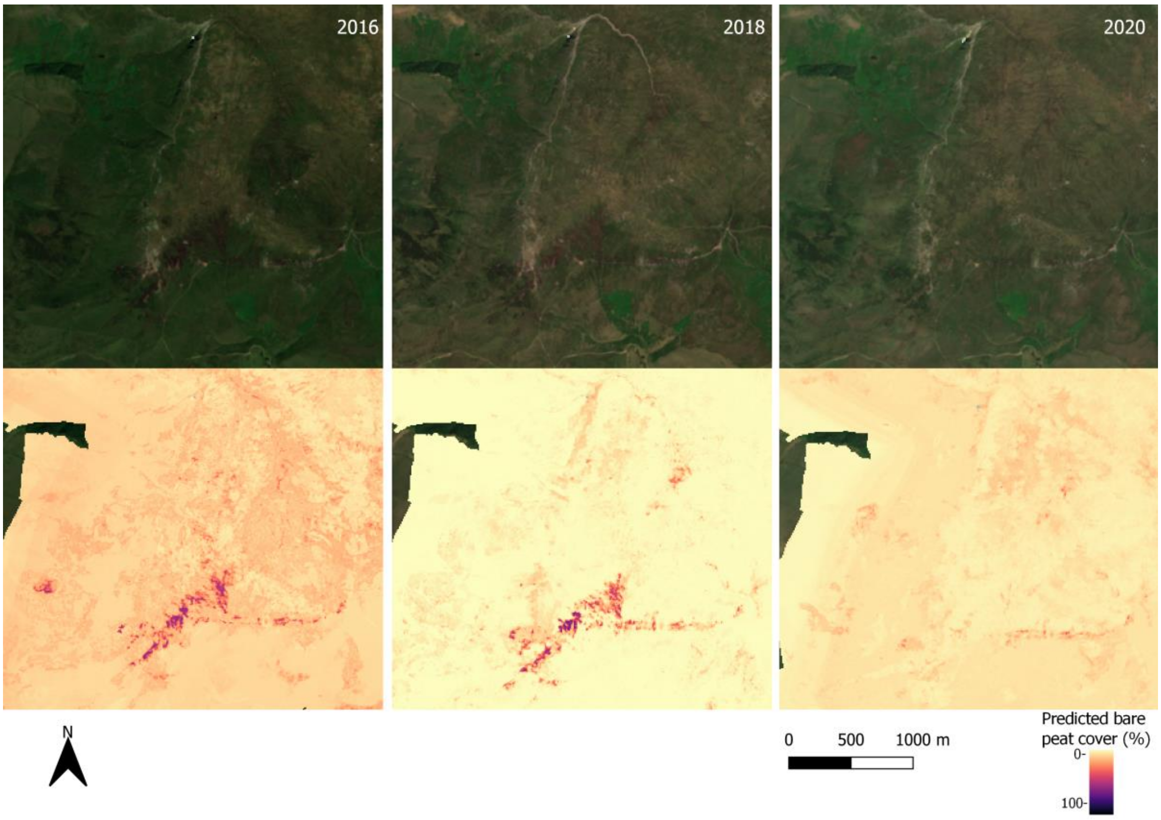


Figure 16: Predicted bare peat cover for Kinder Scout within the Dark Peak site at three different time points: 2016, 2018 and 2020. These are compared to the Sentinel-2 imagery.

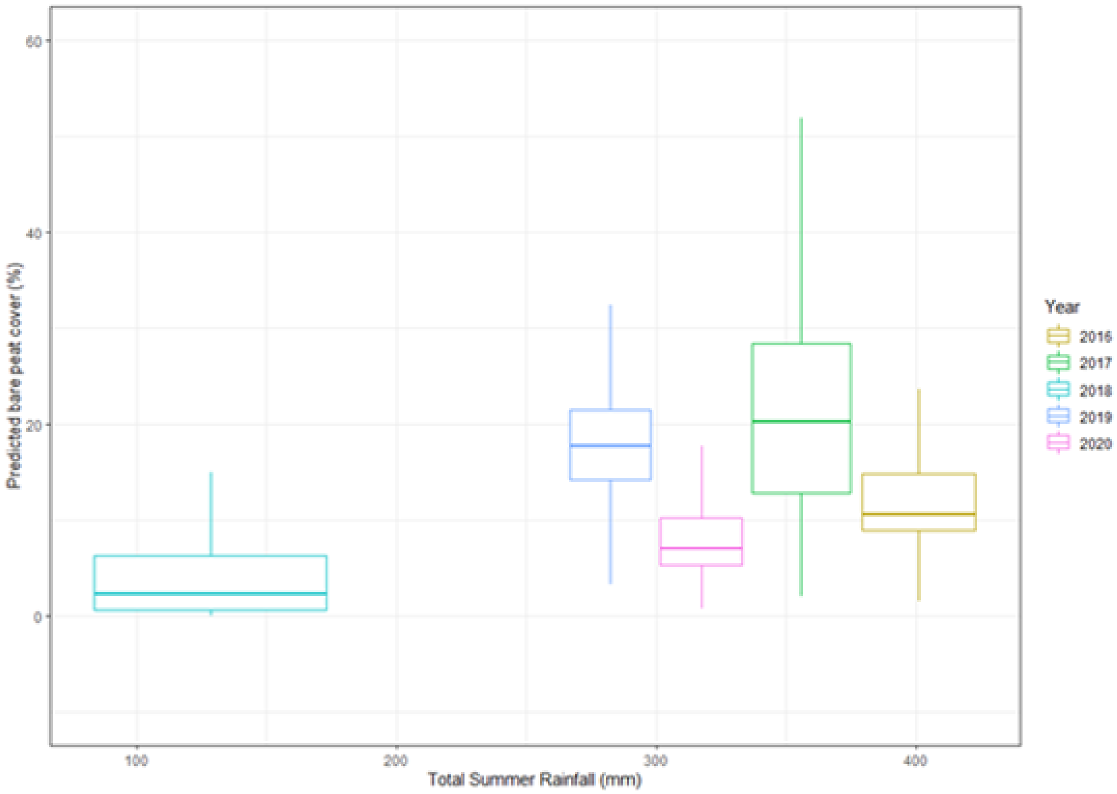


Figure 17: A box plot of the total summer rainfall against the bare peat predictions for each year at the Dark Peak site.

Identified during the desktop study another factor that could explain this observed variation between years and over prediction of bare peat extent in some years, is that cutting and burn heather management areas maybe being miss identified, as bare peat areas. This can be seen at Midhope Moor where a visual spatial relationship between the patterns of cut/burn management areas and bare peat predicted extent. There is a need to take into account cutting and burning areas, which are part of heather management of the Bog to reduce its dominance and bring into better condition. Heather dominated areas are fired or cut as part of management to reduce extent, vary the age and structure each year and could further explain the variation being observed. These areas could have immediately or for a short time after, have some bare peat that has been opened up after cutting or being burnt. That is followed by a re-establishment phase of the heather or grass vegetation that will vary in timescales for each cut/burn area, depending on several factors. These cut areas could remain visible and less productive for a number of years after or the vegetation may even re-establish, more quickly and show a more immediate response with an increase in productivity. These bare peat areas may often be too small to pick up before they recover and become more vegetated, again. Therefore the model could be mapping too much the extent of bare peat, mistaking these burn or cut areas as wholly bare peat areas, due to drop in NDVI giving a false rule set range for the fine scale training data production, leading to over mapping in the time series model outputs. Leading to new burn and cut areas being mapped and maybe even some older ones depending on vegetation re-establishment timescales.

Further investigation of the indicator value ranges used to set the training data rules for identifying bare peat is needed to distinguish between bare peat, burn and cut areas in relation to their re-establishment as vegetation, as there may be some bare peat in those cut or burn areas, for a time after, but not covering the extent of the whole cut area. There is a need to be able to identify bare peat vs the removal of vegetation by burning or cutting.

Nevertheless, the results detect changes in the site to bare peat cover. At Kinder Scout, the recovery between 2016, 2018 and 2020 is evident both in the Sentinel-2 imagery and in the modelled predictions where large patches of bare peat at the site have recovered. Changes in condition is also evident from the Saddleworth Moors to the north of the site (Figure 18), which was the site of a large moorland wildfire burn in 2018. The map of change between the predicted 2017 and 2018 maps do not identify that the burnt areas are bare peat, likely as these differ in their appearance from the bare peat pixels the model was trained on. Instead there is a predicted decrease in bare peat cover in 2018 in this area, with some increases estimated where further erosion has occurred on the surrounding ridges. This highlights the need to train the models on greater amounts of input data, possibly including data from wildfire burns in order to detect this type of change accurately.

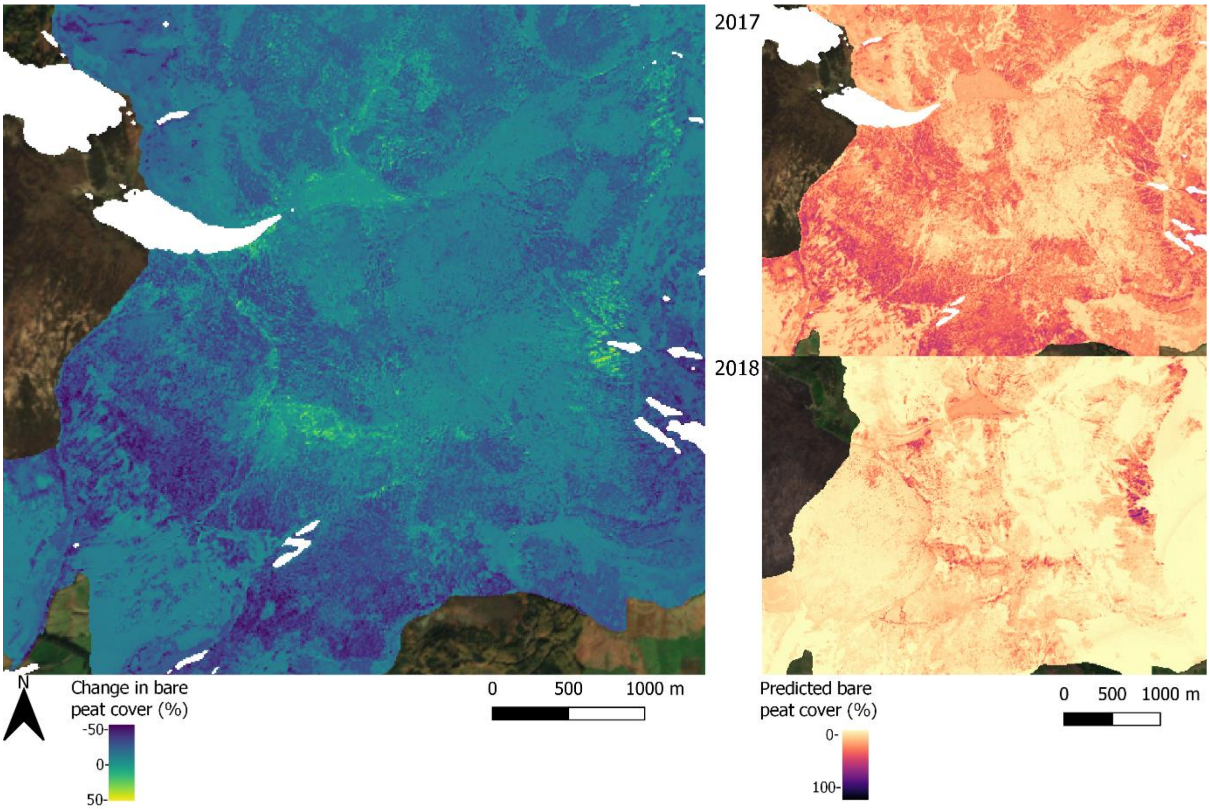


Figure 18: A map showing change in the predicted percentage cover of bare peat over the Saddleworth Moors between 2017 and 2018.

Validation with the ground observations from MMU (2020) demonstrated that in comparison to the observed bare peat cover values, the predictions did not show good agreement (R^2: 0.17, RMSE:54.53). As mentioned previously this could be due to the scale of the observed points being much finer than the 10m predictions produced by the models. Comparisons against the presence and absence of bare peat revealed greatest accuracy against the 2018 predictions (accuracy: 81%, sensitivity 0.82) compared with 2017 (accuracy:17%, sensitivity 0.88) and 2019 (accuracy: 6.6%, sensitivity:1). The high sensitivities suggest that the models are correctly predicting the presence of bare peat, however the varying overall accuracies suggests that outside of 2018 the predictions are not correctly predicting absences. This again points to overprediction in the extrapolated years.

The desktop study has support that the predicted maps outside of managed burn/cut areas as the site experts found the maps to display good spatial correlation with the areas of bare peat, however they noted greater uncertainty in the predicted values particularly where these were low estimates of amounts of bare peat present. This again highlights the issues we observed in the extrapolated year predictions. They also found areas of heather cutting to be misidentified as bare peat, which suggests possibly a misidentification in our training data which warrants further site expertise to aid the initial identification in the VHR imagery, or that the models were detected similarities between the bare peat and the cut regions of the sites, requiring further investigation to explore if these features could be teased out from being detected by the model.

3.3 Humberhead Peatlands NNR, England

3.3.1 Fine-scale mapping

The Humberhead NNR imagery was captured over multiple years, covering different proportions of the Thorne and Hatfield lowland peatland sites each year, described in Appendix 1 - APGB Imagery dates. Imagery captured on 20 October 2019 was late in the season compared to the rest of the imagery taken between late April and July. The bare peat within these images was difficult to distinguish from the vegetation, as the leaves of species such as the common cottongrass, E*riophorum angustifolium,* turns a rusty colour in autumn, looking similar in its appearance in the imagery to bare peat (Small 2020). This is opposed to its greener appearance in spring and summer where the vegetative difference is more apparent. Due to this seasonality, the imagery from October was not used in the creation of the fine-scale maps, with these being informed only by the imagery from 2016 to 2018.

The remaining images were captured over five dates, as listed in Appendix 1 - APGB Imagery dates. Thresholding rules were not transferable between different capture dates, suggesting these to be specific to flight conditions. However, geographically the rules were similar between the Hatfield and Thorne sites where images were captured on the same date, with the two sites located approximately 5km apart. Hatfield was found to have larger amounts of bare peat present compared with Thorne, with the water management present at Thorne creating more algal pools and vegetated fields. The wetting and drying cycles at Hatfield created harsher conditions for vegetation to establish, due to the dynamism of water input from rainfall which changes throughout the seasons related to rainfall patterns, as lacks ability to manage water levels as Thorne does leading to larger patches of bare peat which are clearly visible within the imagery.

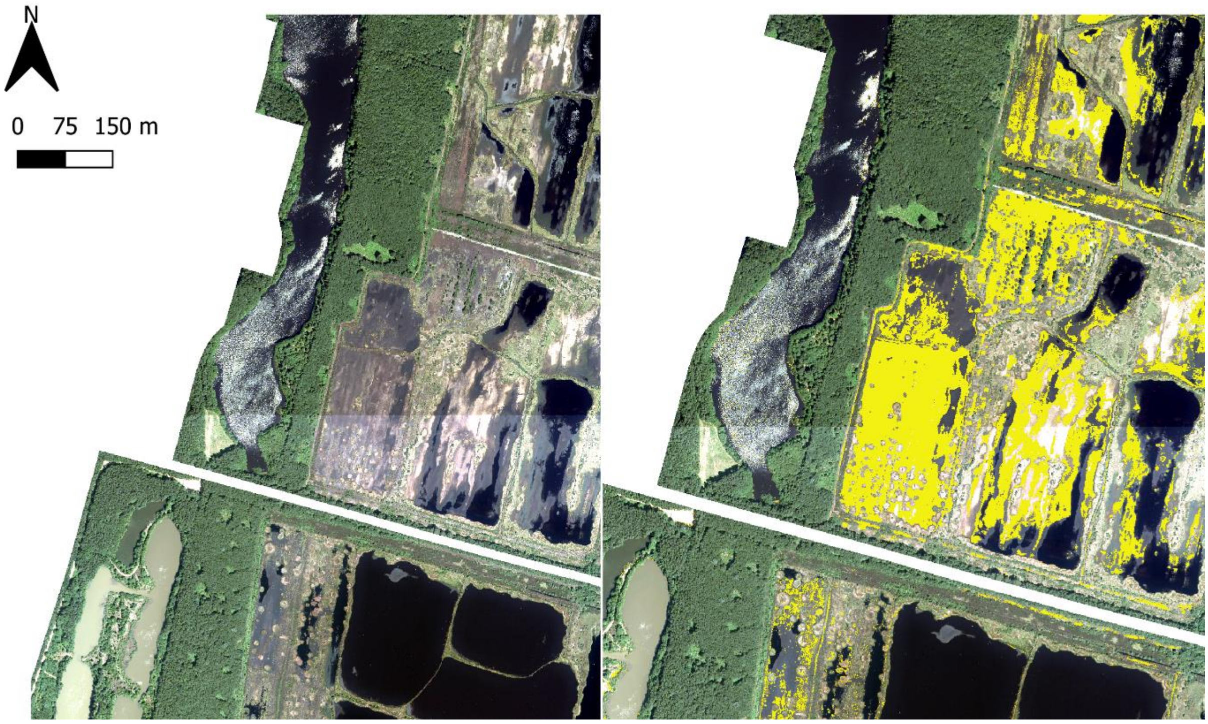


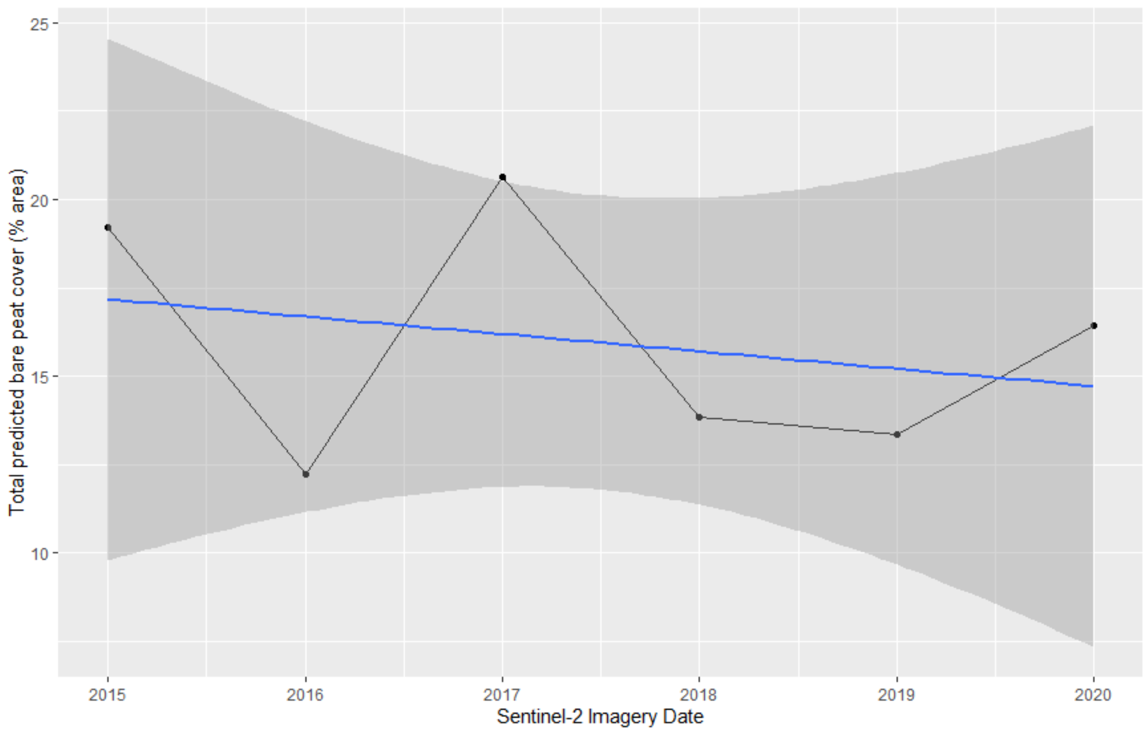
Figure 19: A section of the fine-scale map developed for the Hatfield site, in the north-west corner. The yellow areas highlight the features identified are bare peat, mapped against the APGB imagery (Bluesky International 2019).

Compared with the upland peatland sites, the lowland habitats were harder to separate the bare peat from the rest of the imagery given the varied vegetation and algal mats present.

Maximum and minimum limits were set for all the trialled indices (NDVI, Brightness, NDWI, RG RB, GLI) as well as the near-infrared band, in order to capture as many bare peat pixels as possible from the imagery. Figure 19 demonstrates the areas of bare peat identified in Hatfield, with heavily waterlogged peat and pools of water excluded by the minimum NDWI threshold (-0.12 ± 0.07).

3.3.2 Time-series modelling

Training data for the Humberhead Peatlands NNR were available between 2016 and 2018 covering various sections of the two sites; Thorne and Hatfield. Several combinations of these data were trialled to see which produced the most accurate model. The best results were found when training the models on 2 years of Hatfield data from late April/May 2016 and 1st July 2018 (RMSE 0.14, R^2 0.83), and are reported in Figure 20.



Sentinel-2 Imagery Date	Total predicted bare peat cover (km²)	Total predicted bare peat cover (%)
2015-09-30	5.55	19.20
2016-07-19	3.53	12.22
2017-05-05	5.97	20.64
2018-07-01	4.00	13.84
2019-08-23	3.86	13.34
2020-06-25	4.76	16.45

Figure 20: Summary statistics for the predicted cover of bare peat at the Humberhead Peatlands NNR site. The black line shows the observed totals described in the table below, and the blue line shows a linear trend across the time period with a confidence band in grey.

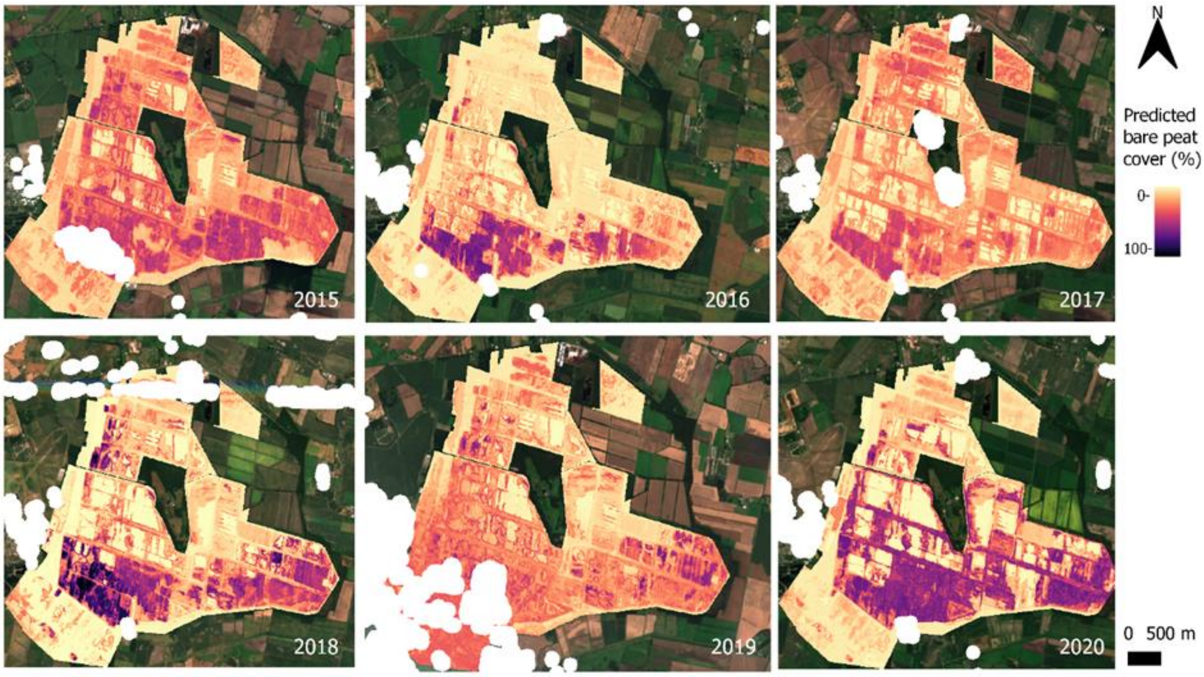


Figure 21: The predicted cover of bare peat at the Thorne site within the Humberhead Peatlands NNR for period 2015-2020, plotted against Sentinel-2 imagery.

Figure 22: The predicted cover of bare peat at the Hatfield site within the Humberhead Peatlands NNR for period 2015-2020, plotted against Sentinel-2 imagery.

This performed better than training on only a single year of Hatfield data (RMSE 0.15, R^2 0.75) and training on all the data from both Hatfield and Thorne, where despite producing slightly higher evaluation scores (RMSE 0.14, R^2 0.84), the resulting maps seemed to underpredict. This may have been due to the low cover values present in the Thorne data.

The results show the variation between the two sites during the time period, with overall the Thorne site having less visible bare peat within the imagery, which is to be expected as the site tends to be populated with denser algal mats, and due to the water level management in place, the bog is in much better condition and more vegetated with bog plant communities compared with Hatfield. This is due to the dynamism of the water levels across the site from not being managed on Hatfield, as does not have a pumping station leading to seasonal flooding eroding and opening up bare peat regularly each, with larger areas of bare peat being exposed resulting in changes in the patterns and extent of bare peat each year, due to these fluctuations. The Normalised Burn Ratio was by far the most important variable in splitting the data, which was not as important to the other site models. The NBR showed to be highly correlated with the areas of bare peat features having values lower than -0.5 and those containing water being above 0.8. As the two Humberhead sites had particularly large pools of water within extraction fields, this would explain why this was such an important variable here, compared with the other study sites.

At Thorne, 2015 and 2017 were modelled with imagery outside of the summer range with data captured in late-September and early-May. This may explain the unexpected results, as the seasonality of the vegetation may have had a greater impact on the results, causing some misidentification with the autumnal rusty appearance of common cottongrass, having an influence here (Small 2020). Despite being modelled on only data from the Hatfield, the Thorne predictions appear to be accurate, picking up some changing conditions occurring at the site. For instance, the top image in Figure 23 illustrates some recovery to the west of the image and increased erosion occurring in 2020. The lakes in the middle finger of the images demonstrate how changing water depths are detected in the model, with these noted as low cover values when very wet changing to higher values of bare peat cover as they dry. This shows quite a notable effect within an annual timestep between 2019 and 2020. The model also detects bare peat around the pools of water giving an edging effect. This wetness differentiation in the model can be further noted in the bottom image in the Figure 23 where the larger pools of water at the Hatfield sites shift to drier segments of bare ground.

Figure 23: Close ups from areas with the Humberhead NNR: a region to the north of the Thorne site during 2018 to 2020 (top) and a region towards the south of the Hatfield site for 2016, 2018 and 2020 (bottom), with mapped Sentinel-2 imagery and bare peat cover predicted maps.

Validation was carried out with ground estimates of bare peat cover per cell from the Hatfield site in October/November 2015 provided by Natural England, pictured in Figure 24 (Kohler 2020). These were partially covered by cloud cover in the imagery, therefore only 14 of the 47 cells were cloud-free and could be summarised to give total bare peat percentage covers per cell. These underpredicted compared with the ground observations, with cover values ranging from 30-42% as opposed to the ground predictions which were all over 60% cover. This underprediction may be a result of the variation in imagery date, with the 2015 imagery from 30th September being trained on a model developed with training data captured in summer. It is also likely that the fluctuations in surface water over the year has caused this underestimation, as some cells of bare peat are covered with films of water, which differs each year linked to the seasonal rainfall patterns throughout the year. This change in extent of surface water algal films needs to be taken into account and could be improved by using Sentinel-1 radar to map and mask changing water levels to get a full picture of bare peat extent. Causing the level of bare peat to be open and not under films of water to vary. Figure 22 shows these wetter features or algal film covered bare peat as present in the top left corner of, which were not considered bare peat by the model.

This may also be due to so overprediction in the ground results where seasonality of the vegetation may cause estimates to be higher, as well as estimation bias from rounding estimates and due to the viewpoint of the observer compared with the Birdseye view we see from the imagery.

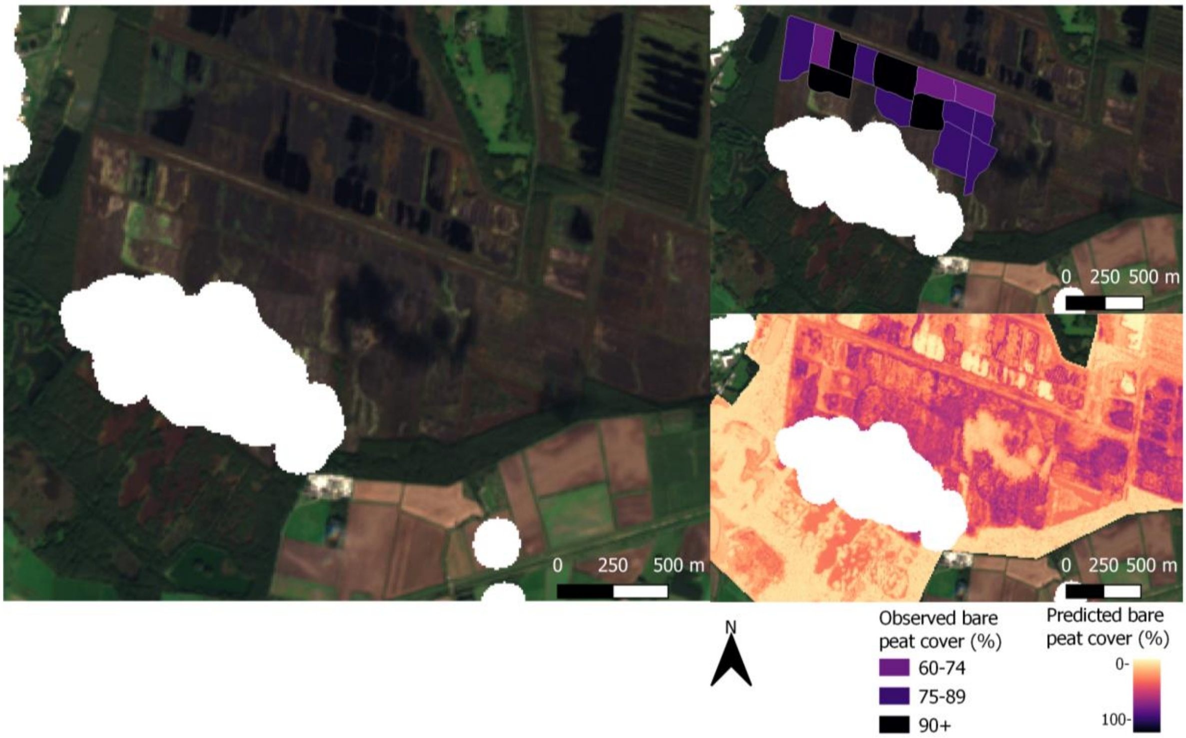


Figure 24: Sentinel-2 imagery for the southern part of the Hatfield site pictured (left) against NE ground observations (top-right) and the predicted bare peat map (bottom-right) for 2015. Contains data supplied by © Natural England, Ordnance Survey data © Crown copyright.

Qualitative validation by site experts for both Thorne and Hatfield found the 2016 predicted map to be highly accurate, with 70% of their digitised vegetated and bare peat polygons found to be accurate, both in their spatial overlap with the polygons and their predicted percentage cover values. Those which were found to be under-predicting were due to fields being flooded during the time the image was captured. Further comparisons with the 2020 bare peat predictions revealed these areas to be accurate in preceding years, as the fields had drained, and the bare peat was identified by the models. This highlights the care that needs to be taken when using these models to assess change, as localised flooding and water management of a site may incorrectly be flagging declines in the amount of bare peat present, simply due to the impact of surface water on the models and the dynamism of the site. All the areas identified as being mostly vegetated and absent of bare peat were noted to be accurately predicted by the model.

Further validation was carried out to assess how stable the predictions were within a year, by using the same models to make predictions for all available cloud-free Sentinel-2 imagery between April and October 2019 for the Thorne site, shown in Figure 25. Thorne was noted to have relatively low levels of bare peat by the site experts, which most correlates with the predictions between June and September. The maps show distinct changes in the predictions throughout the months, although it is worth noting there are significant gaps in the imagery with no images available for July 2019. This echoes our previous conclusions of summer imagery being the most appropriate to use with the most stable and accurate predictions, with imagery from months outside of this season seeming to overpredict.

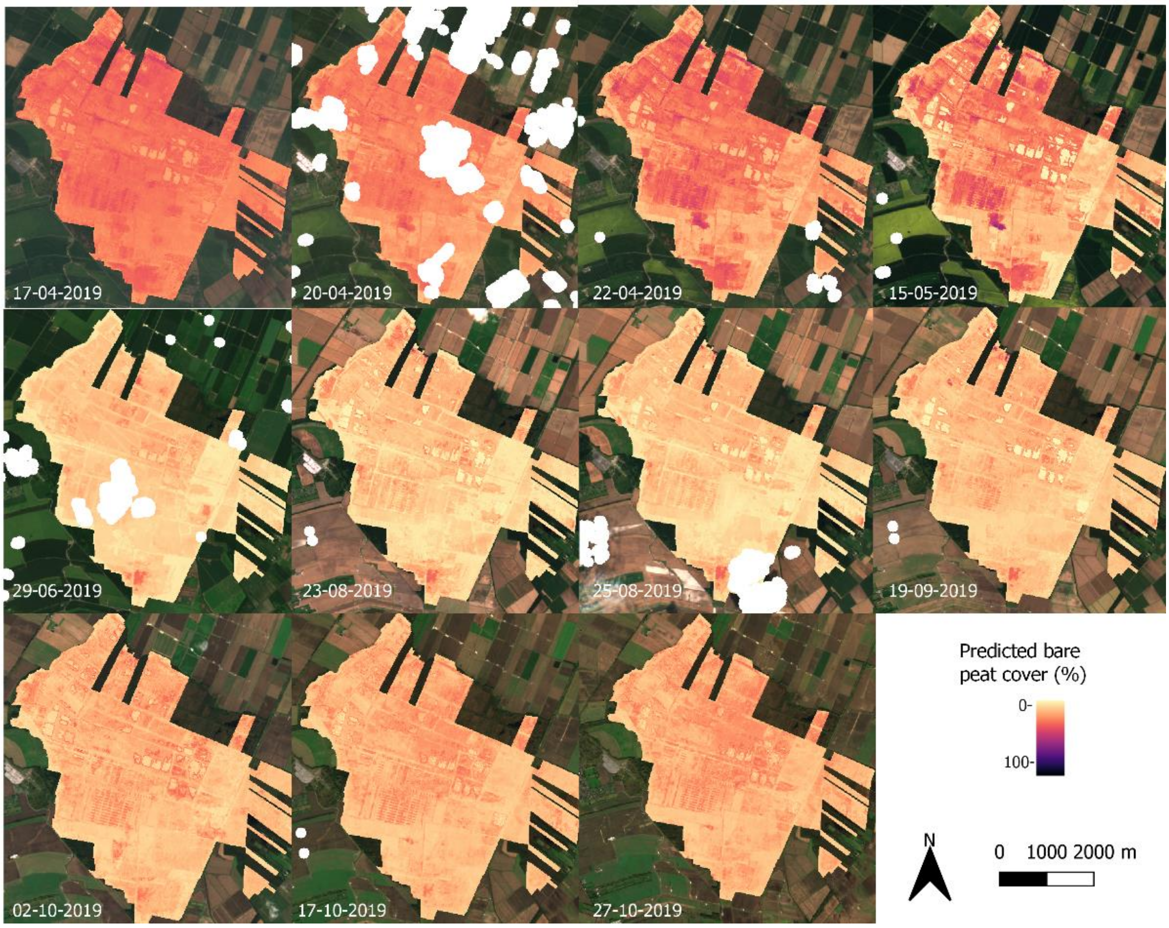


Figure 25: Monthly predictions for 2019 carried out for the Thorne site with cloud free Sentinel-2 imagery between April and October.

3.4 Brecon Beacons, Wales

3.4.1 Fine-scale mapping

The Brecon Beacons site was the largest studied, with aerial photography obtained for three smaller sites within the region demonstrating a mixture of both degraded and pristine peatland conditions. The capture dates were mostly from 2017, with only an additional 0.51% of the total site area covered by imagery captured in 2018. Figure 26 shows a sub-section of the fine-scale map for the site.

The upland sites were uniform with the same thresholding rule demonstrating a good fit across all three sites. This was using a maximum NDVI threshold of 0, NDWI limited between -0.02 and 0.12, and a maximum GLI threshold of 0.02. The limits for the near infrared and brightness indices were more variable amongst the imagery, with the average maximum near infrared band limit of 99.54 ± 11.53 and the brightness limited between 66.34 ±6.12 and 97.8 ±13.10. The threshold values used to separate the bare peat from the imagery were similar for the 2017 and 2018 images, with the maximum limit for the near-infrared band being set slightly lower for the 2018 imagery.

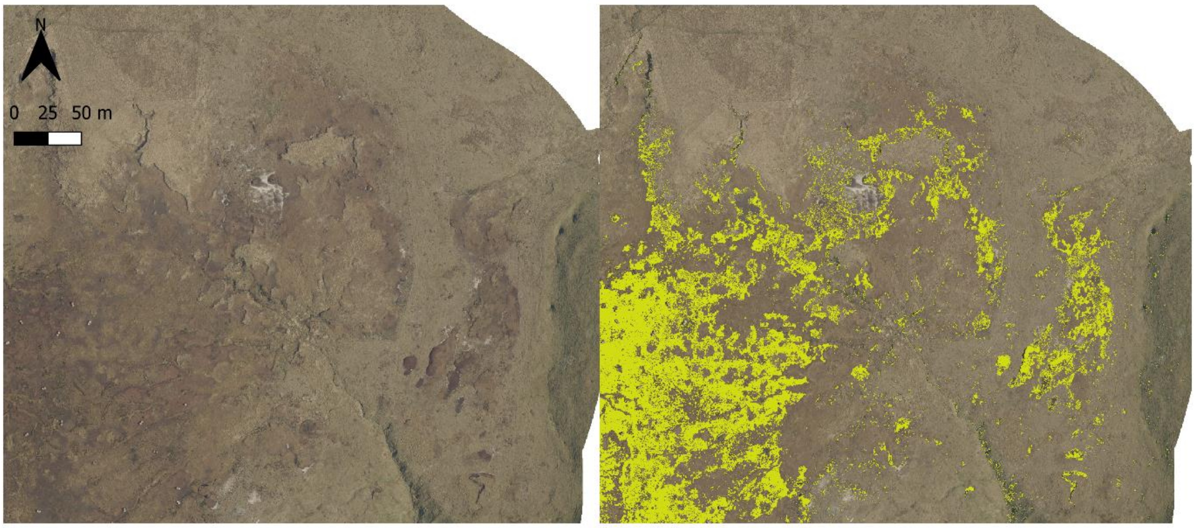
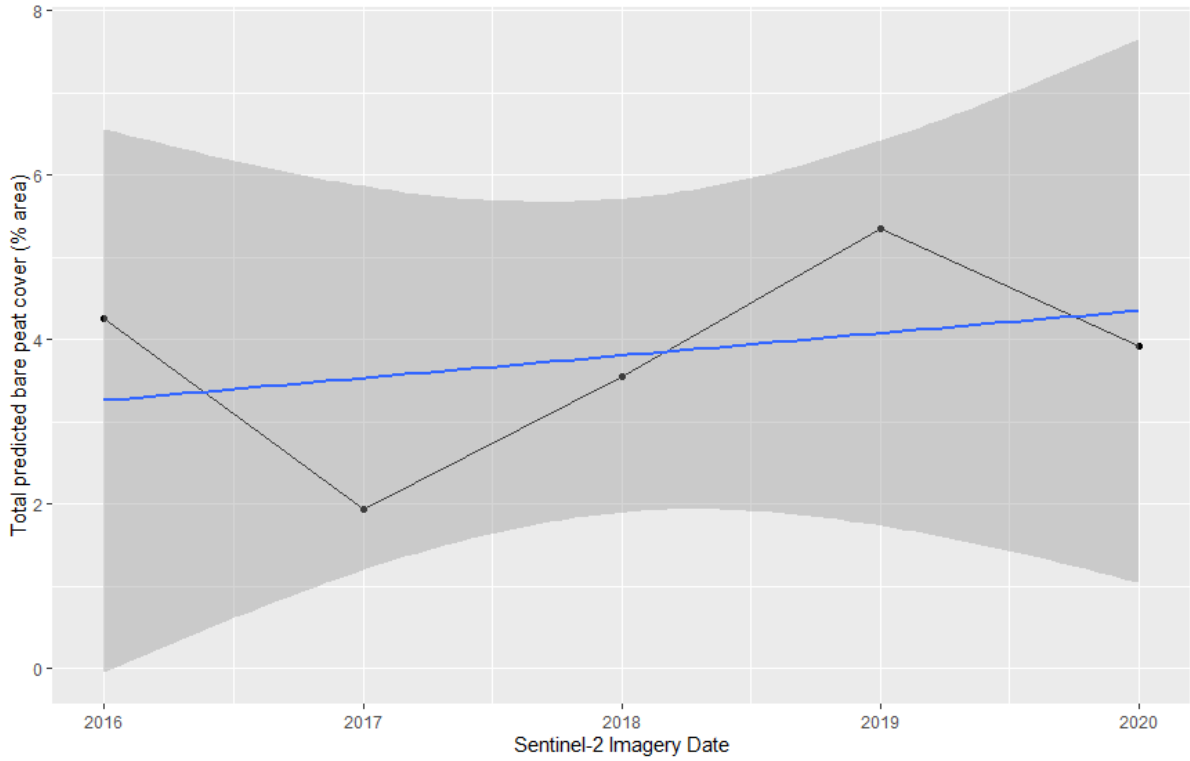


Figure 26: A section of the fine-scale map developed for the Brecon Beacons site. The yellow areas highlight the features identified are bare peat, mapped against the APGB imagery (Bluesky International 2019).

3.4.2 Time-series modelling

The fine scale maps for the Brecon Beacon site covered approximately 4% of the total modelled area, containing 2 years of data from 26 May 2017 and 7 May 2018. Due to fewer training points being available, only 5000 points were used for training the models, to reduce the bias towards lower value ranges. The models were run using training data from only 2017, and again with added data from 2018, although this only covered a very small area of the site (shown in Appendix 1 – APGB Imagery dates). The predictions between the two models were similar, with a slightly better fit found when training the models on both years of data (RMSE 0.081, R^2 0.901), compared with training the model on a single year (RMSE 0.083, R^2 0.896). The predictions for each year of the time series are reported in Figure 28, with summarised percentage cover values in Figure 27.



Sentinel-2 Imagery Date	Total predicted bare peat cover (km^2)	Total predicted bare peat (%)
2016-07-19	13.09	4.26
2017-05-25	5.95	1.94
2018-06-29	10.95	3.56
2019-04-20	16.44	5.35
2020-06-23	12.04	3.92

Figure 27: Summary statistics for the predicted cover of bare peat and pine-needle covered bare peat at the Brecon Beacons site. The black line shows the observed totals described in the table below, and the blue line shows a linear trend across the time period with a confidence band in grey.

The results show relatively similar levels of bare peat overall, with a slight decrease in 2017 likely due to cloud cover present in the imagery, and a slight increase in 2019. The imagery used for 2019 was acquired from earlier in the year in comparison with the rest of the time series, due to the availability of cloud-free imagery being limited. The site was also covered by two Sentinel-2 swaths which meant there was a reduced availability of data capturing the entire area of interest. As a result, no imagery was available for 2015. The April 2019 imagery may have led to inaccuracies in the predictions, as differences between the vegetated and bare regions were less pronounced, in comparison with late-May with which the models were trained on data.

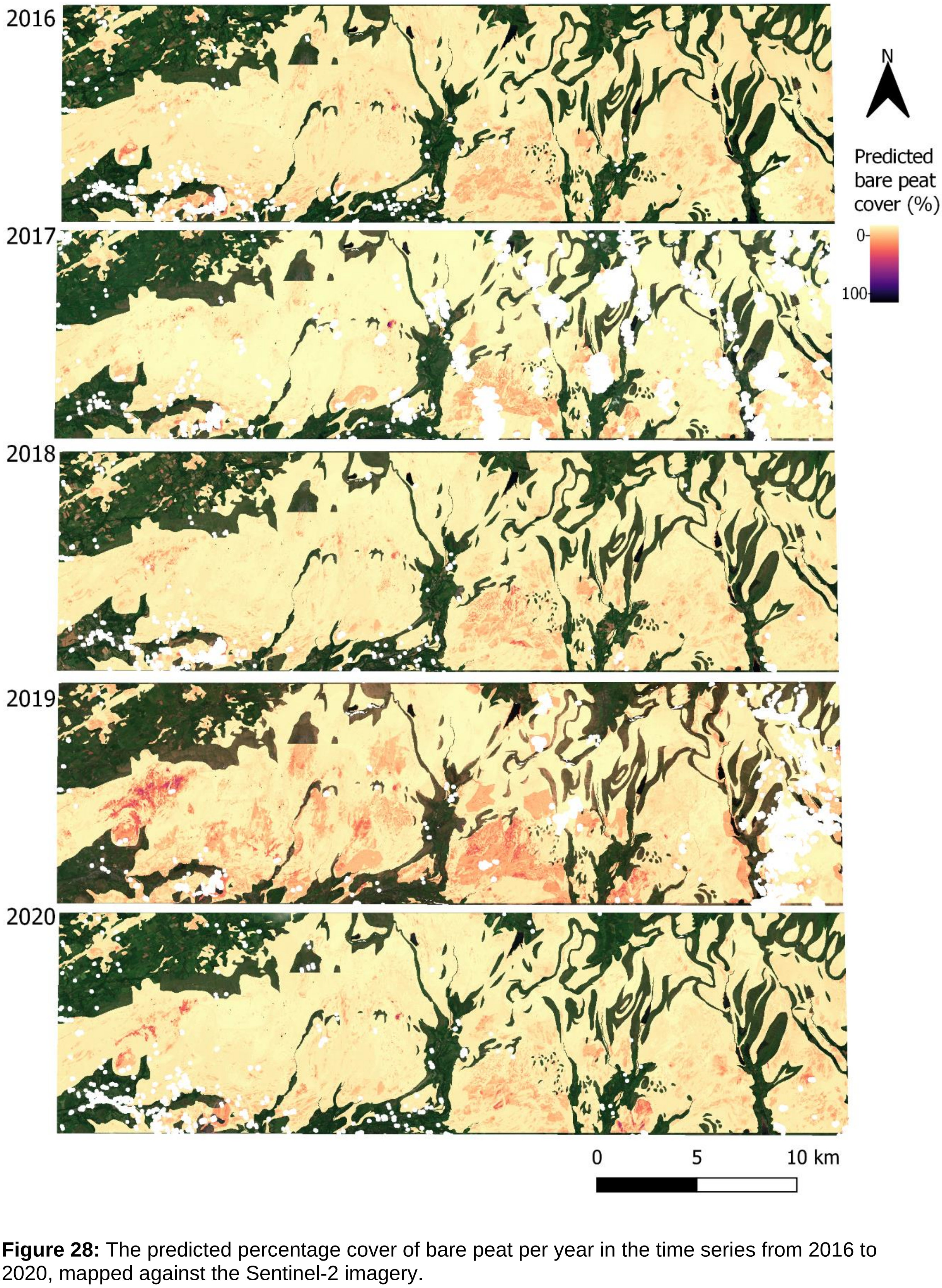


Figure 28: The predicted percentage cover of bare peat per year in the time series from 2016 to 2020, mapped against the Sentinel-2 imagery.

The Waun Fignen Felen site towards the centre of the image displays a prominent bare patch of peat throughout the time series, which can be seen in Figure 29. This doesn't show much change within the time series in both the imagery and predicted maps, however, is consistently flagged as bare, with a slight decrease in bare peat cover seen in 2018 where the site seems to marginally improve. Overall change between 2016 and 2020 demonstrates a slight increase in bare peat towards in the heavily eroded patches, up to 20% in some pixels. However, this may also be due to the capture date and conditions during the comparable years.

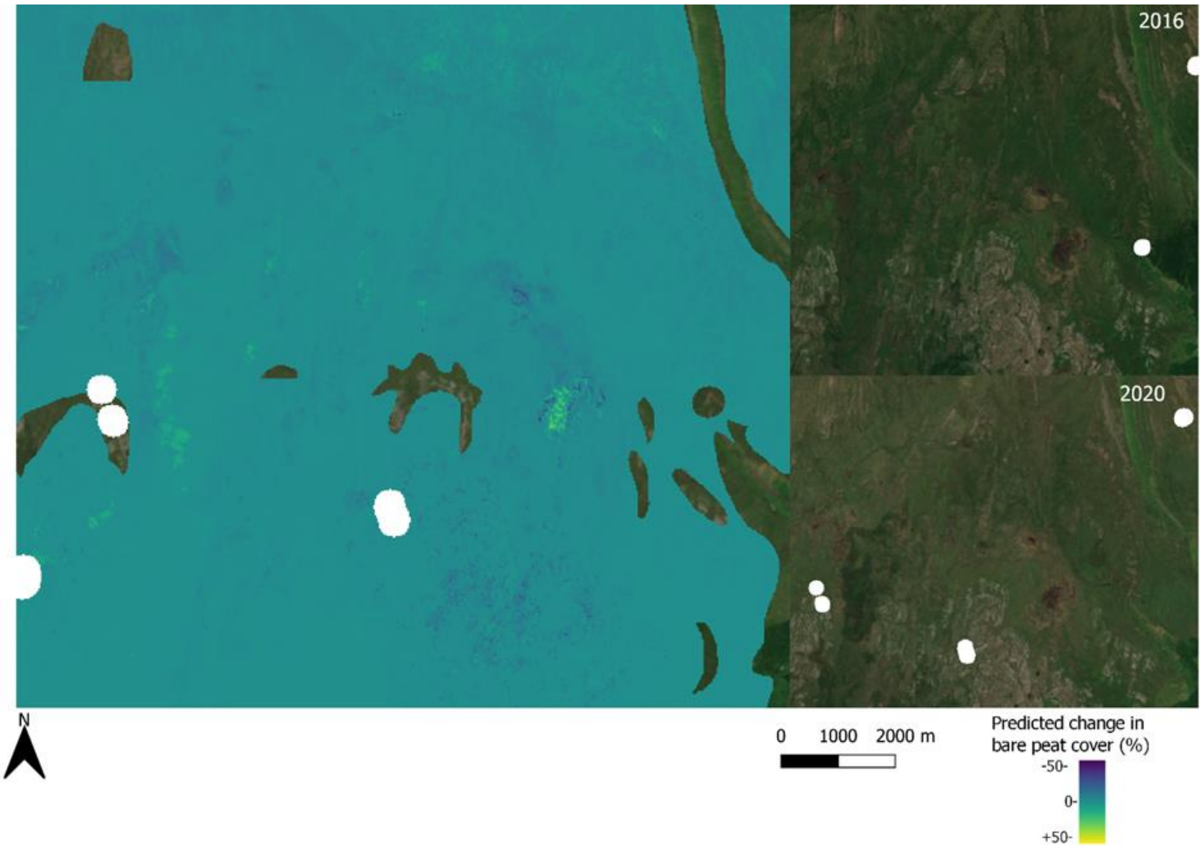


Figure 29: The map of predicted change between 2016 and 2020 for the Waun Fignen Felen site in the Brecon Beacons in 2016 and 2020, visualised against the Sentinel-2 imagery.

Other regions within the Brecon Beacons site detected more variable change in bare peat cover. This is shown to the west of the site in a region containing large areas of bare peat due to erosion, shown in Figure 30. This shows large areas of bare peat towards the south and along the ridge lines, which show some recover in 2018 where the large southern patch has greener vegetated peat. This change is also shown in the predicted maps with these cover values declining however further erosion along the ridge lines has been highlighted, which is again evident in the imagery. In 2020, we see further degradation along the ridges and again some erosion of the southern patch which had revegetation in 2018. This demonstrates how these maps can pick up change where erosion is dynamically changing the landscape.

Validating the time series predictions with 3m Planet imagery (Planet Team 2017) demonstrated no significance with accuracy varying from 60.2 to 80.9%. The lowest accuracy was seen with 2019 which reflects the differences previously noted where bare peat predictions were greater compared with other years. Inaccuracies in the validation process however are foremost introduced where assessments of the presence of bare peat were visual using the Planet imagery which again is remotely sensed not giving the true ground interpretation of where it is truly present. Also, the imagery is a composite compiling of lots of smaller tiles and stitching of different swathes together, with shadow or cloud masking unavailable for the PS2 product. Furthermore, particularly with this site there are a lot of small pockets of bare peat where local erosion and gullying has occurred which may make up less than 10% of a $100m^2$ pixel, which isn’t captured by our validation method.

Validation of the 2019 predicted map against the aerial observations of bare peat revealed a 68.5% accuracy with 37 out of the 54 points correctly predicted to have bare peat present.

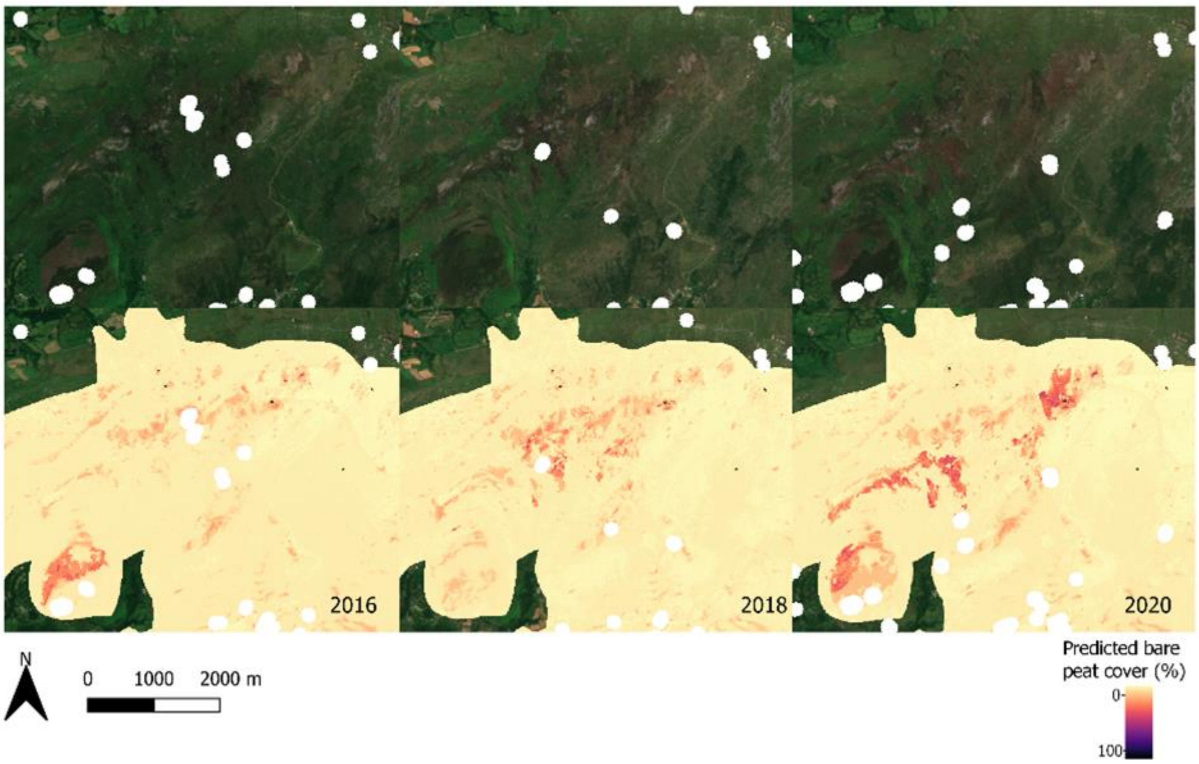


Figure 30: The predicted maps for an area in the west of the Brecon Beacons site for 2016, 2018 and 2020, plotted against the Sentinel-2 imagery.

4 Discussion

Through applying this methodology to all four sites, we were able to distinguish bare peat from the diverse landscapes and explore changes in the predicted amount of bare peat cover over the time series. Through this analysis we have found the availability of summer imagery for both Very High Resolution (VHR) imagery and cloud-free Sentinel-2 imagery to be an influential factor. In the fine-scale mapping, the identified summer period from late-May to the end of August was found to be best for distinguishing bare peat from the surrounding vegetation, when the greened vegetation is most distinct from the bare peat and therefore being easier to separate out these features in the imagery. Imagery captured during autumnal months such as late-October were found to be difficult to determine distinguishing thresholds for bare peat, with the seasonality of the vegetation leading to less distinction between the vegetated and unvegetated regions. Similarly for the time-series predictions, identifying a summer image for each year of the time series proved difficult with suitable images often falling outside of this summer period, and for two sites, Dark Peak and Brecon Beacon, we were unable to model for each year in the time series, with poor conditions and cloud cover obscuring the imagery. Where predictions were made outside of the summer window, the predicted layers were found to overpredict the amount of bare peat cover, with higher bare peat cover values noted in the vegetated regions. This misidentification was likely due to vegetation appearing less greened and distinguishable from the bare peat in comparison to the summer months, with leaf senescence occurring in autumn and the lesser development of leaves in spring. Further investigation of the seasonal differences between imagery dates would help to further understand this relationship and the limitations of the temporal extrapolation range of predictions. These conclusions also highlight the limitations of scaling up using Senitnel-2 optical imagery, particularly for some locations in the UK where cloud-free summer imagery may not be possible every year, limiting the frequency at which we can produce maps of bare peat using this methodology.

The fine-scale methodology was able to distinguish areas of bare peat at all four sites, mapping these to 25cm spatial resolution. This was a time-consuming process requiring manual input to assess the imagery and derive suitable indices from the aerial photography. This needs to be considered when operationalising such an approach, as although this may be appropriate over a small site scale, in order to apply this over a much larger extent would take a considerable effort for achieving this level of detail and thus we would recommend the scaling up approach adopted by the regression modelling. Site expertise were also beneficial in discerning between the different features present and identifying any vegetation species which were particularly similar in appearance to the areas of bare peat. The threshold rules applied for each site can be found in the Supplementary Information. The indices of Brightness, NDVI, NDWI and Red-Green band ratio were used in all the sites, significant to distinguishing bare peat in the imagery. Figure 31 shows how these threshold values differed between the sites. The maximum NDVI thresholds were similar for all of the sites with the majority of rules applied to the imagery falling within the range of 0 to 0.5. The brightness was highly variable with the highest range seen in the planted regions at Dalchork site where we were identifying pine-needle covered bare peat, which as a feature was more variable in its signature. As well as the capture date, geographic variability was found to have an influential role on the threshold values used to separate bare peat in the images. Further investigation into how these threshold rules differ regionally would help to establish whether such an approach could be used on a national scale or automated by considering regional variances. Furthermore, some uncertainty may have also resulted from the subjectivity inherent in identifying the bare peat pixels within the imagery, with differences between analysts, which may have resulted from preferences towards particular index thresholds or through the user interface in Peatpal. Further development of the application and pre-population of values based on training polygon statistics may help to alleviate some of this bias.

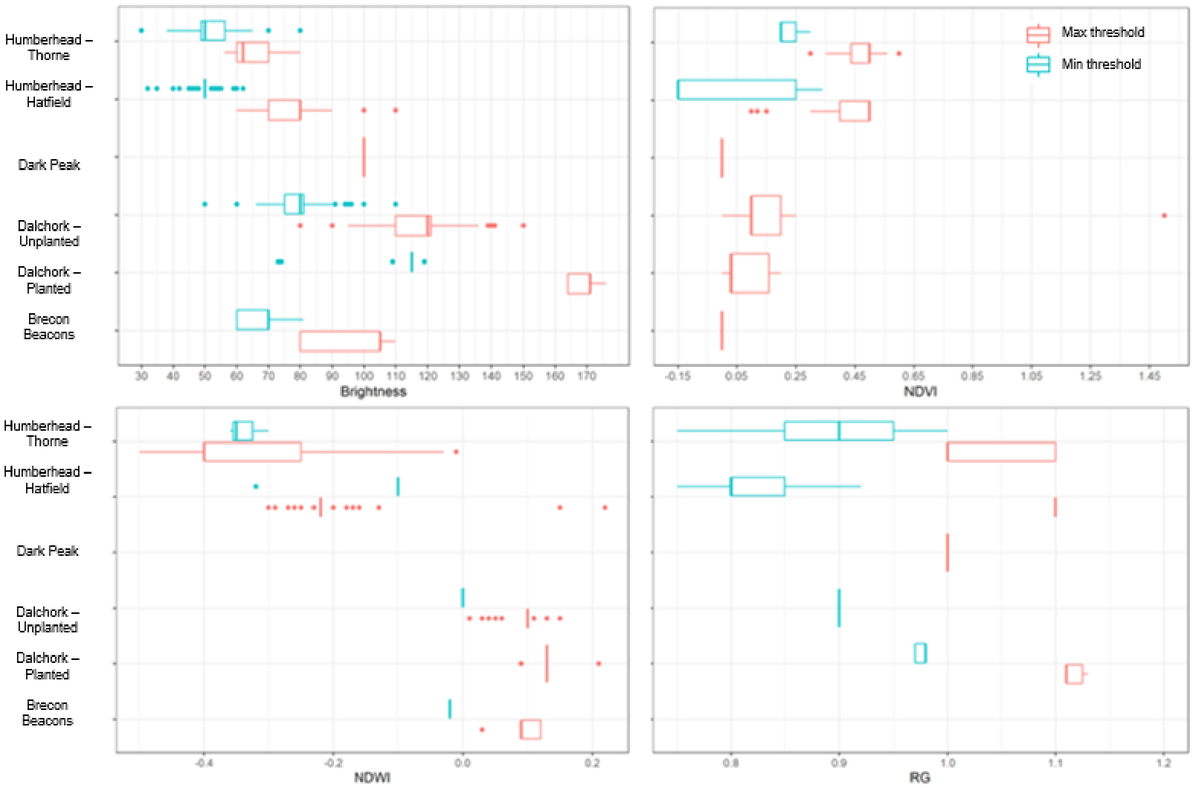


Figure 31: Minimum and maximum threshold values applied to the different sites for separating out the bare peat pixels from the rest of the imagery.

This being a pixel-based methodology, some inaccuracy can be caused where neighbouring bare peat pixels may not meet threshold conditions and so may not be detected. Further investigation into Object Based Imagery Analysis (OBIA) or more sophisticated detection techniques such as Convolutional Neural Networks (CNN) may help to increase the accuracy of image detection with VHR imagery, creating a more complete picture of the areas of bare peat. Further consideration of how best to validate these models and the types of data to use is required in order to properly validate these maps. Comparisons with the 2m predictions from MMU (2020) didn't show much corroboration with our 10m predictions likely due to scale. Further exploration into how we could use these estimates in a comparable way or collate data over 10m plots in the field would help with determining the accuracy of our predictions.

Uncertainty from the fine-scale mapping methodology is also carried over into the time series modelling, highlighted the need for accurate and robust identification of these features in the higher resolution imagery. Where data were skewed to areas with low bare peat cover values, lacking data from larger degraded patches such as seen with the Thone site, this produced models which vastly underpredicted and were unable to detect areas of bare peat within sites. This further demonstrates the need for input data from both pristine and degraded sites, a key finding from the pilot study (Trippier *et al.* 2020). Where training data are identifying more varied features, as seen with the pine-needle covered bare peat at the Dalchork Forest site, this resulted in more noisy predictions. Significant computing resource and time are also needed for running these analyses over large areas where lots of training data are available. This would need to be further considered when applying this approach over a vast region or at a national level.

Through time series modelling, we have been able to make annual predictions in the amount of bare peat cover per 10m pixel and explore the changes shown spatially and temporally. All sites demonstrated where changes had occurred, even where models were trained on relatively few training data. For instance, the Brecon beacons site was trained on 5000 points sampled from data covering over 4% of site and produced an R-squared value of 0.901. Our predictions demonstrated how changes due to different management can cause changes in the amount of bare peat. Known areas undergoing restoration at the Dalchork Forest site showed differing reductions in bare peat with the use of different operations, such as ground smoothing and drain blocking. Further investigation into individual measures and the recovery each year following intervention would help to better describe the rates at which peatlands become revegetated and the effectiveness of different measures. Water management is also evident from our maps with sites where peatlands have become waterlogged, such as the Hatfield region of the Humberhead NNR site, being incorrectly flagged in our models as a change in the amount of bare peat. This could be further refined and be excluded from our change maps through masking out the standing water from the imagery prior to prediction. Exploring the use of Sentinel-1 both in informing these models and aiding in distinguishing the surface water could be valuable in improving our results. The accuracy of predictions varied greatly between the sites, as did the available validation data for evaluating the maps. Ground estimates of predicted cover did not seem to agree with our predictions; however, these were taken at different scales to our predictions, suggesting targeted ground validation monitoring would ideally help to provide an accurate ground estimate for comparison. Knowledge from site experts and comparisons with their known areas of change seemed to provide a good corroboration with our predicted maps at the Humberhead site, with inaccuracies noted where peat soils became waterlogged and therefore no longer detected by the models. Overall, using site expertise to validate the accuracy of our predictions was valuable in informing as to how well the models performed both spatially and in the amount of bare peat being predicted across the site.

The results of the time-series predictions were also influenced by climatic conditions between years. The results from 2018 demonstrated inaccuracies where it was an abnormally hot dry summer in comparison to the other years in the time series. Therefore, predicted maps for this year led to some inaccuracies where the climatic predictions were important to model splitting, for instance demonstrated with the Dalchork Forest site. The differences in the climatic layers between 2018 and the other years in the time series were also demonstrated in the derived indices layers, highlighting a need for long term imagery to establish baseline conditions. The Dark Peak was modelled only on one year of imagery from 2018, where this effect was most notable. This caused overprediction in the extrapolated years of the time series, with the average predicted total percentage cover of bare peat in extrapolated years being three times higher than that for 2018. Avoiding using imagery from anomalous years or training models on multiple years would help to alleviate these effects. This can be seen with the models which were trained on multiple years of data: the Brecon beacons and Humberhead models. The Brecon Beacons model improved in accuracy where modelled on data from both 2017 and 2018 and didn't demonstrate significant differences in 2018 predictions, however only a small area of data for 2018 was used. Similarly, the Humberhead model was improved where two years' worth of data from the Hatfield site were used from 2016 and 2018. Exploring the use of other data sources of VHR and the use of drone imagery would help to substitute additional data for this use and may mean this is more feasible as training can be regularly updated.

5 Conclusions and Recommendations

This project has demonstrated that, using a time series of Sentinel-2 imagery, we can develop models for predicting the amount of bare peat cover per year, informed by VHR. This work has shown that this is not a process that can be highly automated. It requires site expertise to be able to identify the correct features in the VHR at the right time of year and be able to discern these from surrounding vegetation. Further to this, knowledge of the sites has been invaluable in the interpretation of the modelled predictions and understanding the patterns of change which have been flagged, with these being highly specific to management and operations at each site. For instance, this can help discern where changes in bare peat are likely due to genuine change in condition resulting from management measures, or are being flagged due to climatic conditions, such as seen with the Hatfield site where a lack of water management leads to frequent flooding of fields. This could be further improved in the methodology by using Sentinel 1 radar imagery, as this is not affected by cloud cover, to mask any standing water prior to the modelled predictions, removing the influence of the site water management on the maps of condition change.

Our results show value in annual predictions for sites, with changes in the amount of bare peat evident at year intervals. Summer imagery captured between late May to the end of August was found to be best for identifying these features from surrounding vegetation, both in the VHR and Sentinel-2 imagery. Assessing monthly predictions within a year also revealed that predictions between months within this period were consistent. From this we can conclude that this method of assessment would be possible at its highest frequency on an annual basis, if suitable imagery were available. In this methodology, we used just one summer image per year to calculate an annual prediction, with available cloud-free Sentinel-2 imagery being a limiting factor. Using this method, we would suggest developing the baseline with one to three Sentinel scenes from different months each summer rather than a single image, to help remove issues of variation relating to extreme weather conditions. For the Dark Peak site, the results demonstrated a need to differentiate between cut/burn areas from areas of bare peat and reduce the variation in order to be applied more widely in this upland region.

Further exploration into other open source imagery could provide a more regular time-series, for instance investigating the use of Sentinel-1 data to see how information on surface roughness may be used to distinguish bare peat. Severe hagging in eroded bare peat areas is likely to impact upon the roughness on the ground, however, whether this would be able to detect a variety of bare peat patches would require appropriate testing. Similarly, trialling this methodology using other sources of VHR imagery or incorporating imagery from multiple sources may help to substitute our data where we have gaps, overcoming shortages of available summer images which resulted in time series predictions being made outside of the summer period. This could also be used to increase the spatial resolution of time series predictions, to produce maps which may be at a scale more useful for site operations. Furthermore, our results show that training the time series models on multiple years' worth of VHR data produced more accurate predictions and would help to alleviate some of the variability between years and difficulties seen with anomalous climatic conditions. Substituting our data with additional VHR and drone imagery, could overcome the shortages seen with only using APGB imagery and provide data from multiple years.

Our results have flagged locations where increases in the extent of bare peat has occurred at sites, indicating further erosion and declining condition. They have also shown where positive changes have occurred with declining amounts of bare peat between years, and vegetation recovery being evident. At the Dalchork Forest, known management throughout the site revealed differences in recovery rates between restoration operations, such as ground smoothing and drain blocking. Restoration contributes to a number of key policy targets across the UK. Clear assessments of the effectiveness of interventions enabling recovery can help to develop strategies for restoration and monitor changes in condition. Further comparisons of operations such as our example we have demonstrated here, can help provide an indicator for such an assessment and inform on the rate of recovery seen with management measures. This would be of particular interest for sites where it is hard to differentiate which re-wetting management is having the greatest effect and where the timescales of recovery post-intervention can vary due to a range of environmental and topographical factors. This is valuable for helping land managers to design restoration schemes and remotely assess how successful these have been in meeting restoration targets.

On a wider scale, further investigation would be needed in order to see if this type of analysis could be scaled up to a wider regional or national scale. The fine-scale mapping methodology was shown to vary in the threshold values used both regionally and on different capture dates. Further exploration into more sophisticated methods of deriving these training data would be needed to consider how to create maps on a national scale; either through investigating commonalities between the thresholds and applying weightings based on imagery and geographic factors, or through a more accurate means of image detection such as deep learning methods. As well as this, a more reliable approach to validation would be needed for mapping at this scale, with ideally a designed targeted survey covering a range of peatland states with estimates at the appropriate scale. This would allow for reliable assessments of the accuracy of the predicted maps and where changes are being flagged. Besides this, validation with site expertise and knowledge have provided an indication from ground teams as to their accuracy, which has shown some promise in this being an accurate indicator of the extent of bare peat.

Feedback from site teams and peatland experts have shown the work is promising at detecting changes in bare peat and have an operational use for informing where to target measures and assess recovery. They have highlighted its use as a tool for evaluating restoration schemes, reporting on the progress of vegetation recovery and making comparisons between different techniques. Furthermore, these maps could also help target interventions in areas of erosion concern and by deer management groups for flagging heavily trampled areas in poor condition. Bare peat is just one indicator of peatland condition. Exploring methods for monitoring other indicators such as wetness or the recovery of particular species through Earth observation are important to gain a fuller picture of condition and the wider suite of condition states. Assessing bare peat at both the local site scale and regional level as we have shown here can be of value to meet user needs, including landowners implementing measures on the ground and policy managers designing restoration schemes. Being able to make predictions at these different scales can allow us to adapt to problems and make use of the most appropriate data.

Through this project we have been able to narrow down the conditions to best model bare peat and apply this across sites throughout the UK. This has provided indications of change in peatland condition and demonstrated the influence of management on these key ecosystems. Operationalising such an approach and providing site teams with the tools to remotely assess condition can help to better understand landscape changes and how best to support peatland restoration.

6 Supplementary Information

Supplementary Information including the thresholding rules developed in the fine-scale mapping is available on the report entry:
JNCC-Report-674-Supplemental-Data-Fine-Scale-Thresholds-v2.xlsx

All of the code used in this analysis has be made openly available by JNCC at:
https://github.com/jncc/cuu-peatland-mapping.

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Appendix 1 – APGB Imagery dates

Site	Approx. total modelled site area (km^2)	Imagery Date	Number of 1km^2 tiles within masked AOI	Area (km^2)	Percentage of site covered (%)
Dalchork Forest, Sutherland, Scotland - bare	27.90	10/05/2016 01/06/2016 06/06/2016	4 28 33	0.32 4.05 23.53	1.15 14.52 84.34
Dalchork Forest, Sutherland, Scotland - vegetated	14.03	10/05/2016 01/06/2016 06/06/2016	2 23 24	0.04 9.51 4.48	0.29 67.78 31.93
Brecon Beacons, Wales	304.45	26/05/2017 07/05/2018	32 3	11.03 1.55	3.62 0.51
Thorne and Hatfield, England	28.93	20/04/2016 05/05/2016 21/04/2016 25/05/2017 01/07/2018 20/10/2019	3 16 31 5 9 42	0.72 6.05 15.79 2.59 3.78 28.93	2.49 20.91 54.58 8.95 13.07 100
Dark Peak, England	318.24	27/06/2018	333	255.79	80.38

Appendix 2 – Vegetation Indices calculations

JNCC ARD band numbers with Sentinel-2 optical imagery:

JNCC ARD bands	Spectral band	JNCC ARD bands	Spectral band
1	Blue	**6**	Red-edge 3
2	Green	**7**	Near Infrared (narrow)
3	Red	**8**	Near Infrared
4	Red-edge 1	**9**	Short Wave Infrared 1
5	Red-edge 2	**10**	Short Wave Infrared 2

Indices calculations from multispectral imagery bands, derived from IDB Project (2019) alongside expert knowledge from JNCCs EO specialists.

Indices	Indices name	Indices Equation
NDVI	Normalized Difference Vegetation Index	$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$
NDWI	Normalized Difference Water Index	$NDWI = \frac{(Green - NIR)}{(Green + NIR)}$
GLI	Green Leaf Index	$GLI = \frac{2 * Green - Red - Blue}{2 * Green + Red + Blue}$
R/B	Red-Blue ratio	$RB = \frac{Red}{Blue}$
R/G	Red-Green ratio	$RG = \frac{Red}{Green}$
Brightness	Brightness	$Brightness = \frac{(Red + Blue + Green)}{3}$
NBR	Normalized Burn Ratio	$NBR = \frac{\mathrm{NIR} - \mathrm{SWIR}}{\mathrm{NIR} + \mathrm{SWIR}}$

Appendix 3 – Sentinel Imagery dates

Dalchork Forest, Sutherland, Scotland

Extraction time series		
APGB dates	**closest sentinel image**	**closest sentinel date**
10/05/2016	S2A_20160605_lat58lon377_T30VVK_ORB123_utm30n_osgb	2016-06-05
01/06/2016		
06/06/2016		
Modelling time series		
2015	S2A_20150929_lat58lon377_T30VVK_ORB123_utm30n_osgb	2015-09-29
2016	S2A_20160605_lat58lon377_T30VVK_ORB123_utm30n_osgb	2016-06-05
2017	s3://sentinel-s2-l2a/tiles/30/V/VK/2017/9/23/0	2017-09-23
2018	s3://sentinel-s2-l2a/tiles/30/V/VK/2018/6/30/0	2018-06-30
2019	S2A_20190826_lat58lon377_T30VVK_ORB080_utm30n_osgb	2019-08-26
2020	s3://sentinel-s2-l2a/tiles/30/V/VK/2020/5/07/0	2020-05-07

Brecon Beacons, Wales

Extraction time series		
APGB dates	**closest sentinel image**	**closest sentinel date**
26/05/2017	S2A_20170525_lat52lon366_T30UVC_ORB037_utm30n_osgb	2017-05-25
07/05/2018	S2B_20180505_lat52lon366_T30UVC_ORB037_utm30n_osgb	2018-05-05
Modelling time series		
2016	S2A_20160719_lat52lon366_T30UVC_ORB037_utm30n_osgb	2016-07-19
2017	S2A_20170525_lat52lon366_T30UVC_ORB037_utm30n_osgb	2017-05-25
2018	S2A_20180629_lat52lon366_T30UVC_ORB037_utm30n_osgb	2018-06-29
2019	S2B_20190420_lat52lon366_T30UVC_ORB037_utm30n_osgb	2019-04-20
2020	S2B_20200623_lat52lon366_T30UVC_ORB037_utm30n_osgb	2020-06-23

Thorne and Hatfield, England

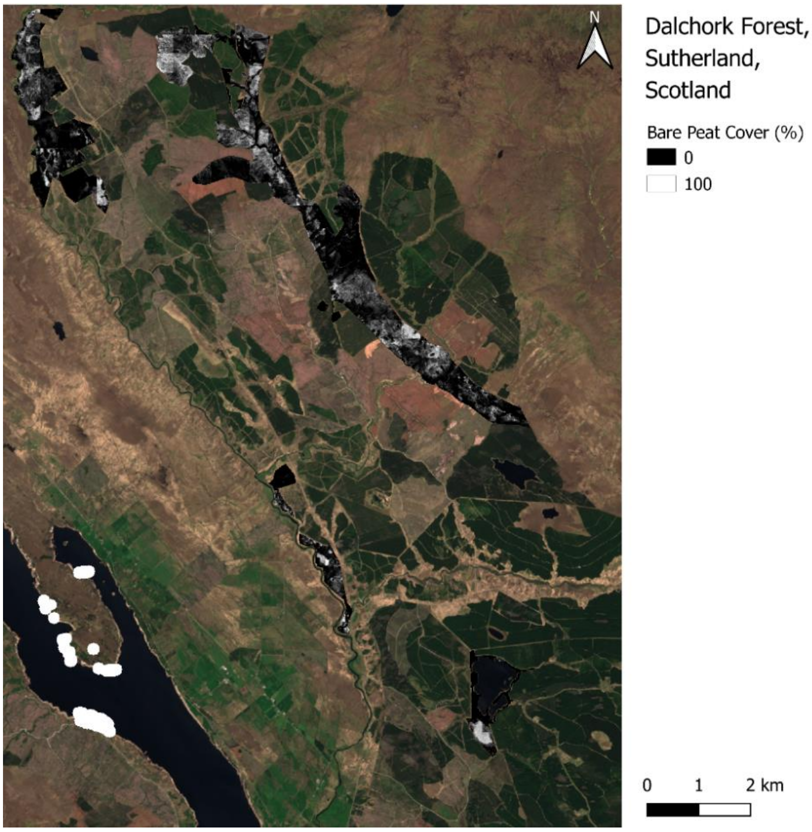
Extraction time series		
APGB dates	**closest sentinel image**	**closest sentinel date**
24/04/2016	S2A_20160420_lat54lon066_T30UXE_ORB037_utm30n_osgb	2016-04-20
05/05/2016	S2A_20160420_lat54lon066_T30UXE_ORB037_utm30n_osgb	2016-04-20
21/04/2016	S2A_20160420_lat54lon066_T30UXE_ORB037_utm30n_osgb	2016-04-20
25/05/2017	S2A_20170505_lat54lon066_T30UXE_ORB037_utm30n_osgb	2017-05-05
01/07/2018	s3://sentinel-s2-l2a/tiles/30/U/XE/2018/7/1/0	2018-07-01
20/10/2019	s3://sentinel-s2-l2a/tiles/30/U/XE/2019/10/17/0	2019-10-17
Modelling time series		
2015	S2A_20150930_lat54lon066_T30UXE_ORB137_utm30n_osgb	2015-09-30
2016	S2A_20160719_lat54lon066_T30UXE_ORB037_utm30n_osgb	2016-07-19
2017	S2A_20170505_lat54lon066_T30UXE_ORB037_utm30n_osgb	2017-05-05
2018	s3://sentinel-s2-l2a/tiles/30/U/XE/2018/7/1/0	2018-07-01
2019	S2A_20190823_lat54lon066_T30UXE_ORB037_utm30n_osgb	2019-08-23

2020	S2A_20200625_lat54lon066_T30UXE_ORB137_utm30n_osgb	2020-06-25

Dark Peak, England

Extraction time series		
APGB dates	**closest sentinel image**	**closest sentinel date**
27/06/2018	S2A_20180629_lat54lon217_T30UWE_ORB037_utm30n_osgb	2018-06-29
Modelling time series		
2016	S2A_20160719_lat54lon217_T30UWE_ORB037_utm30n_osgb	2016-07-19
2017	S2B_20171029_lat54lon217_T30UWE_ORB137_utm30n_osgb	2017-10-29
2018	S2A_20180629_lat54lon217_T30UWE_ORB037_utm30n_osgb	2018-06-29
2019	S2A_20190422_lat54lon217_T30UWE_ORB137_utm30n_osgb_vmsk_sharp_rad_srefdem_stdsref	2019-04-22
2020	S2A_20200625_lat54lon217_T30UWE_ORB137_utm30n_osgb_vmsk_sharp_rad_srefdem_stdsref	2020-06-25

Appendix 4 – Fine Scale maps of bare peat cover



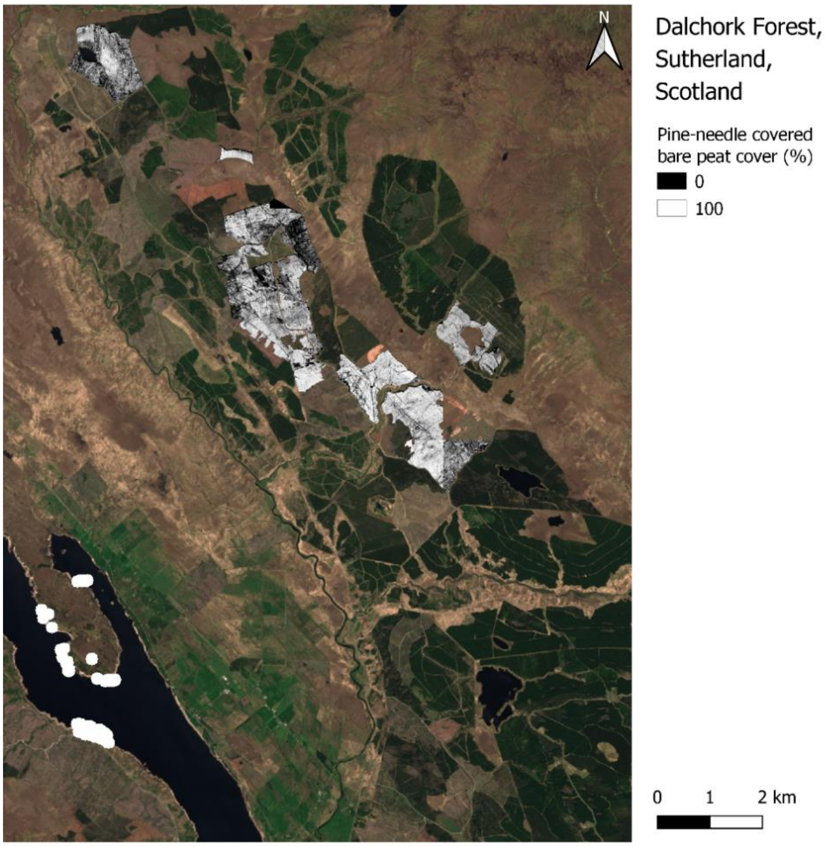


Figure A4.1: The fine-scale maps developed for the unplanted (above) and unplanted (below) regions of the Dalchork Forest site, mapped with the Sentinel-2 imagery from 2016-06-05.

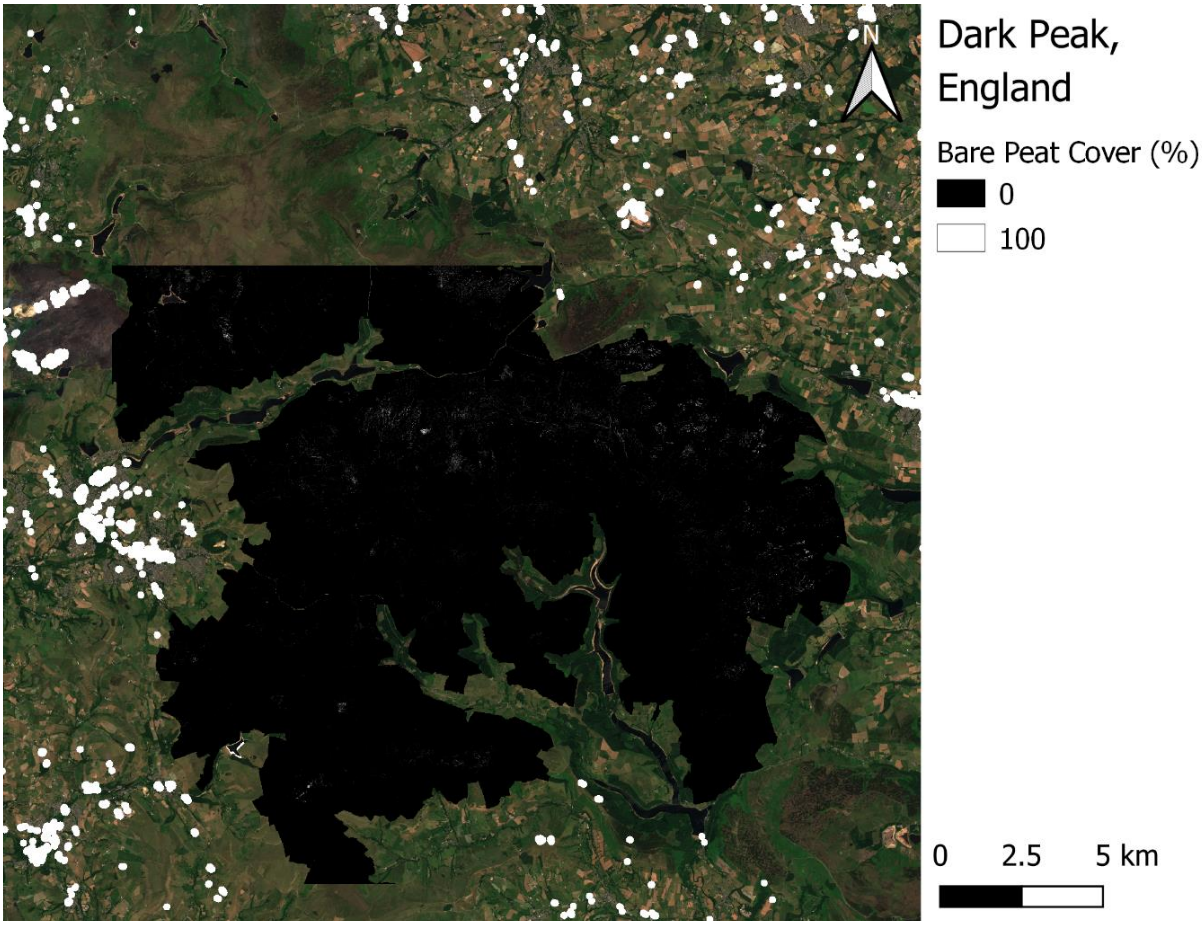


Figure A4.2: The fine-scale map produced for the Dark Peak site, mapped with Sentinel-2 imagery from 2018-06-29.

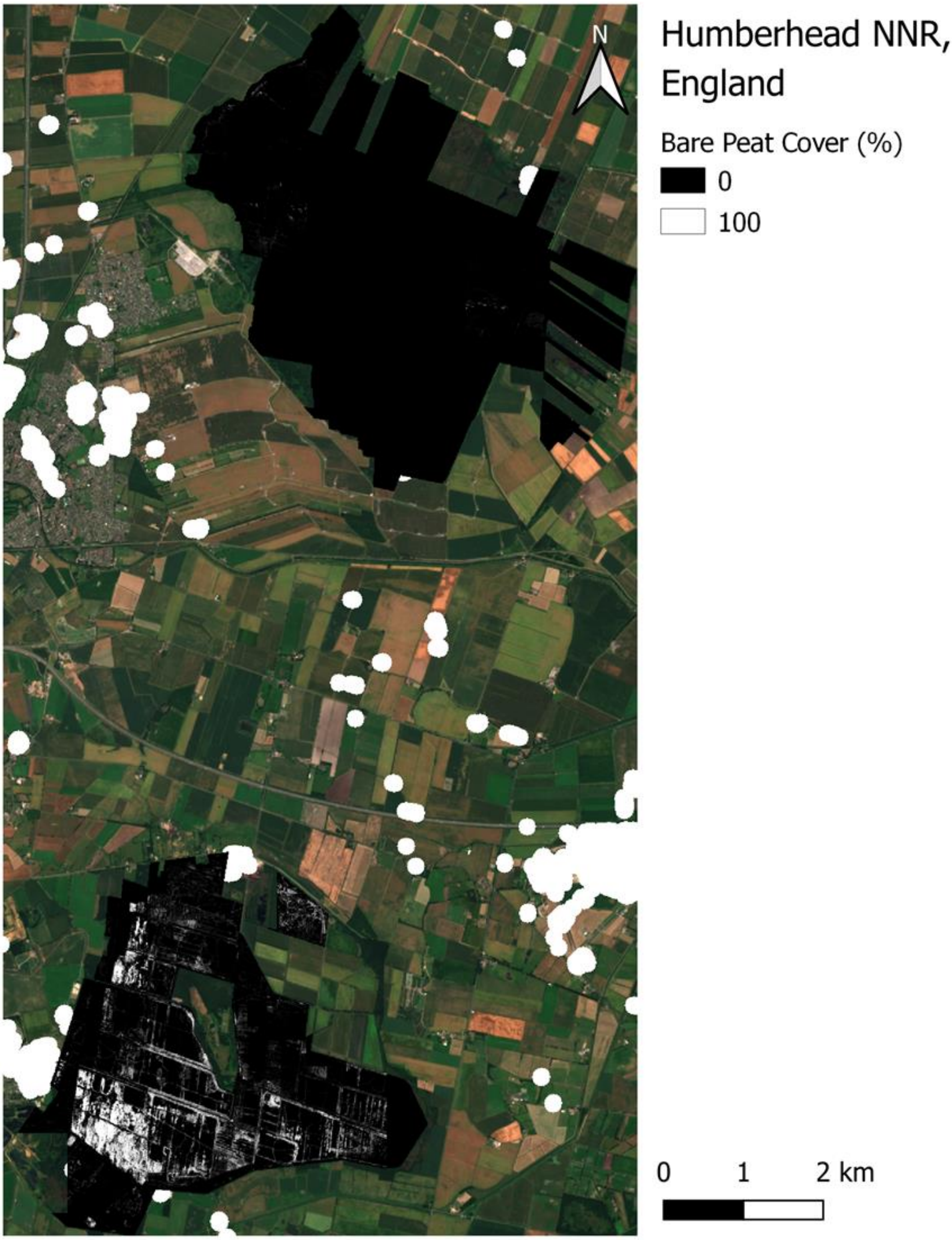


Figure A4.3: The fine-scale map developed for the Humberhead NNR; Thorne (above) and Hatfield (below) sites, using aerial photography from 2016-2018. This is mapped against Sentinel-2 imagery from 2016-07-19.

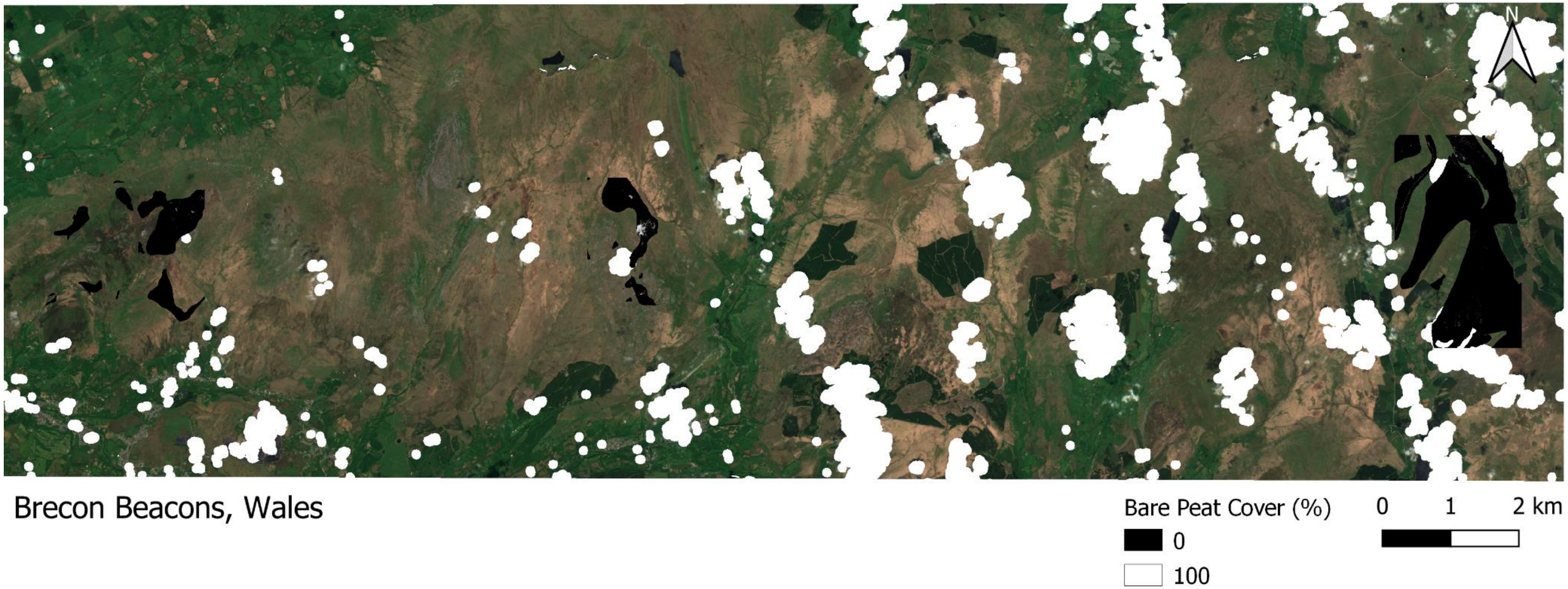


Figure A4.4: The fine-scale map for the Brecon Beacons site, developed using aerial photography from 2017-2018, mapped against the Sentinel-2 imagery.

Appendix 5 – Management summary statistics

Analysis of the Dalchork Forest, Sutherland site polygons showing the restoration operations implemented and the predicted percentage covers of bare peat and pine-needle covered bare peat. The locations of the management operations are show in Figure A5.1 and summary statistics described in Table 1.

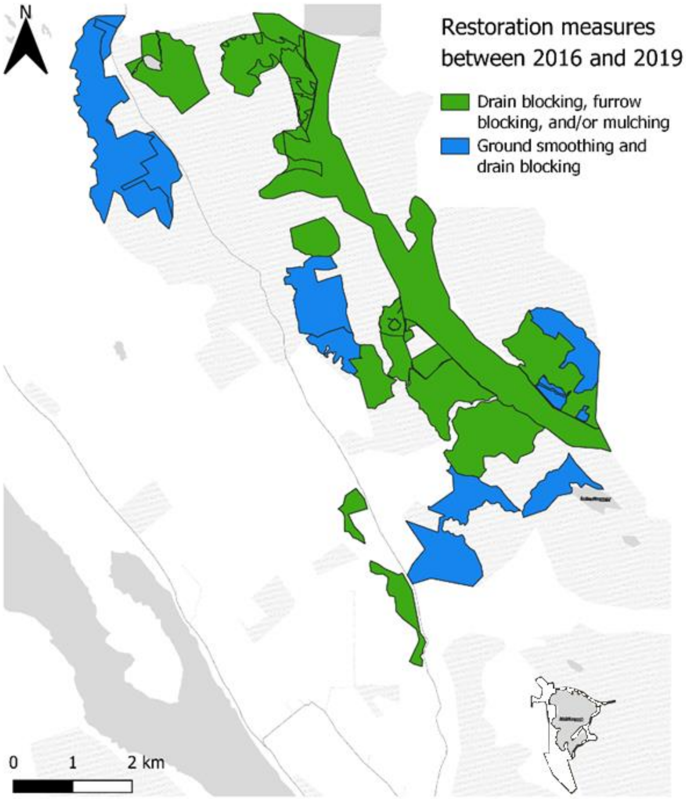


Figure A5.1: A map of the restoration operations occurring at the Dalchork Forest site between 2016 and 2019. Restoration management information kindly provided by Forestry and Land Scotland for use in this project.

Table A5.1: Summary statistics for the difference in percentage cover per polygon with each management type

Unplanted regions – Percentage cover of bare peat				
Management	Mean % cover per polygon for 2016	Mean % cover per polygon for 2019	Mean difference per polygon	Standard deviation of mean difference per polygon
Drain blocking, furrow blocking, and/or mulching	16.4	9.65	-6.89	9.41
Ground smoothing and drain blocking	13.2	5.67	-7.52	4.13
Planted regions – Percentage cover of pine-needle covered bare peat				
Drain blocking, furrow blocking, and/or mulching	40.4	21.0	-19.4	26.9
Ground smoothing and drain blocking	21.9	28.4	6.49	28.3

Appendix 6 – Validation results of the predicted time-series maps with Planet imagery

Planet 3m Imagery	Scene composition	S2 Imagery comparison	Accuracy	95% CI lower	95% CI upper	P-value
20170509_Brecon_PS2Scene 4Band	20180505_104139_100e_3B 20180505_104140_100e_3B 20180505_104141_100e_3B 20180505_104222_1029_3B 20180505_104223_1029_3B 20180505_104224_1029_3B	S2A_20170525_lat52lon366_T30UVC_ORB037_utm30n_osgb	0.622	0.514	0.722	0.892
20180629_Brecon_PS2Scene 4Band	20180629_104321_1010_3B 20180629_104322_1010_3B 20180629_104324_1010_3B 20180629_104451_1009_3B 20180629_104453_1009_3B 20180629_104454_1009_3B	S2A_20180629_lat52lon366_T30UVC_ORB037_utm30n_osgb	0.809	0.712	0.885	0.357
20190420_Brecon_PS2SD Scene 4Band	20190420_110033_71_1066_3B 20190420_110035_72_1066_3B	S2B_20190420_lat52lon366_T30UVC_ORB037_utm30n_osgb	0.707	0.602	0.797	1.0
20190420_Brecon_PSScene 4Band	20190420_105019_1044_3B 20190420_105020_1044_3B 20190420_105021_1044_3B 20190420_105526_1013_3B 20190420_105527_1013_3B 20190420_105528_1013_3B	S2B_20190420_lat52lon366_T30UVC_ORB037_utm30n_osgb	0.602	0.492	0.705	1.0
20200624_103155_Brecon_PS2SD Scene 4Band	20200624_112615_65_105e_3B 20200624_112617_19_105e_3B 20200624_112618_73_105e_3B	S2B_20200623_lat52lon366_T30UVC_ORB037_utm30n_osgb	0.705	0.603	0.794	1.0
20200624_112617_Brecon_PS2SD Scene 4Band	20200624_103155_66_1062_3B	S2B_20200623_lat52lon366_T30UVC_ORB037_utm30n_osgb	0.670	0.566	0.764	0.999