Monitoring rewilding from space: the Knepp estate as a case study

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Abstract: Rewilding is increasingly considered as an option for environmental regeneration, with potential for enhancing both biodiversity and ecosystem services. So far, however, there is little practical information on how to gauge the benefits and limitations of rewilding schemes on ecosystem composition, structure and functioning. To address this knowledge gap, we explored how satellite remote sensing can contribute to informing the monitoring and evaluation of rewilding projects, using the Knepp estate as a case study. To our knowledge, this study is the first to assess the impacts of rewilding as an ecological regeneration strategy on landscape structure and functioning over several decades. Results show significant changes in land cover distribution over the past 20 years inside rewilded areas in the Knepp estate, with a 41.4% decrease in areas with brown agriculture and grass, a roughly sixfold increase in areas covered with shrubs, and a 40.9% increase in areas with trees; vegetation in the rewilded areas also showed a widespread increase in annual primary productivity. Changes in land cover and primary productivity are particularly pronounced in the part of the estate that began its rewilding journey with a period of large herbivore absence. Altogether, our approach clearly demonstrates how freely available satellite data can (1) provide vital insights about long-term changes in ecosystem composition, structure and functioning, even for small, heterogeneous and relatively intensively used landscapes; and (2) help deepen our understanding of the impacts of rewilding on vegetation distribution and dynamics, in ways that complement existing ground-based studies on the impacts of this approach on ecological communities.

Keywords: Rewilding; satellite remote sensing; land cover; environmental monitoring

Introduction

Human activity is leading to rapid and global biodiversity losses and increasing pressure on natural resources, compromising the ability of the planet's natural environment to sustain future generations (IPBES 2019). Among the direct drivers of change in biodiversity with the largest relative global impacts, change in land use ranks particularly high: recent estimates show that three-quarters of terrestrial environments have been considerably altered by agricultural and forestry practices as well as urbanisation (Diaz et al. 2019). The current consensus is that conversion and degradation of habitats is driving global species loss, which in turn compromises the functioning of ecosystems and delivery of services (Cardinale et al. 2012; Pimm et al. 2014).

With its potential for enhancement of biodiversity and ecosystem service delivery, rewilding is increasingly considered as a potential tool to repair some of the ecological damages associated with land use change (Carver 2016; Svenning et al. 2016). Originally associated with the restoration of large, connected wilderness areas that support wide-ranging keystone species such as large carnivores (Soulé & Noss 1998), rewilding can be broadly defined as the reorganisation of biota and ecosystem processes to set an identified social-ecological system on a preferred trajectory, leading to the self-sustaining provision of ecosystem services with minimal ongoing management (Pettorelli et al. 2018a). It is currently used as an umbrella term for a wide range of conservation activities, from accepting natural vegetation succession on abandoned agricultural land to translocating functional analogues of extinct species to restore trophic networks (Pettorelli, Durant & du Toit 2019). "Wild" ecosystems are expected to play an important role in the protection of ecosystem functions such as freshwater provision, nutrient regulation, air quality and supporting habitats (Pereira & Navarro 2015); these ecosystems have also been proven to supply higher quality services, for example, higher carbon storage and sequestration than other types of ecosystems (Cerqueira et al. 2015).

However, despite burgeoning interest in the concept, uncertainties and difficulties associated with the practical implementation of rewilding projects remain. One major research area recently highlighted as being of paramount importance to develop the global rewilding agenda is facilitating the emergence of a comprehensive and practical framework for the monitoring and evaluation of rewilding projects (Pettorelli et al. 2018a; Torres et al. 2018). Long-term, practical and scientifically sound monitoring and evaluation of rewilding projects are required to make sure, among other things, that the trajectory of change and original environmental targets set at the start of the project remain desirable for the social–ecological system considered. Targets, in this context, are likely to be centered on changes in indicators of ecosystem functioning, including the facilitation of existing or new ecological processes. How to measure changes in ecosystem functioning is however still open to debate, and the practical challenges are substantial. For example, carbon stocks in a forested system can be assessed in a cost-effective way in a single visit, but monitoring decomposition requires repeated measurements over years.

Research on monitoring options for ecosystem processes and functions has grown substantially in the past decade, and these efforts could be used to support the identification of a relevant and practical framework for the monitoring and evaluation of rewilding projects. Satellite remote sensing, for example, offers promising avenues for the cost-effective monitoring of ecosystem processes, functions and services, such as disturbance dynamics (Chuvieco et al. 2020), primary productivity (Juntilla et al. 2021), and climate regulation (del Río-Mena et al. 2020), and could help inform such a framework (Pettorelli et al. 2018b). To date, however, little practical information is available to gauge the benefits and limitations of using satellite remote sensing technology to quantitatively assess the impacts of a rewilding scheme on ecosystem composition, structure and functioning. To address this gap in knowledge, we here explore how satellite remote sensing can contribute to inform the monitoring and evaluation of rewilding projects, using the Knepp estate as a case study. Specifically, we explore how rewilding impacted land cover and primary productivity, two parameters that significantly shape several ecosystem functions in terrestrial ecosystems (Pettorelli et al. 2018b), have changed over the past two decades. While doing so, we test the following hypotheses: (H1) Rewilding is driving a directional vegetation change, moving from dominance of crops and grasses to vegetation communities with significant amounts of shrubs and trees. This hypothesis is based on the fact that the rewilding approach on the Knepp estate included a withdrawal of agricultural activities, and (across parts of the rewilded areas) an initial protection from herbivory, two factors which tend to suppress woody species in agricultural landscapes in the temperate zone (e.g. Prevosto et al. 2011, Prach et al. 2014). We thus expect significant increases in shrubs and trees to have occurred in the rewilded parts of the Knepp estate since a rewilding approach was introduced, as opposed to areas that have not undergone rewilding. (H2) We also hypothesise that rewilding is driving an increase in primary productivity, partly due to changes in vegetation community composition, but also in response to increased nutrient availability, and other benefits to growth conditions (Vuichard et al. 2008). We thus expect increases in primary productivity to be stronger than those (if any) observed in the areas neighboring the rewilded areas, and, in addition, primary productivity increases to be larger in rewilded sites than surrounding areas that showed the same increase in woody vegetation.

Material and Methods

Study area

Knepp is a 1,400-hectare estate of heavy weald clay in West Sussex, England, and lies 50.9834° N, 0.3547° W (Figure 1A). The estate had previously been intensively farmed since World War II until 2001, when it was deemed unprofitable (Tree 2018). The estate has four separate blocks, three of which are fenced and have experienced different regeneration histories (Northern, Middle, Southern; Figure 1). The Middle block (242ha), which had formerly been a park designed in the style of Humphry Repton, was taken out of agricultural production in 2001. Fallow deer were introduced in 2002, followed by English long-horn cattle (2003), Exmoor ponies (2005), and red deer (2013). The fields of the Southern block (452ha) were phased out of production between 2001 and 2006, starting with the least productive fields. The Southern block was fenced in 2009 with English longhorn cattle, Exmoor ponies, and Tamworth pigs introduced the same year, followed by fallow deer (2010) and red deer (2013). The Northern block (215ha) was taken out of production in 2004 and English longhorn cattle introduced in the same year. The major difference between blocks is that fields in the Southern block were left fallow for 3-8 years without large herbivores being introduced. The estate now hosts a diversity of species, including the rare turtle doves (*Streptopelia turtur*), nightingales (*Luscinia megarhynchos*), peregrine falcons (*Falco peregrinus*) and purple emperor butterflies (*Apatura iris*), which all breed onsite (Rewilding Britain 2020).

Satellite imagery

To track changes in land cover over the past two decades, we used Landsat Collection 2 Tier 1 Surface Reflectance products (georeferenced, terrain-corrected and atmospherically corrected; note that this product is distributed with all bands resampled to 30m resolution) processed on-demand by the United States Geological Survey (USGS), as these are recognised as the most accurate pre-processed products (Young et al. 2017). The use of satellite data from different seasons has been shown to increase land cover classification accuracy (Lopes et al. 2020) as it captures land cover class-specific seasonal changes. We thus identified, for both 2001 and 2020, cloud-free scenes from different points during the year, though scene availability was significantly restricted by the frequent cloud cover experienced by this part of the UK. This resulted in the use of three scenes for 2001 (with one scene each from February, August and December 2001) and two scenes for 2020 (from February and August 2020; see Table S1 in Supplementary Materials for scene ID and precise dates). Bands considered for analysis were bands 1-7 for both Landsat 5 and 8; all captured information at a 30m resolution. In addition, we calculated three additional indices for each scene: the Normalized Difference Vegetation Index (NDVI), the Normalized Burn Ratio (NBR), and the Modified Soil-Adjusted Vegetation Index 2 (MSAVI2), to capture differences in the spectral properties of different land cover classes not directly reflected by the original bands. The NDVI is derived from the red (RED): near-infrared (NIR) reflectance ratio (NDVI = (NIR – RED)/(NIR + RED)), where NIR and RED are the amounts of near-infrared and red light reflected by the vegetation and captured by the sensor of the satellite. NDVI values range from -1 to +1. Green leaves have high visible absorption and high near-infrared reflectance, which results in values closer to +1; negative values correspond to an absence of vegetation (Pettorelli 2013). The NBR is based on the shortwave infrared (SWIR) and NIR bands, calculated as (NIR-SWIR)/(NIR+SWIR). It also ranges from -1 to +1 and is commonly used to assess post-fire vegetation recovery; we considered this index because it is sensitive to changes in vegetation phenology (Granero-Belinchon et al. 2020). The MSAVI2 is based on RED and NIR reflectance, as the NDVI, but attempts to adjust for variability in the spectral properties of background soil, improving the (vegetation) signal-to-noise ratio (Qi et al. 1994).

The NDVI was moreover used to track changes in the spatial and temporal distribution of primary productivity. NDVI data were extracted from the MODIS 16-day product (MOD13Q1, L3 Global 250m version 6), which was freely available through the USGS Earth Explorer data portal. MOD13Q1 provides NDVI data every 16 days at a spatial resolution of 250m in a sinusoidal projection. NDVI data from February 2000 to December 2020 was considered for analysis. A geo-referenced shapefile providing information on the borders of the rewilded areas within the Knepp estate was used to identify pixels corresponding to the rewilding sites. To test our second hypothesis (H2), a 1 km buffer zone was created around the entire Knepp estate (Freemantle et al. 2013); land cover within this buffer zone, in addition to non-rewilded areas of the Knepp estate (together referred to as "buffer zone", mainly consisted of agricultural land and fields.

Land cover classification and accuracy assessment

We used a post-classification land cover change analysis to detect changes in land cover across the study site. All analyses were carried out in R (R Core Team 2021). We used the Random Forest classifier to produce our land cover maps as this algorithm makes no *a priori* assumptions on the statistical distribution of predictive variables and is robust across different ecological settings (Wegmann et al. 2016). 500 trees were grown for each classification. Training and validation data were collected using Google Earth images from January 2001 and April 2020. Based on these Google Earth images, three land cover categories were differentiated: (1) brown agriculture and grassland; (2) scrub; and (3) trees. Brown agriculture in this study corresponds to ploughed, recently seeded fields or fields that display limited to no greenery on satellite imagery. Humanmade structures such as roads and buildings were visually identified in both the buffer zone and estate, and removed from the images before analysis, as were sparse water bodies. A total of 96 training and 94 validation polygons (1635 and 1278 pixels, respectively) were used to classify the 2001 image. For the 2020 image, 79 training and 79 validation polygons (2047 and 1412 pixels, respectively) were considered (see Table S2 in Supplementary Materials). Producer's and user's accuracies were calculated for both land cover maps. Producer's accuracy quantifies the probability that a given pixel will be assigned to the correct land cover class by the random forest algorithm (also called recall). The user's accuracy estimates the probability that the assigned class of a given pixel is correct (also called precision). We moreover calculated the F1 score (the harmonic mean of user and producer accuracy for a given class, giving a balanced view of both true and false positives for a given class), as well as the overall accuracy across all land cover classes (the proportion of all assessed pixels that are classified correctly, which is a good indicator of the overall prevalence of true positives and true negatives).

Primary productivity analyses

NDVI pixels covering the rewilded areas and the buffer zone were extracted from the MODIS images. Pixels overlapping with humanmade structures such as roads and buildings were identified and removed before analysis. To correct for environmental noise, the NDVI values were smoothed, following the method established by Garonna and colleagues (Garonna et al. 2009). Specifically, the data for each pixel checked for rapid decreases or increases (a difference of 0.3 or more from one date to the next) that were immediately followed by a rapid return to previous values. These drops in NDVI are attributed to environmental noise and were replaced by the average of the previous and following values to 'smooth' the annual NDVI curve for that pixel. If two consecutive contaminated values were present, the average of the closest NDVI values was calculated (Garonna et al. 2009).

Two parameters capturing important ecosystem functioning features (Pettorelli et al. 2012) were calculated: (1) annual maximum (MAX NDVI), which is the annual maximal value in NDVI (and therefore primary productivity); and (2) annual integrated NDVI during the growing season (March-November; I-NDVI), which is used as a proxy for cumulative annual primary productivity. Mann-Kendall trend tests were used to assess the significance of any temporal trend in both time series for all pixels within the rewilded areas and buffer zone, with significant slopes assumed for p-values < 0.05 (Pettorelli et al. 2012; Freemantle et al. 2013).

To assess differences in NDVI changes in response to land cover change, the overall direction and magnitude of land cover change for each MODIS pixel was calculated as follows: for each pixel in the land cover map, the direction and magnitude of change was determined. Pixels which remained in the same land cover class were assigned a value of 0. Pixels which moved a single class towards a vegetation class with more woody elements (i.e., from agriculture/grassland to shrubs, or from shrubs to trees) were assigned a value of 1; if they moved two classes (i.e., agriculture/grassland to trees), they were assigned a value of 2. Pixels that moved one [two] class[es] in the opposite direction, indicating a decline in woody vegetation cover, were assigned values of -1 [-2]. Then, for each MODIS pixels, the sum of all land cover change values was calculated, with high values corresponding to a MODIS pixel in which all land cover pixels (n = 64) indicated a shift from agriculture/grassland to trees, and a value of -128 the opposite. The values were then plotted against the magnitude (tau) of change in (1) maximum NDVI and (2) I-NDVI.

Results

The random forest classification returned good accuracy for both the 2001 and 2020 land cover classifications, with overall accuracies of 97.2% and 92.6% respectively (Table 1). The land cover class that was most frequently misclassified was shrub in 2020, with 30% of pixels that were classified as shrub actually being agriculture/grassland (Table S2). However, most pixels that were classified as shrub, when they were in fact agriculture/grassland, were located outside of the rewilded areas, meaning that identification of shrub inside the rewilded areas was accurate (Figure S1). As expected from (H1), significant shifts towards vegetation with more woody plants occurred between 2001 and 2020 in the rewilded areas, with a 41.8% decrease in areas with brown agriculture and grass, a roughly sixfold increase in areas covered with shrubs, and a 40.9% increase in areas with trees (Table 2). These changes heavily contrasted with the changes observed in the buffer zone, where, for example, areas covered by brown agriculture decreased by only 10.7% (Table 2). Changes were particularly spectacular in the southern block, which converted from a predominantly brown agriculture and grass covered area to an area predominantly covered with shrubs and trees (Figure 2).

NDVI-based analyses also supported our second hypotheses, with Mann-Kendall trend tests showing that 89% and 68% of the 197 MODIS pixels in the rewilded areas experienced a significant increase in I-NDVI and MAX NDVI respectively, over the 2001-2020 period (Table 3; Figure 3). In the buffer zone, however, only 46% and 29% of the 450 pixels saw a significant increase in I-NDVI and MAX NDVI, respectively (Table 3). Only a very small number of pixels within the rewilded areas exhibited a significant decrease in both MAX NDVI and I-NDVI (2 and 1 respectively), which was due to the recent development of a new building. Increases in I-NDVI and MAX NDVI, while clearly linked to increases in woody vegetation (either shrubs or trees), tended to be larger in the rewilded areas than in areas undergoing land cover change of a similar direction and magnitude in the buffer zones (Figure 4), again supporting our second hypothesis.

Discussion

After 20 years of rewilding at Knepp estate, the landscape is almost unrecognizable from its initial state. Our results show how rewilding has drastically impacted vegetation cover and dynamics over the past twenty years in the Knepp estate, particularly in the Southern block, thereby likely triggering changes in regulating, provisioning and supporting ecosystem functions including provision of food, raw materials and supporting habitats, water and nutrient regulation and soil retention. To our knowledge, our work is the first to report on the impacts of rewilding as a regeneration strategy on landscape structure and functioning over decades. Rewilding encouraged natural vegetation growth in Knepp, with tree and shrub cover increasing and brown agriculture and grass decreasing between 2001 and 2020. Such trends contrast with land cover trajectories in neighbouring areas, where, for example, agricultural fields did contract, but at a much slower pace.

Interestingly, those parts of Knepp estate that were not part of the rewilding project (but remained under livestock grazing, agriculture and woodland, Greenaway 2006) show similar changes in land cover and NDVI dynamics as those in which herbivores were introduced rapidly after taking fields out of conventional agricultural production. This stands in contrast to the southern block, which exhibited the largest change in land cover between 2001 and 2020, with the area dramatically switching from brown fields and grassland dominated to shrub and tree dominated (Figure 2). Fields in this part of the Knepp were gradually left fallow between 2001 and 2006, and, in contrast to the other blocks, no large herbivores were introduced until 2009. This led to a huge surge in vegetation reported on the ground and a rise in the diversity of invertebrates, birds and small mammals, including rare species (Tree 2018). This illustrates that the regeneration timescales of different ecosystem components (e.g., woody vegetation, small herbivores, large herbivores) are likely to differ substantially across rewilding projects, depending on how wild species communities assemble, with cascading effects on ecosystem trajectories.

Contrary to existing literature on protected areas, which generally describe a hardening of edges between protected lands and neighbouring areas (Woodroffe, Thirgood & Rabinowitz 2009), our results show that the increases in tree and shrub cover within the rewilding project itself were partially mirrored in the buffer zone as well as non-rewilded parts of the estate. For small rewilding sites, such as at Knepp, this decline in contrast is likely to benefit the ecosystem inside the core area (Boesing et al. 2018), but higher habitat connectivity between core rewilding sites and the surrounding matrix could also have negative effects. For example, encouraging species movement into the buffer zone could increase the flow of ecosystem services, but also the potential for human-wildlife conflict (Pascual-Rico et al. 2020). While this issue will be most important for rewilding projects which include carnivores or large herbivores (e.g., Smith et al. 2016), a recent attempt to introduce a breeding pair of beavers in the Knepp estate failed because the animals quickly moved out of the core rewilding site (Knepp 2021). This highlights that monitoring environmental conditions in the area surrounding rewilded sites may play an important role in understanding (and responding to) ecological changes inside such sites.

Annual primary productivity and annual maximum level of primary productivity increased in the rewilded areas and buffer zone over the past two deacades, although such significant increases were more prominent in the rewilded areas than in the buffer zone. These significant increases may be due to changes in vegetation cover (as, e.g., I-NDVI and NDVI MAX are expected to increase when transitioning from brown agriculture to shrubs and trees). However, these increases in primary productivity cannot be entirely explained by changes in land cover alone, as these increases tend to be smaller outside rewilded areas, even when controlling for the magnitude and direction of land cover change. Observed trends in NDVI dynamics could be attributed to the impacts of warming conditions in South England over the past two decades on the photosynthetic capacity of plants (Yang et al. 2019). Vegetation inside the rewilded sites seems to have been more sensitive to these climatic changes than vegetation in the surrounding landscape. This could be an early signal of autonomous internal change of this system in response to climate change, allowing the ecosystem at the study site to adapt to the altered abiotic environment. Alternatively (or additionally), it could be the result of agricultural fields switching to semi-natural grasslands, which tend to have higher primary productivity (Abdalla et al. 2013), a land cover transition we are unable to detect with our classification. However, since those parts of the Knepp estate that have not been rewilded showed similarly strong changes in NDVI, it cannot be ruled out that other mechanism(s) are behind these trends. As the climate continues to change (IPCC 2014), understanding what shapes the response of ecosystems in rewilded sites is key to anticipating, mitigating against, and adapting to potentially harmful ecological change.

Our approach clearly demonstrates how freely available satellite data can provide vital insights about long-term changes in ecosystem composition, structure and functioning, even for small, heterogeneous and relatively urbanized landscapes. Such data provides important information to contextualise other ecological changes quantified via ground-based observations, such as changes in animal and vegetation community composition and functioning, to build up a comprehensive understanding of the different dimensions of rewilding outcomes (Torres et al. 2018). Long-term trend assessments in land cover and primary productivity, such as the ones presented here, do however have their limitations: because multispectral data is the primary source of information for exploring changes in vegetation distribution and dynamics over decades, only images with low cloud cover can be used for analysis (Pettorelli, Durant & du Toit 2019). In countries such as England, this can drastically reduce the number of images available for classification. The reliance on multispectral data to classify vegetation types, without for example combining it with radar data, can then hamper the accuracy with which certain vegetation classes are mapped (Schulte to Bühne & Pettorelli 2018). In our case, the mapping of shrubs would have likely been more accurate, should have we been able to access radar information for the site and period considered (Lopes et al. 2020).

Our study aimed to provide spatially explicit evidence on the impacts of rewilding on vegetation distribution and dynamics as well as landscape structure. Rewilding in Knepp started in 2001, and at that time, very few space missions were in orbit to capture information about the state of biodiversity. Since then, new missions have increased the breadth of options for monitoring ecosystems from space. For example, the Sentinel missions have radically transformed access to multispectral-radar data fusion prospects for ecologists, thereby improving opportunities to reliably map land cover change across the world (Schulte to Bühne & Pettorelli 2018). Spaceborne hyperspectral sensor missions (such as the Environmental Mapping and Analysis Program (EnMAP), the Hyperspectral Infrared Imager (HyspIRI), and the Hyperspectral Precursor of the Application Mission (PRISMA – Italian Space Agency) are about to enable ecologists to track changes in surface chemistry and structure in great detail (Pettorelli, Durant & du Toit 2019). Monitoring of biomass and canopy structure will be transformed by the availability of global LiDAR data from spaceborne missions (e.g., ICESat-2 and GEDI). As new ecological regeneration strategies such as rewilding continue to be implemented in various sites around the world, these missions and the data they will be collecting in the years to come provide a significant opportunity to study how landscapes respond to drastic changes in land use.

Studies such as this demonstrate one of the main assets of satellite data: they enable ecologists to retrospectively analyse spatio-temporal changes in vegetation distribution and dynamics, even when they had not planned to do so in the first place. Global satellite data archives provide access to ecological baselines that may have not been collected on the ground, thereby enabling the standardized, transparent, cost-effective tracking of ecological change over time. In this case, they have deepened our understanding of the impact of rewilding on ecosystem composition, structure and functioning, in ways that nicely complement existing ground-based studies on the impacts of this management approach on ecological communities (see e.g., Brompton 2018, Tree 2018, Wallace 2019).

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TABLES

Table 1. User and producer accuracies for the brown agriculture/grass, shrub, and tree cover classes, as well as overall accuracy of the land cover maps generated for the study area with a 1km buffer for 2001 and 2020.

	2001			2020		
	Producer's accuracy (%)	User's accuracy (%)	F1 (%)	Producer's accuracy (%)	User's accuracy (%)	F1 (%)
Agriculture/Grass	99.8	96.6	98.1	92.1	98.8	95.3
Shrub	43.4	92.0	59.0	61.5	51.3	56.0
Tree	98.7	99.4	99.0	96.5	91.8	94.1
Overall	97.2			92.6		

Table 2. Percentage area cover for 2001 and 2020 and percentage area cover change in the rewilded areas and the rest of the study site.

Area	Class	2001 area cover (%)	2020 area cover (%)	
Rewilded areas	Agriculture/Grass	78.8	45.9	↓
	Shrub	4.8	31.0	↑
	Tree	16.4	23.1	↑
Other areas	Agriculture/Grass	75.5	67.4	↓
	Shrub	6.6	11.7	↑
	Tree	17.8	21.0	↑

Table 3. Number of pixels (out of 197 for the rewilded areas, 450 for the other areas) displaying significant and insignificant changes in MAX NDVI and I-NDVI. Significance was assessed with Mann-Kendall trend tests (n = 21 years, p = 0.05).

Area	Parameter	Significant Increase	Insignificant Increase	Insignificant Decrease	Significant Decrease
Rewilded areas	MAX NDVI	133	53	9	2
	% pixels	67.5%	26.9%	4.6%	1.0%
	I-NDVI	175	14	7	1
	% pixels	88.8%	7.1%	3.6%	0.5%
Other areas	MAX NDVI	132	240	78	0
	% pixels	29.3%	53.3%	17.3%	0.0%
	I-NDVI	206	180	54	10
	% pixels	45.8%	40.0%	12.0%	2.2%

FIGURES

Figure 1. Location of the study site, Knepp estate in Sussex, with the three main areas where rewilding occurred: northern, middle and southern blocks (dark grey, A). Google Earth imagery taken (B) illustrates the increase in shrub and tree covering the rewilding sites. As there was not enough high-resolution imagery available to visualize the entire site during comparable seasons, we chose four examples across the area where most of the shrub increase has taken place. Imagery from Google Earth 2021, (c) Bluesky, Landsat, Copernicus 2021.

Figure 2. Land cover classification maps for 2001 (A) and 2020 (B) as derived from a supervised random forest classification approach.

Figure 3. Spatial variation in vegetation dynamic parameters (MAX and I-NDVI) in rewilded areas and the rest of the study site.

Figure 4. The magnitude of change in vegetation dynamic parameters (tau of the Mann-Kendall trend test) for (A) maximum and (B) integrated NDVI against the magnitude of land cover change which occurred in each pixel. “Maximum increase” means that, for a given MODIS pixel (nominal resolution: 250m), all assessed Landsat pixels (nominal resolution: 30m) transitioned from agriculture/grassland to shrubs, or shrubs to trees, or from agriculture/grassland to trees; maximum decline corresponds to the pixels that were all

assessed Landsat pixels transitioned from trees to shrubs, shrubs to agriculture/grassland, or trees to agriculture/grassland.

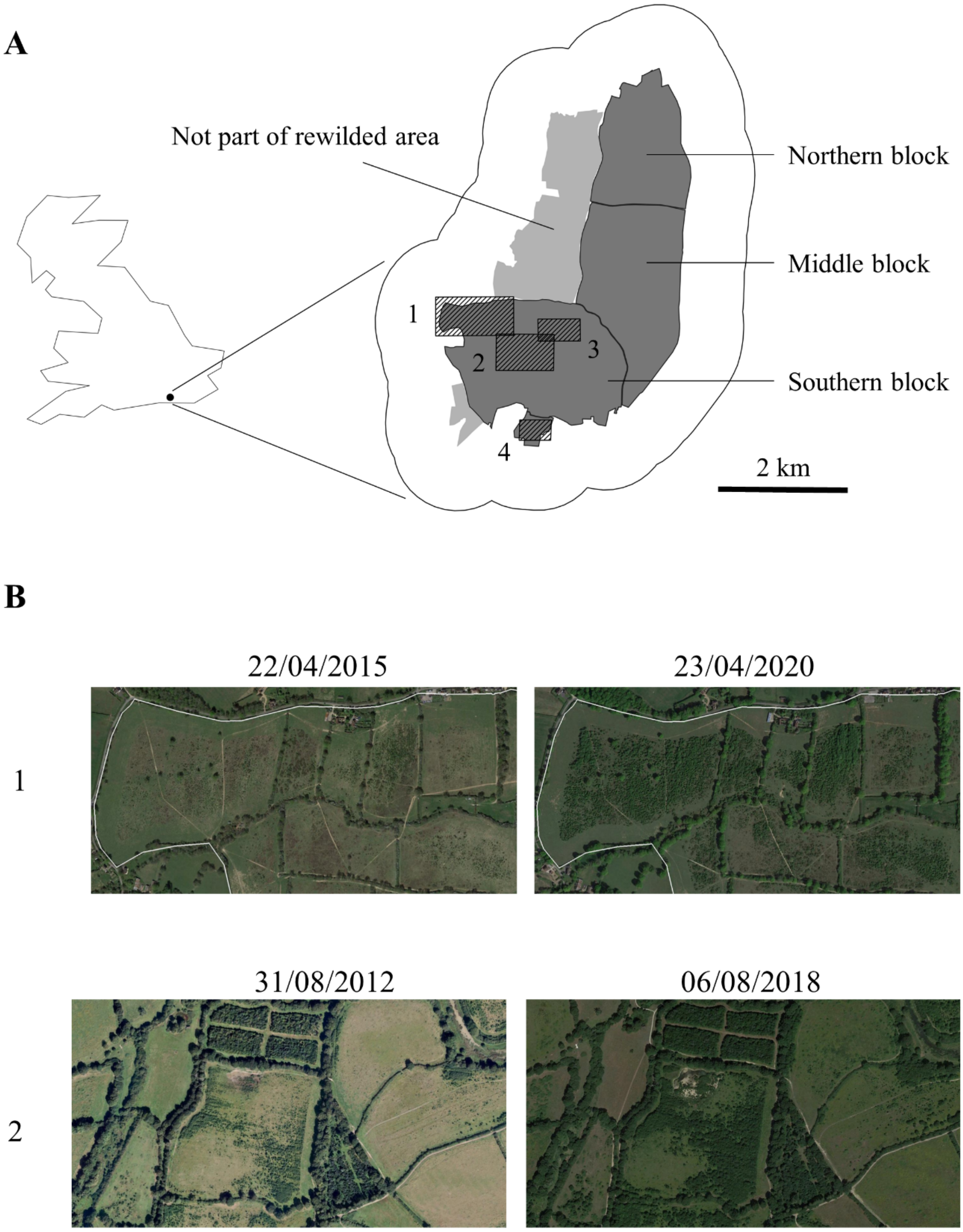
A
Not part of rewilded area
Northern block
Middle block
Southern block
1
2
3
4
2 km
B
22/04/2015
23/04/2020
1
31/08/2012
06/08/2018
2

Figure 1

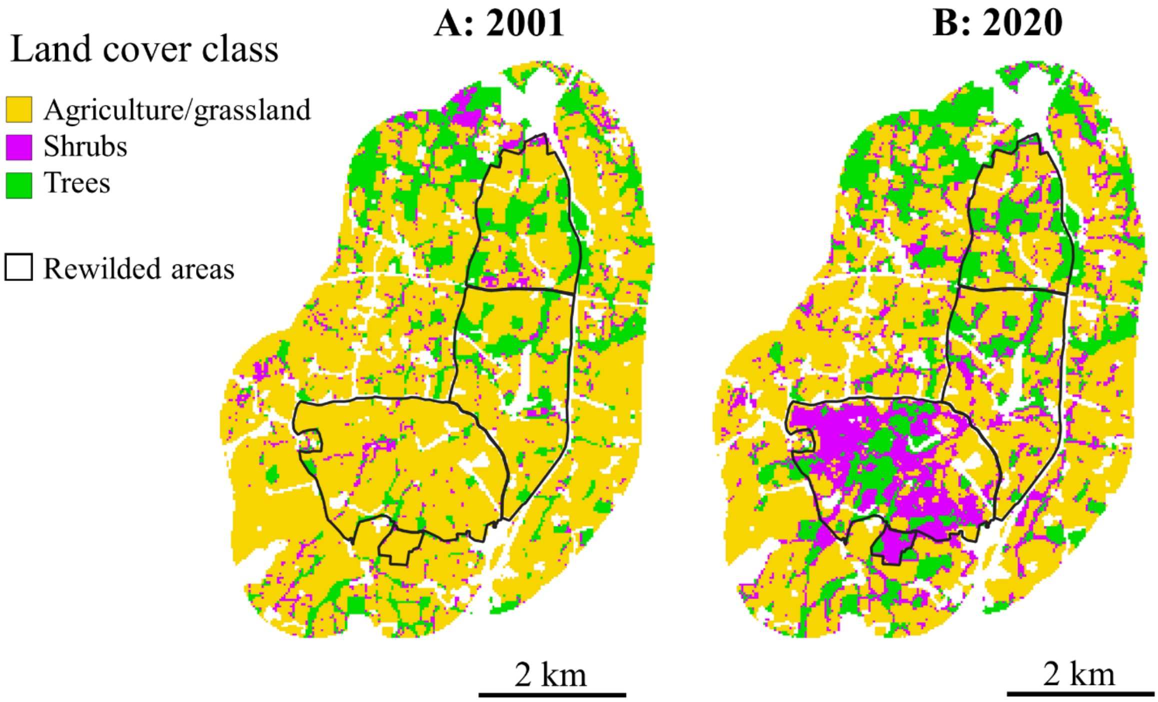
Land cover class
Agriculture/grassland
Shrubs
Trees
Rewilded areas
A: 2001
B: 2020
2 km
2 km

Figure 2

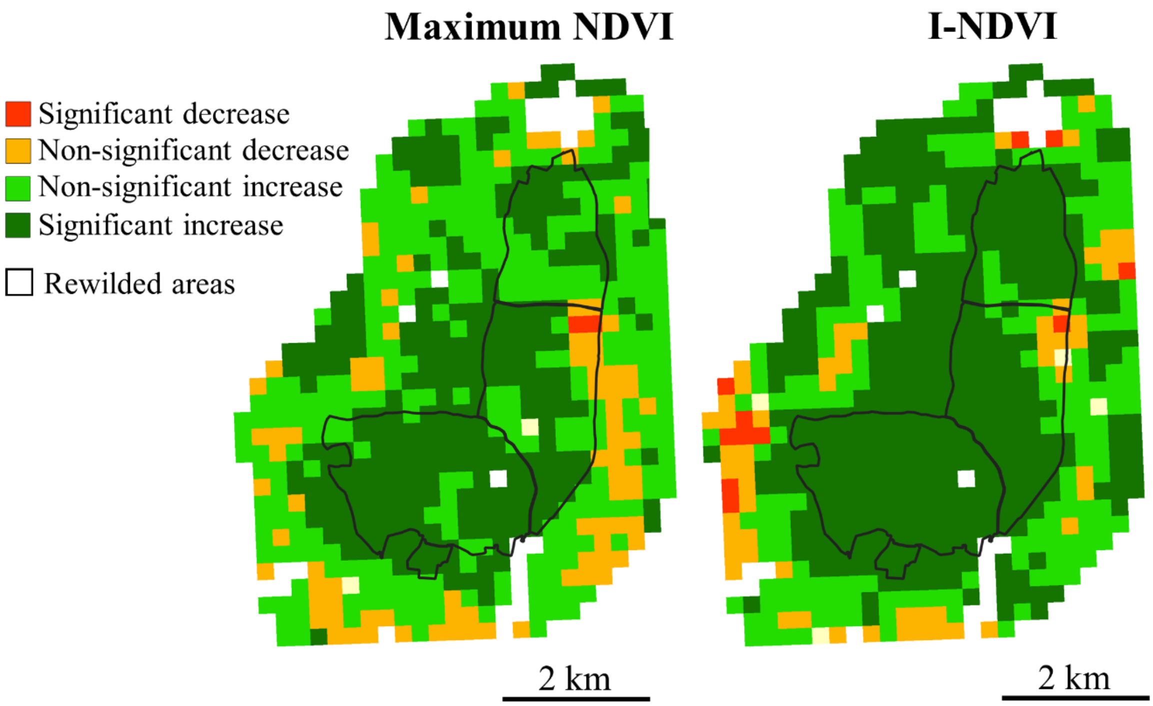
Maximum NDVI
I-NDVI
Significant decrease
Non-significant decrease
Non-significant increase
Significant increase
Rewilded areas
2 km
2 km

Figure 3

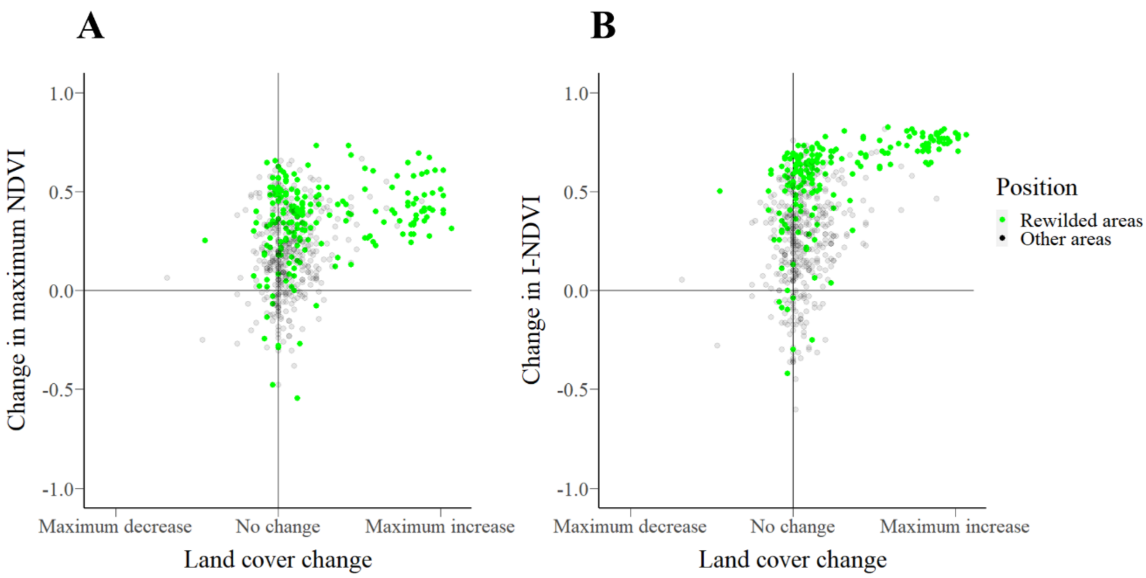
A
B
1.0
0.5
0.0
-0.5
-1.0
Change in maximum NDVI
Change in I-NDVI
Maximum decrease
No change
Maximum increase
Land cover change
Position
Rewilded areas
Other areas

Figure 4

Supplementary Materials

Table S1: Scene IDs of satellite imagery used for land cover classification

Year	Month	Scene IDs
2001	February	LT05_L2SP_202024_20010213_20200906_02_T1
	August	LT05_L2SP_202024_20010824_20200905_02_T1
	December	LT05_L2SP_201025_20011207_20200905_02_T1
2020	February	LC08_L2SP_201024_20200211_20200823_02_T1
	August	LC08_L2SP_202024_20200812_20200919_02_T1

Table S2: Confusion matrices for the land cover classifications in 2001 (A) and 2020 (B).

A	Reference: agriculture/grassland	Reference: shrubs	Reference: trees
Prediction: agriculture/grassland	911	28	4
Prediction: shrubs	2	23	0
Prediction: trees	0	2	308
B	Reference: agriculture/grassland	Reference: shrubs	Reference: trees
Prediction: agriculture/grassland	661	7	1
Prediction: shrubs	33	56	20
Prediction: trees	24	28	582

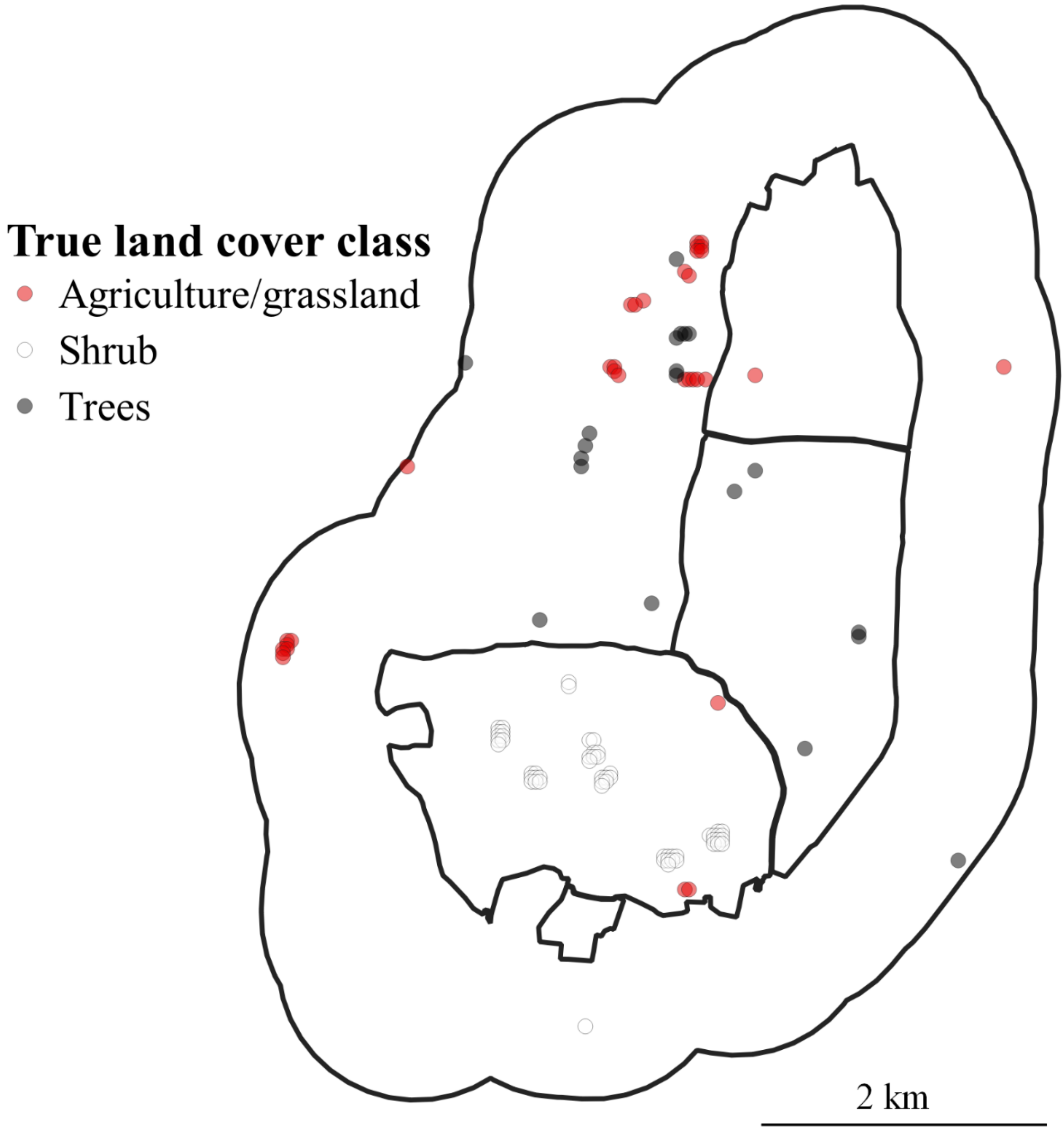

Figure S1: All validation data points classified as shrub in 2020. Most erroneously classified pixels (especially agriculture or grassland mistaken for shrubs) fell outside of the rewilded areas.