

The rewilding of Chernobyl: A long-term monitoring of passive rewilding after land abandonment using remote sensing

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ABSTRACT

In 1986, the nuclear disaster in Chernobyl caused large-scale land abandonment which resulted in one of the largest unintended experiments of passive rewilding, yet no study has combined remote sensing land cover classification using a pre-disturbance baseline with vegetation productivity analysis across the full Chernobyl-Palieski Reserve under an explicit rewilding framework.

This thesis quantifies land cover change and vegetation productivity dynamics between the Chernobyl-Palieski Reserve and its surrounding buffer zone between 1986 and 2018. To achieve this, a locally trained Random Forest classification of Landsat imagery is performed and the Enhanced Vegetation Index 2 is used as a proxy for vegetation productivity.

Inside the reserve, 89.2% of pixels that were not classified as vegetation in 1986 had transitioned to vegetated cover by 2018 through spontaneous ecological succession, while only 49.8% did so in the surrounding area, with agriculture to shrubland as the dominant transition. Vegetation productivity increased across both zones, with the reserve displaying slightly higher values, consistent with human exclusion as the primary driver. Cross-product comparison with a global land cover product reveals that global products may be insensitive to the transitional shrubland stage through which passive rewilding occurs.

Findings from this thesis contribute a large-scale remote sensing case to the emerging evidence base for passive rewilding and highlight limitations of global monitoring products to capture transitional vegetation classes central to ecological succession.

Keywords: Physical Geography and Ecosystem analysis, Passive rewilding, land cover change, remote sensing, ecological succession, Chernobyl Exclusion Zone, Random Forest classification, vegetation productivity

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List of abbreviations

BSI: Bare Soil Index
CEZ: Chernobyl Exclusion Zone
CPR: Chernobyl-Palieski Reserve
CRS: Coordinate Reference System
DEM: Digital Elevation Model
EPSG: European Petroleum Survey Group
ESA: European Space Agency
EU: European Union
EVI: Enhanced Vegetation Index
EVI2: Enhanced Vegetation Index 2
FCC: False Colour Composite
GCP: Ground Control Point
GLC-FCS30D: Global Land Cover Fine Classification System 30m
GLCM: Grey-Level Co-occurrence Matrix
GPP: Gross Primary Productivity
IUCN-CEM: International Union for Conservation of Nature Commission on Ecosystem Management
IQR: Interquartile Range
KH-9: KeyHole-9
LaSRC: Land Surface Reflectance Code
LEDAPS: Landsat Ecosystem Disturbance Adaptive Processing System
MCC: Matthews Correlation Coefficient
MDA: Mean Decrease Accuracy
MNDWI: Modified Normalised Difference Water Index
MODIS: Moderate Resolution Imaging Spectroradiometer
MSS: Multispectral Scanner
NDBI: Normalised Difference Built-up Index
NDMI: Normalised Difference Moisture Index
NDVI: Normalized Difference Vegetation Index
NIR: Near Infra-Red
OA: Overall Accuracy
OLI: Operational Land Imager
OOB: Out-of-Bag
PA: Producer's Accuracy
PRR: Palieski Radioecological Reserve
RF: Random Forest
RMSE: Root Mean Squared Error
SRTM: Shuttle Radar Topography Mission
SWIR1: Short Wave Infra-Red 1
SWIR2: Short Wave Infra-Red 2
TM: Thematic Mapper
UA: User's Accuracy
USGS: United States Geological Survey
UTM: Universal Transverse Mercator

1. Introduction

Global biodiversity is rapidly declining, with nearly a third of monitored vertebrate species experiencing population reductions and range contractions (Ceballos et al., 2017). This alarming decline has prompted a global push for large-scale ecological restoration, exemplified by the United Nations' Decade of Ecosystem Restoration (2021-2030) (UN, 2019) or the Bonn Challenge, which aims to restore 350 million hectares of degraded land by 2030 (Pettorelli et al., 2021). Additionally, this call is reflected at the policy level, with the European Union mandating that Member States restore 20% of land and sea ecosystems by 2030, with all ecosystems requiring restoration addressed by 2050 (European Parliament, 2024). To effectively address this global environmental crisis, attempts to plan biodiversity recovery must be integrated with climate change mitigation efforts, creating a more holistic approach to conservation (Pettorelli et al., 2021). Within this context, rewilding has emerged as a promising strategy, offering benefits for both biodiversity enhancement and climate change mitigation, surpassing traditional restoration methods such as afforestation (Wang et al., 2023b). Rewilding provides a restoration strategy focused on creating self-sustaining ecosystems with minimal human intervention, particularly in passive rewilding which does not involve active land management. This contrasts with traditional restoration approaches, which pursue a defined endpoint regardless of management intensity (Corlett, 2016).

The Chernobyl Exclusion Zone (CEZ) has been described as “one of the most iconic natural experiments on rewilding in recent history”, as it embodies one of the largest and longest-running examples of unmanaged ecological succession globally (Perino et al., 2019). The cessation of human activities following the 1986 nuclear disaster triggered spontaneous natural regeneration across a vast area, creating an unintended large-scale experiment in ecological recovery. Although satellite remote sensing is increasingly used in ecology, its potential for monitoring rewilding efforts remains underexplored (Pettorelli & Schulte to Bühne, 2023), and no study has addressed land cover changes in the CEZ through remote sensing under an explicit rewilding framework.

The present thesis addresses this gap through the combination of a locally trained Random Forest land cover classification using Landsat imagery and an Enhanced Vegetation Index 2 (EVI2) productivity analysis across the CEZ and the Palieski Radioecological Reserve (PRR) from 1986 to 2018. Declassified KH-9 reconnaissance imagery from 1982 provides a unique pre-disturbance reference, and results are compared against a global land cover product to assess the capacity of global datasets to capture rewilding dynamics. Therefore, this thesis aims to quantify land cover change and vegetation productivity dynamics across the reserve and its surroundings between 1986 and 2018. Four research questions frame this aim: (i) How did land cover change across the reserve and its surroundings between 1986 and 2018? (ii) Which land cover classes show the strongest rewilding signal over the study period? (iii) Did vegetation productivity increase within the reserve between 1986 and 2018? (iv) Did vegetation productivity increase more within the reserve than outside of it?

2. Background

Rewilding has emerged as a distinct conservation paradigm, yet its theoretical foundations remain contested and its relationship to adjacent concepts such as conservation and restoration is frequently misunderstood. This section situates rewilding within the broader conservation literature and examines its application in the Chernobyl context, including the current state of vegetation change research in the exclusion zone. It then reviews the use of remote sensing in rewilding monitoring and identifies remaining gaps.

2.1. Rewilding

In recent years, the umbrella terms of conservation, restoration and rewilding have been used extensively and in entangled ways in the conservation literature, making it necessary to disentangle their meanings (Corlett, 2016a).

2.1.1. A brief review of conservation techniques

Conservation has historically been guided by two main philosophical approaches: functionalism, which aims to preserve or restore ecological functions regardless of species composition, and compositionism, which focuses on conserving or restoring the mosaic of species and populations present in an ecosystem at a designated baseline (Callicott et al., 1999; Gillson et al., 2011). Restoration finds its roots in this tradition, sharing the assumption that the targeted ecosystem is well described and that the aim is to assist its recovery back towards a historical species composition, structure or function (SER, 2004; Hobbs et al., 2009; Corlett, 2016a). While conservation aims to prevent a system from being degraded by abiotic and biotic changes, restoration seeks the mitigation of those changes (Hobbs et al., 2009). Rewilding is a more recent concept that has been gaining increasing attention in the literature since the 2010s (Pettorelli et al., 2019), as well as criticism (Nogués-Bravo et al., 2016; Lorimer & Driessen, 2014). Rewilding as a scientific discipline was conceptualized by Soulé and Noss who first described rewilding as the “scientific argument for restoring big wilderness based on the regulatory roles of large predators” (Soulé & Noss, 1998). This vision was formulated in the North American conservation context where large extents of nearly untouched nature referred to as wilderness remained and the primary missing ecological elements were large apex carnivores (Carver et al., 2021). This approach was conceptualized through an ecological triptych, the “Three C’s”: Cores (large habitat), Corridors (connectivity between cores), and Carnivores. The authors argued that restoring these components would reinstate top-down trophic regulation by keystone predators over large herbivores and thus help recover ecosystem processes and spatial heterogeneity (Soulé & Noss., 1998). As the concept reached Europe, it was influenced by the work of Frans Vera on grazing ecology and forest dynamics (Vera, 2000) and evolved towards a greater focus on the reintroduction of large herbivores to restore natural disturbance regimes such as grazing as a way to recover the functionality of ecosystems (Carver et al., 2021). In contrast, some efforts were directed at reducing the effect of grazing by fencing areas to allow for ecological succession (Carver et al., 2021). Rewilding can imply different

levels of management. In trophic rewilding, the path towards functioning ecosystems is designed through the reintroduction or translocation of megafauna (keystone predators or herbivores) to restore ecological functions that have been lost or degraded. This can be achieved through the reintroduction of native species or species that act as proxies and play similar ecological roles to those of locally extinct species (Navarro & Pereira, 2015; Perino et al., 2019). Passive rewilding, however, promotes a hands-off approach by allowing for the natural occurrence of ecological succession through the limitation or restriction of human intervention (Gillson et al., 2011; Perino et al., 2019). Depending on the context in which rewilding is considered, the ecological framework differs. In Europe, where large areas of agricultural land are being abandoned at a significant rate (van der Zanden et al., 2017; Castillo et al., 2018) and where policies towards climate and biodiversity loss mitigation have been promoted, rewilding appears as a serious candidate for large-scale ecological recovery (Perino et al., 2019).

2.1.2. Criticism: is rewilding bringing more than restoration?

As often with new concepts, rewilding has raised questions and criticism regarding its relevance, its consequences, and its added value to the conservation movement (Jørgensen, 2015; Nogués-Bravo et al., 2016). A first criticism that has been addressed by researchers concerns the meandering aspect of rewilding and the lack of a consistent method, goal or definition. Jørgensen (2015) highlighted no less than six ecological methods used or conceptualized for rewilding among scholars. This diversity of methods grouped under a single term has caused some researchers to believe it could lead to confusion and thus ineffective action. Additionally, concerns about the lack of certainty regarding the ecological consequences of rewilding on potential long-term effects have emerged. This concern relates mainly to trophic rewilding efforts and whether the introduction of proxy species could in fact mimic the top-down control on the ecosystem that locally extinct species had. A further concern relates to the increasing popularity and activism associated with rewilding, where action by individuals with limited ecological understanding could have potentially far-reaching consequences (Nogués-Bravo et al., 2016).

2.1.3. Towards a unified definition of rewilding

To overcome the criticisms made about a lack of consistency in the definition of rewilding, the International Union for Conservation of Nature Commission on Ecosystem Management (IUCN-CEM) mandated a working group to work towards a unifying and internationally recognised definition of rewilding (Carver et al., 2021). The central aspect of this definition is that:

"The ultimate goal of rewilding is the restoration of functioning native ecosystems containing the full range of species at all trophic levels while reducing human control and pressures. Rewilded ecosystems should — where possible — be self-sustaining. That is, they require no or minimal management (i.e., natura naturans [nature doing what nature does]), and it is recognised that ecosystems are dynamic." (Carver et al., 2021).

Although rewilding and restoration are closely related, they differ in both their philosophy and methods (Corlett, 2016a). As the definition shows, rewilding emphasises the functionality of native ecosystems containing the full range of species at all trophic levels. What brings modern rewilding further away from traditional conservation is the consideration of human control over ecosystems. In rewilding, the ideal is for humans not to intervene, through a recognition of the temporal and natural dynamic of ecosystems (Perino et al., 2019; Carver et al., 2021). This forward-looking orientation is reinforced by a broader recognition in the ecological literature that ecosystems are dynamic and that future ecosystem states cannot always be predicted (Hobbs et al., 2009; Lindenmayer et al., 2008; Corlett, 2016a), making the rewilding approach particularly relevant in contexts of long-term unmanaged succession.

To summarise, the evolution of rewilding from its origins to the most recent years is captured by Perino et al. (2019): what began as a strategy to maintain corridors for large carnivore conservation has evolved into a broader effort to restore dynamic and complex ecological processes, accepting their future trajectory once human intervention is withdrawn. In this sense, rewilding differs from traditional conservation both ecologically, in its embrace of ecosystem dynamism rather than a fixed target state, and philosophically, in its emphasis on reducing rather than directing human control over nature.

2.1.4. The Rewilding of Chernobyl

On 26 April 1986, one of history's worst nuclear disasters occurred when reactor number four of the Chernobyl Nuclear Power Plant in Ukraine (former USSR) suffered a catastrophic meltdown (Møller & Mousseau, 2006). Following the subsequent fire, which burned for over ten days, large quantities of radionuclides spread across the atmosphere, contaminating large parts of Europe including Ukraine and Belarus (Møller & Mousseau, 2006). Around 100,000 people were evacuated directly after the disaster and another 200,000 individuals from surrounding territories of Ukraine, Belarus, and Russia had to leave their homes (Anspaugh, 2005). In the aftermath, the Ukrainian government created the CEZ, a 30 km radius zone from the Chernobyl site covering 2,600 km², from which human habitation was permanently prohibited and within which approximately 1,400 km² of agricultural land was abandoned (Perino et al., 2019; Matsala et al., 2021). In 1988, Belarus created the PRR, initially covering around 1,300 km² and later expanded to roughly 2,150 km² in 1993 (Perino et al., 2019). Human pressure further declined following the collapse of the Soviet Union in 1991, with up to 36% of agricultural land in Ukraine and Belarus falling out of use in subsequent years (Hostert et al., 2011; Perino et al., 2019).

After the accident, much of the scientific focus was legitimately on the radiological health risks associated with exposure to humans (Moysich et al., 2002; Møller & Mousseau, 2006). It is only at a later stage that concern for the environment gained weight in the scientific literature. The most dramatic and visible environmental effect was the so-called "Red Forest," where intense radiation deposition caused the complete die-off of Scots pine over approximately 4 to 6 km², with measurable growth suppression in coniferous stands extending over a further 120 km² (Matsala et al., 2021). At the organism level, studies have documented radiation-associated

effects including higher mutation rates and reduced survival in several species inhabiting the most contaminated areas (Møller & Mousseau, 2006). However, on a larger scale, the ecological dynamics of the CEZ and PRR appear to be driven by factors beyond radiation alone. Deryabina et al. (2015) found no evidence of radiation having a detrimental effect on large mammal populations, with wolves, wild boars, roe deer, and elk recorded at significantly higher abundances inside the zone than in surrounding areas. Vegetation productivity also seems to have increased after the accident, suggesting resilience of local flora to radionuclide contamination (Gemitzi, 2020). While the debate on radiological effects on individual organisms is important and justified (Møller & Mousseau, 2006), and such effects are not disputed here, they do not appear to have prevented the remarkable landscape-scale ecological changes observed across the reserve. Rather, the near-total and sustained withdrawal of human activity appears to be the defining ecological variable at landscape scale, consistent with the mammal abundance and vegetation productivity patterns reported above (Deryabina et al., 2015; Gemitzi, 2020).

The lack of human access has created conditions for spontaneous ecological succession: vegetation has progressively colonised formerly cultivated and disturbed surfaces, forest canopy has densified on previously open land, and species composition has begun shifting following successional dynamics (Matsala et al., 2021; Didukh et al., 2023). This directly corresponds to the definition of passive rewilding outlined above with limited human intervention, no management, and the self-organisation of the ecosystem (Perino et al., 2019; Carver et al., 2021). The CEZ and PRR therefore represent an unplanned experiment of what happens when humans leave, offering conditions for observing rewilding dynamics that are rarely achievable in intentionally managed conservation contexts (Perino et al., 2019).

Trophic rewilding also occurred within the CEZ and PRR, though its spatial and demographic scale remains limited. Przewalski's horses were introduced into the CEZ between 1998 and 2004, reaching a peak population of 65 individuals and occupying an area of approximately 565 km² by 2008, a fraction of the total reserve extent (Zharkikh & Yasynetska, 2008; Schlichting et al., 2020). European bison were introduced into the PRR as part of a separate trophic rewilding initiative (Perino et al., 2019). Both introductions occurred over a decade after the onset of ecological succession, and separating their landscape-scale effects from those of naturally recovering wildlife remains challenging. Wolves, for instance, re-colonized the zone naturally following human withdrawal, illustrating that faunal recovery is not exclusively the product of deliberate intervention (Deryabina et al., 2015). Passive and trophic rewilding must therefore be understood as occurring simultaneously. However, the remote sensing framework applied in this study cannot distinguish their respective contributions to vegetation dynamics, and this study focuses on passive rewilding as the primary lens through which landscape-scale land cover change is interpreted.

The CEZ and PRR together represent the largest and oldest example of rewilding in Europe. As Gemitzi (2020) notes, the rewilding of Chernobyl is fundamentally tied to the absence of human activity, aligning with the IUCN-CEM principle of reduced human control as the enabling condition for ecosystem self-organisation. The year 1986 represents a natural baseline against which landscape change can be measured, coinciding with the near-total cessation of human

activity following the disaster. It is within this context that the present thesis analyses land cover change and vegetation productivity dynamics between 1986 and 2018, documenting the net outcome of over three decades of unmanaged ecological succession at a spatial scale and temporal depth rarely documented in the rewilding literature.

2.2. Current use of remote sensing in rewilding science

Over the past decades satellite remote sensing has become a standard tool in ecological research, advancing what field monitoring allows by offering vast spatial and long-term coverage, as well as the capacity to monitor ecosystem composition, structure and functioning at spatial and temporal scales that are difficult or impossible to achieve through field-based methods alone (Pettorelli & Schulte to Bühne, 2022). This makes it particularly well suited to rewilding research, where processes like vegetation succession, land cover transition or changes in primary productivity unfold over large areas and long timescales. Beyond multispectral satellite data, airborne lidar has proven valuable for capturing structural dimensions of rewilding that spectral indices cannot resolve, including canopy heterogeneity and multi-decadal structural maturation of spontaneously regenerating forests (Thers et al., 2019; Broughton et al., 2021). Remote sensing has also been integrated with wildlife tracking to monitor faunal rewilding: Mata et al. (2021) combined GPS tracking of reintroduced species with satellite-derived habitat classification to map realized and potential occupancy spatially, offering a quantitative measure of ecological integrity that extends rewilding monitoring beyond vegetation dynamics. Applications have further extended to urban contexts, where satellite-derived Normalized Difference Vegetation Index (NDVI) has been used to detect spontaneous vegetation development in city green spaces (Sikorska et al., 2021). Despite this growing diversity of applications, the use of remote sensing in rewilding research remains surprisingly limited. Existing applications have focused on land cover mapping and habitat distribution, with relatively few studies examining changes in ecosystem functioning such as primary productivity dynamics (Pettorelli & Schulte to Bühne, 2022). Because of the scarce use of remote sensing in rewilding science, practical guidance on how to monitor rewilding effects from space remains limited, and the integration of land cover change analysis with productivity assessment within an explicit rewilding monitoring framework is, to our knowledge, represented by only two studies to date.

In a study combining Random Forest classification of a Landsat image and a Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI time series, Schulte to Bühne et al. (2022) found that 20 years of rewilding at the Knepp estate in England produced a near-sixfold increase in shrub cover and a large increase in annual primary productivity relative to surrounding agricultural land. In another study, Elphick et al. (2024) applied a comparable approach to the Greater Côa Valley in Portugal, studying land cover change after 15 years of rewilding. Using Landsat data, they found an increase in area for scrub and forest classes as well as a significant NDVI increase after land abandonment, and called for satellite-based vegetation monitoring to be integrated more frequently into rewilding management decisions. Together, these two studies establish that multispectral satellite data can capture land cover and

productivity signals of rewilding at landscape scale, providing ecologically meaningful information that complements field research.

Long-term, large-scale remote sensing studies of rewilding remain rare, and the Chernobyl case has yet to be approached within an explicit rewilding monitoring framework. Existing remote sensing work in the Chernobyl region has examined land cover change, vegetation dynamics and NDVI trends, as well as the risks associated with wildfire and radionuclide dispersal (Gemtzi, 2020; Matsala et al., 2021; Santos, 2018; Ager et al., 2019; Fedoniuk et al., 2024). Hostert et al. (2011) compared land use change between Ukraine and Belarus focusing on the exclusion zone along with adjacent areas, but the analysis was limited to farmland abandonment dynamics and framed under a political and social context linked to the post-Soviet era. To our knowledge, no remote sensing study has approached the Chernobyl case within an explicit rewilding monitoring framework, nor combined a locally trained multi-class land cover classification with vegetation productivity analysis across the full extent of the Chernobyl-Palieski Reserve and its surrounding buffer zones over the full 1986-2018 period of land abandonment. The present study addresses these gaps, and also provides a high-resolution pre-disturbance visual reference by utilizing declassified KH-9 reconnaissance imagery from 1982, a reference that no prior remote sensing study of this landscape has employed.

3. Study area

The study area sits between the Kyiv Oblast in Ukraine, where the Chernobyl Exclusion Zone (CEZ) is located, and the Gomel Region in Belarus, home to the Palieski Radioecological Reserve (PRR). In the scientific literature, terminology has been slightly inconsistent as some studies use CEZ or ChEZ to refer to the Ukrainian zone only, while others use them to refer to the combined area. To avoid ambiguity, we use the term Chernobyl-Palieski Reserve (CPR) in this study to refer to the combined Ukrainian and Belarusian area. A buffer zone of 15 kilometres was used to expand the study area beyond the CEZ and PRR boundaries. This buffer was selected as a control area for comparing the effects of strict environmental restrictions with those of an adjacent zone where human activities continued at a reduced level, and which shares a similar ecological history. The total area of the CPR is 5 125 km² (2 340 km² for the CEZ and 2 785 km² for the PRR), while the buffer spans 5 835 km² (3 200 km² on the Ukrainian side and 2 635 km² on the Belarusian side). These figures are derived from the boundary layers digitised for this study and may differ slightly from published estimates due to differences in boundary delineation. The comparable size of the reserve and buffer zones supports their use as a paired comparison. The study area extends from 50.94° N to 51.98° N and from 29.04° E to 30.84° E. All spatial data were visualised and analysed in QGIS and the project CRS was set to UTM Zone 35N projection (EPSG:32635). Although a small portion of the study area falls within UTM Zone 36N, the majority lies within UTM Zone 35N, justifying the use of this projection throughout (Figure 1).

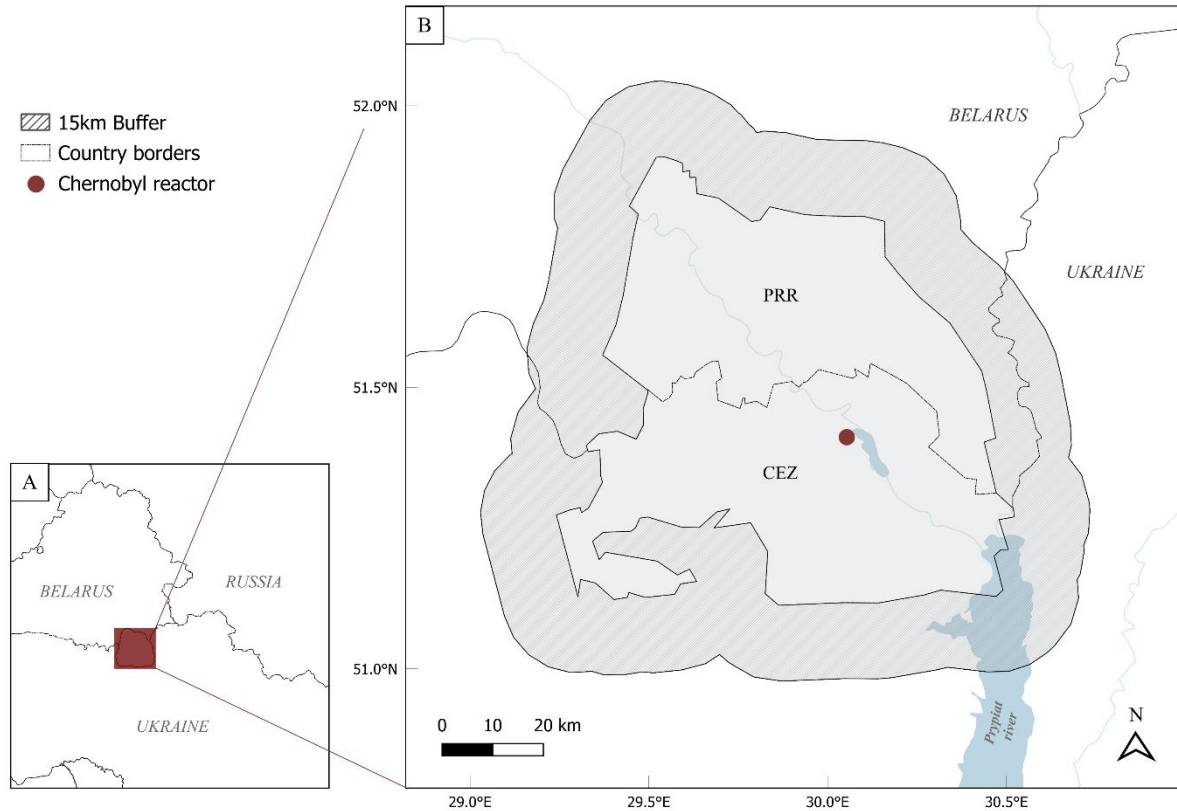


Figure 1. The Chernobyl Exclusion Zone (CEZ) and Palieski Radioecological Reserve (PRR) together form the Chernobyl-Palieski Reserve (CPR). The 15 km buffer surrounds the CPR and the Ukraine-Belarus border is represented by the dashed line. The Pripjat River crosses the CPR on a northwest diagonal while the Dnipro River follows the eastern border from the Kyiv Reservoir (or Pripjat River) in the south to Belarus.

The CEZ is now a strictly regulated area under Ukrainian governance where permanent human presence is very limited. Forests within the CEZ are largely unmanaged and only subject to localised activities related to sanitary logging of small forest stands (Matsala et al., 2021). All agricultural activities were prohibited and ceased in 1986. The zone has also been affected by several significant wildfire events, recorded in the early 1990s, 2016, and 2020 (Matsala et al., 2021; Ager et al., 2019). The PRR was established in 1988 as the Belarusian counterpart to the CEZ, following the Ukraine-Belarus border, and has remained subject to minimal human management since its creation (Perino et al., 2019; Schlichting et al., 2020). The reserve functions as an ecological continuation and wildlife corridor to the CEZ. Both reserves occupy the Polesie lowland, a flat landscape ranging in elevation from approximately 90 to 212 m above sea level. Soils are predominantly sandy and peaty sod-podzolic types, characteristic of this region (Hostert et al., 2011). The vegetation is dominated by Scots pine (*Pinus sylvestris*), Silver birch (*Betula pendula*), Black alder (*Alnus glutinosa*), Common aspen (*Populus tremula*), and European oak (*Quercus robur*). The climate is continental, with a mean annual temperature of 8.20°C and mean total annual precipitation of 619 mm recorded over the period 1955-2019 (Matsala et al., 2021). The Pripjat River crosses the CEZ in the west while the Dnipro River is

found along the north-south axis in the east. These two rivers, with their associated floodplain system, structure much of the low-lying landscape, giving rise to extensive swamps, meadows, and grass communities across the region (Didukh et al., 2023).

While the reserves were subject to strict restrictions on human presence, the broader region experienced significant socioeconomic disruption following the collapse of the Soviet Union (Hostert et al., 2011). This affected land use patterns outside the reserve boundary, with land abandonment documented across both countries, though to differing degrees; studies suggest that post-Soviet land abandonment affected Ukraine at approximately twice the rate observed in Belarus, reflecting differences in post-independence agricultural and land use policies (Hostert et al., 2011).

4. Data

This study relies on satellite-derived imagery to analyze the land cover changes and the vegetation productivity and patterns in the Chernobyl Exclusion Zone and the Palieski Radioecological Reserve. Three main datasets are used: (i) declassified KH-9 reconnaissance images providing high-resolution (0.6-1.2 m) historical coverage of the area in May 1982, (ii) Sentinel-2B scenes from May 2018 and (iii) Landsat multispectral imagery offering long-term monitoring, covering the two dates of the scenes used in this study (May and October scenes for 1986 and 2018). All information about the data is summarized in Table 1.

Historical coverage of the study area is provided by a declassified KH-9 reconnaissance satellite image captured on 18/05/1982, obtained from the United States Geological Survey (USGS) Earth Explorer platform (USGS EROS, 2018). The KH-9 programme was part of the KeyHole (KH) satellite series developed by the USA during the Cold War, consisting of 20 reconnaissance satellites that operated between 1972 and 1986 (Burnett, 2012). The satellites were equipped with panoramic film cameras obtaining images at 0.6 to 1.2 metre resolution, and 12 of the 20 satellites additionally carried mapping cameras producing imagery at 6 to 9 metre resolution (Burnett, 2012; Surazakov et al., 2010). Almost all imagery was declassified in 2011 and is now available for research purposes (USGS EROS, 2018). KH-9 data has since been used across a range of environmental studies including glacier dynamics (Masiokas et al., 2015; Maurer et al., 2019), land cover change (Kivinen & Kumpula, 2014), and forest fragmentation (Olariu et al., 2022); to our knowledge, no prior study has used KH-9 imagery specifically for monitoring rewilding. Four adjacent tiles (f, g, h, i) from scene D3C1217-100073A012 together cover the CEZ from east to west at a ground sample distance of 0.6 to 1.2 metres, and were used as the primary reference layer for drawing training polygons for the 1986 classification. Georeferencing of these tiles is described in the preprocessing section.

Similarly, four Sentinel-2B tiles from 2018 were used as a visual aid for drawing training polygons in the 2018 classification.

The imagery used for classification and subsequent land cover change analysis in the CPR was collected from the Landsat archive on the USGS website. Landsat missions have provided continuous multispectral satellite coverage since 1972 and offer an open-source long-term

archive commonly used for land cover mapping and change detection (Wulder et al., 2019). This study makes use of two different Landsat generations: Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI). Images were acquired as Level-2 Surface Reflectance products at 30m resolution. Each classification year uses two distinct scenes: a spring image from late May and an autumn scene from October. An additional Landsat 4 Multispectral Scanner (MSS) image from 15/05/1983 at 60m resolution was collected as it provides spectral information bridging the KH-9 imagery of 1982 and the first Landsat 5 scene of 1986.

The GLC_FCS30D Global 30-metre Land Cover Change Dataset (Zhang et al., 2024) is used for cross-product comparison purposes. It is a global land cover product generated from dense Landsat time series using a continuous change detection method, providing five-year interval maps from 1985 to 2000 and annual maps from 2000 onward at 30m resolution (Zhang et al., 2024). For this study, the 1985-1990 map was used for comparison with the 1986 classification and the 2018 annual map for comparison with the 2018 classification. Both were accessed through Google Earth Engine. The CEZ and PRR boundary vector layers were digitised manually using available cartographic reference layers, while country borders were downloaded from Natural Earth Data (Admin 0 - Countries). The Google Satellite basemap and ESRI imagery (accessed via QGIS) were used for visual inspection of the study area.

All spatial data were processed and visualised in QGIS 3.40.6, statistical analyses and classification were performed in RStudio (R 4.5.0), and other tabular data were managed with Microsoft Excel.

Table 1. Datasets used in this study, including sensor type, spectral bands, spatial resolution, acquisition date, and source. Full product identifiers and tile references are provided in Appendix Table S1.

Dataset	Sensor	Bands	Resolution	Date	Source
KH-9	Panchromatic	Pan	0.6m-1.2m	18/05/1982	USGS
Sentinel-2B	Multispectral	B2-B4, B8, B11*	10m	26/05/2018	ESA Copernicus
L4 MSS (Level-1)	Multispectral	B4-B7	60m**	15/05/1983	USGS
L5 TM (Level-2)	Multispectral	B1-B5, B7	30m	31/05/1986, 03/10/1985	USGS
L8 OLI (Level-2)	Multispectral	B2-B7	30m	23/05/2018, 14/10/2018	USGS
SRTM	SAR	Elevation only	1-ARC	23/09/2014	USGS

* B11 originally at 20m resolution, resampled to 10m by bilinear interpolation for visual inspection purposes only.

** Originally at 60m resolution, resampled to 30m for consistency with Landsat 5 and 8 imagery.

Landsat 5 TM was selected for the 1986 classification as it has a comparable band configuration to Landsat 8 OLI at 30m resolution, which is not the case for Landsat 4 MSS. The 1986 scene

(31/05/1986) was selected as the earliest cloud-free Landsat 5 TM acquisition available for the study area. Although acquired one month after the disaster and subsequent human withdrawal, this scene can be treated as a baseline of pre-abandonment landscape conditions, given that no event of sufficient magnitude to alter land surface conditions at landscape scale occurred in this interval. This assumption was further supported during training data collection, where KH-9 imagery from May 1982 showed no evidence of substantial land cover change relative to the 1986 Landsat scene. The 2018 scene (23/05/2018) was selected as the latest suitable cloud-free acquisition prior to the wildfire of 2020 and the onset of military activity in the region from 2022 onward, while also maintaining sufficient distance from the wildfire events of 2015-2016 which affected parts of the CEZ. Within that window, 2018 represented the cleanest available scene, capturing over three decades of unmanaged ecological succession from the 1986 baseline.

5. Methods

5.1. Preprocessing

5.1.1. Georectification of KH-9 data

The four KH-9 panchromatic tiles used in this study (f, g, h, i) were georectified in QGIS using the Georeferencer tool. In total 31 Ground Control Points (GCPs) were placed on each tile using Google satellite imagery as a reference layer. Temporally stable and recognisable features visible in both the 1982 KH-9 and contemporary imagery were used as GCPs. These included among others road intersections, bridges, buildings, and drainage channel bends. A third-order polynomial transformation and bicubic (4×4 kernel) resampling was then applied, producing a smooth output, necessary for identifying physical features on the ground such as clear forest edges. Similarly, second-order polynomial transformation and bilinear resampling were tested but yielded higher RMSE values across all tiles (Table 2). A visual inspection was performed after each transformation to verify that no overfitting had occurred at tile edges.

Table 2. Root Mean Squared Error (RMSE) of the 31 GCPs for the KH-9 georeferenced tiles using polynomial second order and Polynomial third order transformations.

Tile	RMSE Polynomial 2	RMSE Polynomial 3
f	11.14 m	5.10 m
g	10.90 m	5.75 m
h	9.07 m	5.58 m
i	7.79 m	6.41 m

The accuracy of the georectification was estimated in two stages. Firstly, with the in-built QGIS RMSE calculator in the ‘georeferencer’ mode which reported GCP residuals for the 31 control points per tile under both transformation orders as well as the RMSE value (Table 2). Secondly, for each tile, eight independent validation points were placed on identical features in

the reference (Google satellite) and georectified layers (output tiles). The RMSE was then calculated from their Euclidean distances using the following equation:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n [(x_i - x'_i)^2 + (y_i - y'_i)^2]} \quad [1]$$

where n is the number of validation points; x and y are the coordinates from the reference Google satellite layer, and x' and y' are the corresponding coordinates from the georectified KH-9 images. Third-order polynomial transformation consistently outperformed second-order across all tiles in both assessments (Table 2, Table 3).

Table 3. Root Mean Squared Error (RMSE) for the 8 independent validation points for each georeferenced tile and the corresponding transformation that is tested.

Tile	RMSE Polynomial 2	RMSE Polynomial 3
f	8.49 m	5.04 m
g	5.26 m	2.99 m
h	13.69 m	10.69 m
i	12.40 m	11.14 m

For the georeferenced layers, third-order transformation yielded RMSE values ranging from 5.10m to 6.41m across the four tiles (Table 2). Independent validation RMSE ranged from 2.99m to 11.14m, with tiles h and i showing higher errors. These can be attributed to a greater geometric distortion of the western tiles h and i suffering from a north-south stretch more pronounced than the other tiles (Table 3). All values were below the Landsat pixel size of 30m, which was the accuracy threshold aimed at given that the georectified KH-9 imagery was used solely for visual interpretation and not as classification input. Georectification error at this level cannot introduce pixel-level misclassification in the 30m classification output.

5.1.2. Resampling Strategy

Throughout the study, for each preprocessing step involving resampling of the data, methods were selected according to the nature of the data. For continuous data such as raw Landsat bands, spectral indices or the digital elevation model (DEM), bilinear resampling was used when reprojecting to UTM Zone 35N or aligning grids between datasets. This was always the case except for the bicubic resampling of the KH-9 tiles. On the other hand, nearest-neighbour resampling was applied to all discrete data, that is the classified maps, including the GLC reclassified raster. This choice was made to preserve integer class values, that way preventing the introduction of false values at class boundaries.

5.1.3. Cloud & Shadow Masking

Cloud and cloud shadow masking was performed independently for each of the four Landsat scenes using the QA_PIXEL band provided within Landsat Level-2 Collection 2 products, implemented in R using the terra package. All masks were aligned to the UTM Zone 35N processed band grid using a nearest-neighbour resampling prior to application.

For the two Landsat 5 scenes, cloud detection used high-confidence cloud flags (QA_PIXEL bits 8-9), and extended masking to medium-confidence flagged pixels where green band surface reflectance exceeded 0.20 (May 1986) or 0.15 (October 1985). Adding this threshold on the green band prevented bright land surfaces such as bare soil from being incorrectly masked. Shadow detection combined QA shadow flags (bits 4 and 6-7) with spectral thresholds requiring NIR values below 0.08 and MNDWI below 0.10. This protected dark water bodies from misclassification as shadow. The October 1985 mask additionally incorporated the dilated cloud flag (bit 1), since clouds were more persistent than in the May scene. Both Landsat 5 masks then used a 7×7 focal sum filter to mask a pixel if 15 or more of its 49 neighbours were already flagged. This was to fill existing gaps within clouds that were resistant to the existing mask. Finally a 3×3 maximum dilation was applied to extend the mask to the cloud edges.

For the Landsat 8 May 2018 scene, the base mask flagged bits 1 to 4 (dilated cloud, cirrus, cloud, and shadow). Since this mask was creating false positives (masking non-cloud and shadows), a combined rule was applied to reinstate flagged pixels that were not clouds. Pixel would be unflagged if SWIR1 digital number (DN) was below 24,000, as well as if NDVI exceeded 0.12, and blue band DN remained below 12,000. No additional spatial filtering was applied to this scene. For the October 2018 scene, only high-confidence cloud pixels (bit 3) were masked, with shadow masking omitted. This is because clouds were very thin and did not carry shadows and adding a shadow mask would remove many valid pixels. Speckle removal used a 7×7 modal filter applied to the mask layer to reduce over-masking without altering surface reflectance values.

Per-date union masks were then constructed for each classification year by combining the May and October scene masks and any pixel flagged in either scene was excluded. These union masks were applied during Random Forest classification and cross-product comparison with the GLC. A master union mask combining all four scenes was then applied for the land cover change and productivity analyses, ensuring that only pixels with valid observations across all dates entered the comparison.

All spectral thresholds were determined empirically through iterative visual inspection of masked outputs.

5.2. Land Cover Classification

5.2.1. Random forest

Random Forest (RF) is a widely used machine learning method in remote sensing which can be utilized for land cover classification as well as for regression analysis. It is an ensemble

classifier based on many decision trees making each a vote on the predicted output. Each decision tree in the forest is trained on a random subset of the data with replacement (bootstrapping), and at each node, a random subset of features is considered to determine the optimal split. For classification tasks, the final prediction is derived from a majority vote of the individual trees, while for regression tasks, the output is calculated as the average of the predictions (Breiman, 2001; Gislason et al., 2006). RF is robust to overfitting and can handle large datasets and many trees (Breiman, 2001; Gislason et al., 2006) and does not require any assumption on the distribution of the data (Niemeyer, 2014). For these reasons, RF was selected as the classification algorithm for both dates in this study.

5.2.2. Landsat scene selection following phenological criteria

Two scenes per classification year were selected to better discriminate land cover classes. May scenes were prioritised as they correspond to full leaf-out conditions in the temperate continental climate of the study area, maximising spectral separability between vegetation classes (Matsala et al., 2021). An additional October scene was included for each year as a phenological discriminator, exploiting the contrasting seasonal spectral responses between classes that are difficult to separate in spring alone. For the 1986 classification, the autumn scene was sourced from October 1985 rather than 1986, as no suitable cloud-free image was available for that year. Given that the seasonal spectral effects exploited here are driven by climate rather than year-specific conditions, the use of an October scene from an adjacent year is considered acceptable. Together, the two scenes provide complementary information that substantially improves class separability beyond what a single-date classification could achieve.

5.2.3. Classification Schema

A systematic classification workflow was used for the classification of both dates, resulting in seven identified classes: Coniferous forest (Coniferous), Deciduous forest (Deciduous), Open Woodland and Shrubland (Open/Shrub), Grassland, Agriculture, Urban and disturbed (Urban), and Water. Class boundaries were defined through a combination of visual interpretation criteria and spectral characteristics applied consistently for both dates.

Forest classes were separated from the Open/Shrub class by setting a visual canopy cover threshold: areas with tree cover above 50% of the pixel area were classified as Deciduous or Coniferous, while areas below 50% canopy cover were assigned to open woodland and shrubland, consistent with the threshold applied by Matsala et al. (2021). Within the forest class, Deciduous was separated from Coniferous subclasses using false colour composite (FCC). The deciduous populated forests appeared in a distinct bright red while coniferous forests displayed a dark red in FCC. This contrast was confirmed by the EVI2 index, with deciduous forest showing a higher EVI2 response in May and a distinct drop in October reflecting leaf senescence. Conversely, coniferous forests showed a more stable EVI2 response across both dates.

Open Woodland and Shrubland was distinguished from Grassland by the presence of visible woody texture on the high resolution KH-9 layers (1982) and Google Satellite and ESRI layers (contemporary images). Grassland was recognizable with a unique smooth visual texture coupled with a stable and relatively high EVI2 value between May and October. Although texturally smooth, Agriculture behaved in the opposite way by displaying sharp spectral transitions between May and October, reflecting human management of crops, as well as a structural rectangular shaping unique to this class. Water was the least ambiguous class, easily identified through a combination of strong negative values in vegetation indices (NDVI and EVI2) and high MNDWI values.

In this study, urban and disturbed land was treated as a single class for both dates, populated by mixed pixels containing the spectral information of settlements, roads, and bare or disturbed surfaces as a signal of human activities. For 1986, the limited spatial extent of the KH-9 coverage was insufficient for selecting pure urban pixels only. Bare surfaces near settlements and in more rural areas were spectrally similar to urban land at 30m resolution and were therefore merged with urban into a single human-footprint class. For 2018, bare and disturbed surfaces were sampled alongside urban pixels within the same class, as the entire scene provided sufficient coverage to extract spectral information from buildings, roads, and barren surfaces within settlements. Ambiguous areas, including the abandoned settlements such as Pripjat which had become a unique mixture of abandoned buildings and dense deciduous forest by 2018, were not assigned to any class but left for the RF classifier to decide.

Known spectral overlap was acknowledged between Grassland and Open Woodland, where signatures are nearly indistinguishable in all indices. To overcome this limitation, texture metrics were selected as additional discriminating features for these classes, as described in the feature stack section. Moderate overlap between agriculture and urban in BSI and NDBI was also noted, with EVI2 texture providing the primary discriminating information.

5.2.4. Feature Stack

The feature stack selected for each classification was composed of spectral bands, spectral indices, texture metrics, and an elevation layer. For both years, each scene (May and October) contained six surface reflectance bands: Blue, Green, Red, Near Infra-Red (NIR), Short Wave Infra-Red 1 (SWIR1), and Short Wave Infra-Red 2 (SWIR2), totalling twelve bands per year. Additionally, six spectral indices were calculated per scene: EVI2 (Jiang et al., 2008), a two-band enhanced vegetation index selected for its robustness in dense vegetation conditions where NDVI tends to saturate; NDVI (Rouse et al., 1974) as a standard vegetation measure; the Normalised Difference Moisture Index (NDMI; Gao, 1996) for canopy moisture content; the Modified Normalised Difference Water Index (MNDWI; Xu, 2006) for water body detection; the Bare Soil Index (BSI; Rikimaru et al., 2002) for bare soil and disturbed surfaces; and the Normalised Difference Built-up Index (NDBI; Zha et al., 2003) for built-up areas, totalling twelve indices per year. Four Grey-Level Co-occurrence Matrix (GLCM) texture layers were derived per scene by calculating the standard deviation of EVI2 and NDVI at 3×3 and 5×5 pixel windows (Haralick et al., 1973). Standard deviation was selected as the texture metric as it

directly quantifies local variability in spectral response across the neighbourhood window. Two window sizes were used to represent texture at different spatial scales (90m and 150m respectively), to better discriminate classes with similar spectral signatures, particularly Grassland and Open/Shrub. Finally, one DEM layer, shared across both dates, was included as an ancillary feature to help separate lowland from upland ecosystems. Ultimately, the complete feature stack comprised 33 variables per classification year: twelve bands, twelve indices, eight texture layers, and one DEM.

5.2.5. Training Data

Training polygons were drawn manually by visual interpretation and each classification date was addressed independently. The primary reference layer for May 1986 was the declassified KH-9 panchromatic image, which provided a high spatial detail unachievable by any other source for the Polesie region at this time. The panchromatic limitation of the KH-9 data was overcome using spectral indices produced from multispectral bands from the Landsat 5 scenes. To account for the four year temporal gap between the two datasets (May 1982 for KH-9, May 1986 for Landsat 5) a Landsat 4 TM scene from May 1983 was additionally consulted as a temporal bridge to verify landscape stability between the two dates; polygons were only retained where land cover appeared consistent across all three dates. For 2018, polygons were drawn using Sentinel-2 imagery (false colour composite, RGB composite and EVI2, 26 May 2018, three days after the Landsat 8 acquisition) as the primary reference. Additionally, the use of ESRI and Google satellite basemaps allowed for a high resolution tool for spectrally ambiguous classes, particularly Grassland and Open Woodland, where individual trees and small shrub patches visible at basemap resolution provided spatial context that Sentinel-2 could not resolve. When contextual information from a high resolution basemap was retrieved, a polygon was only drawn if this context was reflected on the 2018 Sentinel-2.

Table 4. Training dataset composition per land cover class for 1986 and 2018, reporting the number of polygons and pixels used for Random Forest classification.

Class	Polygons		Pixels	
	1986	2018	1986	2018
Agriculture	390	191	49 740	39 972
Coniferous	674	747	30 921	41 786
Deciduous	566	481	14 012	30 695
Open / shrubland	85	153	2114	7932
Grassland	210	275	5654	9136
Urban / disturbed	169	82	3370	2661
Water	100	345	18 716	34 781
Total	2194	2274	124 527	166 963

Polygons were drawn to capture the full range of spectral variability within each class. Once all polygons were drawn, a 10m interior buffer was applied prior to pixel extraction to remove boundary pixels with potentially mixed spectral signatures from neighbouring classes. Pixels intersecting with the per-date union cloud and shadow mask were subsequently excluded from the training dataset. After applying both filters, the final training dataset comprised 124 527 pixels across 2194 polygons for 1986 and 166 963 pixels across 2274 polygons for 2018. The polygon and pixel representation per class is presented in Table 4.

5.2.6. Configuration and Feature selection

To identify the optimal classification configuration, nine combinations of spatial clustering threshold and pixel balancing mode were tested. For the spatial threshold, three distances were tested (100m, 300m, and 500m), defining the minimum separation distance between spatially independent cluster groups. Polygons were buffered outward at half the threshold distance and merged with any other polygon with which buffers overlapped, thus creating spatial clusters of the defined threshold distance around the original polygons. A 70/30 training-validation split was then applied at the cluster level, meaning entire spatial clusters were assigned to either training or validation rather than individual polygons or pixels. The split was stratified to ensure all classes were represented in both training and validation sets, as randomly assigning clusters could leave a minority class concentrated on one side of the split. This spatial clustering approach ensures high spatial independence of the data, preventing spatially adjacent pixels from appearing on both sides of the split, which would artificially inflate validation accuracy through spatial autocorrelation (Roberts et al., 2017; Abdi & Wang, 2026). Cluster counts per class were verified across both training and validation sets to confirm sufficient representation of minority classes, with a minimum of three validation clusters required per class.

Three balancing modes were also tested for each threshold setting: balanced (5,000 pixel limit per class), semi-balanced (15,000 pixel limit per class), and imbalanced (no cap). All nine configurations were first run with 300 trees to generate feature importance rankings per configuration using Mean Decrease Accuracy (MDA) (Breiman, 2001). All other Random Forest parameters were left at their default values in the randomForest R package (Liaw & Wiener, 2002), including mtry set to the square root of the number of features and nodesize set to 1. The MDA ranks were then averaged across all nine configurations and features ranking above 20 in the averaged ranking were excluded. The threshold of 20 was selected arbitrarily and retained following satisfactory classification accuracy in subsequent analyses. This selection produced a final feature set of 21 variables for 1986 and 20 for 2018, reported in Table 5 alongside the average MDA values.

Table 5. Feature importance ranking and selection for the 1986 and 2018 Random Forest classifications, ranked by average Mean Decrease Accuracy across nine classifier configurations. Feature names follow the convention: spectral band or index name, window size where applicable (3x3 or 5x5 pixels for standard deviation texture metrics), and acquisition season (May or Oct). Features marked with an asterisk (*) exceeded the average rank threshold of 20 and were excluded from the final classification, resulting in 21 retained features for 1986 and 20 for 2018.

1986			2018		
Feature name	Avg MDA	Avg Rank	Feature name	Avg MDA	Avg Rank
DEM	38.18	1.11	NDVI_5x5_Oct	42.23	1.33
Green_May	31.43	3.11	NDVI_5x5_May	37.72	2.33
EVI2_5x5_Oct	30.29	3.56	DEM	31.29	3.44
Blue_Oct	29.32	4.78	NDVI_3x3_Oct	33.77	3.56
NDVI_5x5_May	30.33	4.78	MNDWI_Oct	29.05	4.56
NDVI_5x5_Oct	25.99	8.11	Red_May	24.44	7.56
EVI2_3x3_Oct	24.79	9.78	NDVI_3x3_May	23.71	8.67
Green_Oct	24.21	10.56	NDVI_May	23.08	9.56
Red_May	24.18	11	EVI2_5x5_Oct	23.57	10.22
MNDWI_Oct	24.36	11.33	Green_May	21.78	12.11
NDVI_3x3_May	23.32	12.22	SWIR1_Oct	22.25	12.11
NIR_May	23.47	12.56	SWIR2_Oct	21.91	12.22
SWIR1_Oct	23.38	13	NDVI_Oct	20.41	14
Blue_May	22.22	15.33	NIR_May	20.37	14.67
NDVI_3x3_Oct	21.97	16	Blue_Oct	20.26	14.89
EVI2_May	21.65	17.22	Green_Oct	20.25	14.89
NDVI_May	21.27	17.89	EVI2_May	19.68	16.44
NDBI_May	21.37	18	EVI2_3x3_Oct	19.58	16.78
Red_Oct	20.68	19.33	EVI2_Oct	18.53	18.11
EVI2_5x5_May	20.53	19.67	Blue_May	17.82	20
NDMI_May	20.83	19.78	BSI_May*	17.31	20.78
NIR_Oct*	20.52	20.11	Red_Oct*	17.14	20.78
SWIR2_Oct*	20.01	20.67	NDMI_May*	16.61	22.78
BSI_May*	20	21.56	NDBI_May*	16.33	23.89
EVI2_3x3_May*	19.28	21.56	SWIR2_May*	15.78	24.89
SWIR2_May*	18.52	25	MNDWI_May*	15.74	25
EVI2_Oct*	18.39	25.22	EVI2_5x5_May*	14.86	25.56
NDVI_Oct*	17.92	25.78	NDBI_Oct*	14.4	27.56
SWIR1_May*	17.11	27.67	SWIR1_May*	14.41	28.22
BSI_Oct*	16	29.33	NDMI_Oct*	14.14	29.11
NDMI_Oct*	14.13	31.22	NIR_Oct*	12.38	31
MNDWI_May*	14.95	31.33	BSI_Oct*	12.65	31
NDBI_Oct*	13.49	32.44	EVI2_3x3_May*	7.81	33

All nine configurations were then run in full with 500 trees and the selected feature set, and evaluated on the held-out validation set using overall accuracy (OA), Matthews Correlation Coefficient (MCC), and per-class F1 scores. Out-of-Bag (OOB) error was not used as a

selection criterion as it is sensitive to class imbalance and may not reliably reflect true predictive performance across classes (Mitchell, 2011). The Threshold 500 Balanced (T500-B) configuration was selected for both dates based on its spatial independence and resistance to majority class bias, while maintaining acceptable performance across minority classes.

Although Grassland returned the lowest F1 score in both dates, this was considered acceptable given the known spectral confusion between Grassland and Open Woodland (Matsala et al., 2021) rather than a configuration-specific failure; this limitation is discussed further in the Discussion. Final models were trained with 500 trees, a default mtry (number of features randomly sampled as candidates at each node split) set to the square root of the total number of features, and a fixed random seed of 42 for reproducibility (Breiman, 2001).

5.2.7. Classification accuracy

Classification accuracy was evaluated against the validation set containing 30% of the spatial clusters. Per-class metrics reported include Producer's Accuracy (PA), User's Accuracy (UA), omission error, commission error, and F1 score. Overall accuracy (OA) and Matthews Correlation Coefficient (MCC) were reported as summary statistics. MCC was preferred over the Kappa coefficient as it has been shown to be more robust to class imbalance (Chicco & Jurman, 2020). Full accuracy results for the selected T500-B configuration are presented in the results section.

5.3. GLC cross-product comparison

The land cover maps obtained through RF classification were independently compared against the GLC_FCS30D Global 30-metre Land Cover Change Dataset (Zhang et al., 2024). A consistent spatial offset of 15m was noticed between the GLC grid and the local classification grid and to correct it, the GLC raster was warped to the exact Landsat extent using nearest-neighbour resampling.

While this study focused on seven land cover classes, the GLC product presented a total of 24 classes across the study area. Reclassification was therefore necessary to match the seven-class schema used in this study. Crosswalk decisions were made on the basis of ecological proximity between GLC classes and the RF classification for those classes that did not map directly onto the schema (Table 6).

Notably, open broadleaved classes (codes 51 and 61) were reclassified into deciduous forest upon visual inspection, as these classes fell predominantly into areas classified as deciduous in the RF classification. Swamp and marsh classes (181 and 182) were reclassified as grassland as they appeared predominantly as grassland in the RF classification rather than water. Bare land (200) was reclassified as urban for consistency with the merged urban and disturbed class used in this study.

Table 6. Reclassification crosswalk between the Global Land Cover Fine Classification System 30m (GLC_FCS30D) land cover classes and the seven land cover classes defined for this study, with decisions based on ecological proximity between products.

GLC Code	GLC Class Name	Reclassification
10	Rainfed cropland	Agriculture
11	Herbaceous cropland	Agriculture
12	Tree/shrub cropland	Agriculture
20	Irrigated cropland	Agriculture
51	Open evergreen broadleaved	Deciduous
52	Closed evergreen broadleaved	Deciduous
61	Open deciduous broadleaved	Deciduous
62	Closed deciduous broadleaved	Deciduous
71	Open evergreen needleleaved	Coniferous
72	Closed evergreen needleleaved	Coniferous
81	Open deciduous needleleaved	Coniferous
82	Closed deciduous needleleaved	Coniferous
91	Mixed broadleaved forest	Coniferous
120	Shrubland	Shrub/Open Woodland
121	Evergreen shrubland	Shrub/Open Woodland
130	Grassland	Grassland
140	Lichens and mosses	Grassland
150	Sparse vegetation	Shrub/Open Woodland
181	Swamp	Grassland
182	Marsh	Grassland
183	Flooded flat	Water
190	Impervious surface	Urban
200	Bare land	Urban
210	Water body	Water

Prior to comparison, the per-date union masks were applied to each classification independently to exclude cloud and shadow-affected pixels. A joint NA mask was then applied to retain only pixels with valid data in both products, ensuring that the comparison was conducted over an identical spatial extent across both dates and accounting for any remaining isolated data artifacts.

5.4. Land Cover Change Analysis

Land cover change between May 1986 and May 2018 was estimated through post-classification comparison of the two independently classified maps. This approach avoids the need for cross-sensor radiometric harmonisation, as the comparison occurs on the classified rasters rather than the reflectance values of the original scenes (Coppin et al., 2004).

Prior to comparison, the master union mask was applied to both classification maps, setting pixels to NA where any of the four input scenes (Landsat 5 May 1986, Landsat 5 October 1985, Landsat 8 May 2018, Landsat 8 October 2018) contained cloud, cloud shadow, or no-data values. This ensured that only pixels with valid observations across all dates entered the change analysis. Pixel alignment of the two classified maps was verified before cross-tabulation to confirm identical CRS, resolution, and grid origin. Land cover changes were then quantified through a transition matrix across the seven land cover classes. Per-class areas were calculated in hectares based on pixel counts, with each $30\text{m} \times 30\text{m}$ pixel corresponding to 0.09 ha. Results are illustrated with a Sankey diagram matrix (Figure 5) and reported per class, per date, and per spatial zone. Four zones are considered: the CEZ, the PRR, the Ukrainian buffer, and the Belarusian buffer. Land cover transitions shown in the Sankey diagrams exclude flows below 100 hectares to improve readability.

A rewilding map was derived from the binary reclassification of both classified maps to spatially represent greening dynamics across the study area. Each classification was independently reclassified into a binary vegetation/non-vegetation layer: vegetation classes comprised Coniferous forest, Deciduous forest, Grassland, and Open/Shrub, while non-vegetation classes comprised Agriculture and Urban and disturbed land. Water pixels were excluded from this analysis by extending the master union mask to include water, as water surfaces cannot be vegetated and would introduce noise into the rewilding signal. The two binary layers were then combined across dates to produce four categories: Persistent Vegetation (vegetated in both dates), Rewilding Signal (non-vegetated in 1986, vegetated in 2018), Persistent Non-Vegetation (non-vegetated in both dates), and Loss Signal (vegetated in 1986, non-vegetated in 2018). Area statistics per category per zone are reported in hectares and as percentages alongside the map.

5.5. Productivity Analysis (EVI2)

Vegetation indices are widely used in remote sensing to monitor vegetation parameters and estimate the photosynthetic activity of vegetation as well as the gross primary productivity (GPP) of an ecosystem (Shi et al., 2017). The most widely used vegetation index is the Normalized Difference Vegetation Index (NDVI), which exploits the difference between high NIR reflectance and low red reflectance due to chlorophyll absorption to discriminate vegetation from other surface types. However, NDVI can saturate at high vegetation densities and is sensitive to soil brightness and composition (Huete, 1988; Huete et al., 2002). EVI2 is a two-band enhanced vegetation index that addresses these limitations by expressing the blue band correction as a function of the red band, requiring only the NIR and red bands (Jiang et al., 2008):

$$EVI2 = 2.5 \frac{N-R}{N+2.4R+1} \quad [2]$$

where N and R are the NIR and red band reflectances respectively (Jiang et al., 2008).

Vegetation productivity was assessed using EVI2 as a proxy, following the established empirical relationship between EVI and gross primary productivity across multiple biomes (Shi et al., 2017; Huete et al., 2002). As EVI2 is functionally equivalent to standard EVI (Jiang et al., 2008), this relationship is considered transferable. EVI2 values were extracted from the May scenes for both 1986 and 2018. EVI2 was preferred over NDVI for two reasons: it shows substantially less cross-sensor bias than NDVI when combining Landsat 5 and Landsat 8 data (Zhu et al., 2016), which is particularly important given that no cross-calibration was applied between dates; and it is more robust at high vegetation density, avoiding the saturation that affects NDVI in dense canopy conditions (Huete et al., 2002; Jiang et al., 2008). It is acknowledged that transitioning between Landsat 5 TM and Landsat 8 OLI introduces a potential sensor bias in EVI2 values, arising from both spectral band differences between sensors (Roy et al., 2016) and differences between the atmospheric correction algorithms applied with LEDAPS for Landsat 5 and LaSRC for Landsat 8 (Zhu et al., 2016). Zhu et al. (2016) found that when mixing Landsat 5, 7, and 8 data, EVI showed only a small negative bias (−0.019) compared to a substantially larger positive NDVI bias (+0.042), and explicitly concluded that EVI data can be used for vegetation greenness analysis without further modification when combining these sensors. As EVI2 omits the blue band, which is identified by Zhu et al. (2016) as the primary driver of cross-sensor bias between Landsat generations, the residual bias in EVI2 is likely smaller still than for standard EVI. No additional cross-sensor correction was therefore applied. The implications of this residual bias for the interpretation of results are discussed further in the Discussion. Negative EVI2 values were set to NA prior to analysis, as healthy vegetated surfaces produce positive EVI2 values while negative values indicate water or sensor noise providing no meaningful ecological interpretation. The water and cloud union mask was applied to both EVI2 rasters. For the analysis, all remaining valid pixels were used without random sampling, ensuring the full spatial distribution of EVI2 values was represented. Analysis was conducted at the pixel level and each pixel contributes equally to the distributional statistics regardless of the total area occupied by its class, so that productivity signals from smaller classes are not obscured by larger dominant ones. To assess vegetation productivity as indicated by EVI2, two complementary analyses were performed. First, a regional comparison at the human restriction level contrasted EVI2 distributions between the CPR and the outer buffer (combining both countries) for both dates, providing a comparison between the exclusion zone and the surrounding landscape where human activities continued. This is presented as violin plots informing on the distributional shape of the data, with internal boxplots displaying the median and interquartile range; whiskers extend to 1.5 times the Interquartile Range (IQR) and values beyond this range are not shown. Second, a per-class productivity comparison was designed to examine EVI2 distributions for all non-water classes and for the entire study area. These results are presented as class paired boxplots following the

same conventions. This per-class analysis was conducted across the whole study area without regional subdivision, as splitting by zone would result in small pixel counts for several classes within individual zones, introducing noise into the distributional summaries. As EVI2 distributions are non-normal in several classes, IQR is reported alongside standard deviation as a more robust measure of spread.

6. Results

6.1. Accuracy assessment

The Random Forest classifier ran with the selected configuration based on a 500m cluster threshold and balanced classes achieved strong overall performance for both dates, with overall accuracy (OA) of 0.941 and a Matthews Correlation Coefficient (MCC) of 0.906 for the 1986 classification, and OA of 0.978 and MCC of 0.972 for 2018 (Tables 7 and 8).

Table 7. Classification accuracy metrics for the 1986 Random Forest model configuration using the 500 threshold balanced configuration, reporting overall accuracy, Matthews Correlation Coefficient, and per-class producer accuracy, user accuracy, omission error, commission error, and F1 score across the seven land cover classes.

Land Cover Class	Performance Metrics (1986)				
	Recall (PA)	Precision (UA)	Omission Error	Commission Error	F1 Score
Agriculture	0.921	0.984	0.079	0.016	0.952
Coniferous	0.993	0.993	0.007	0.007	0.993
Deciduous	0.995	0.974	0.005	0.026	0.984
Grassland	0.790	0.412	0.210	0.588	0.542
Shrub/Open	0.837	0.811	0.163	0.189	0.824
Urban	0.936	0.811	0.064	0.189	0.869
Water	1.000	0.996	0.000	0.004	0.998
Mean± StdDev	0.925 ± 0.08	0.854 ± 0.21	0.075 ± 0.08	0.146 ± 0.21	0.880 ± 0.16
Overall accuracy = 0.941					
Matthews correlation coefficient = 0.906					

Per-class performance was high and consistent across spectrally distinct classes. Water achieved near-perfect recall and precision in both dates (F1 = 0.998 and 1.000 respectively), while coniferous and deciduous forest returned F1 scores above 0.98 across both classifications. Agriculture performed strongly in both years (F1 = 0.952 in 1986; 0.980 in 2018).

Table 8. Classification accuracy metrics for the 2018 Random Forest model configuration using the 500 threshold balanced configuration, reporting overall accuracy, Matthews Correlation Coefficient, and per-class producer accuracy, user accuracy, omission error, commission error, and F1 score across the seven land cover classes.

Land Cover Class	Performance Metrics (2018)				
	Recall (PA)	Precision (UA)	Omission Error	Commission Error	F1 Score
Agriculture	0.967	0.994	0.033	0.006	0.980
Coniferous	0.997	0.998	0.003	0.002	0.998
Deciduous	0.985	0.995	0.015	0.005	0.990
Grassland	0.862	0.865	0.138	0.135	0.863
Shrub/Open	0.886	0.749	0.114	0.251	0.812
Urban	0.965	0.937	0.035	0.063	0.951
Water	1.000	1.000	0.000	0.000	1.000
Mean± StdDev	0.952 ± 0.06	0.934 ± 0.10	0.048 ± 0.06	0.066 ± 0.10	0.942 ± 0.07
Overall accuracy = 0.978					
Matthews correlation coefficient = 0.972					

Performance was weaker for transitional vegetation classes. In 1986, grassland recorded the lowest F1 score across all classes and dates ($F1 = 0.542$), driven by a commission error of 0.588, indicating significant misclassification into this class from other land cover types. Shrub/open woodland also returned a moderate F1 score in 1986 (0.824), with persistent commission error noted for this class across both dates. In 2018, grassland and shrub/open woodland returned F1 scores of 0.863 and 0.812 respectively. Urban classification improved from $F1 = 0.869$ in 1986 to 0.951 in 2018, coinciding with a reduction in commission error from 0.189 to 0.063.

6.2. Classification maps

The 1986 classification (Figure 2a) is visually dominated by Agriculture, which occupies extensive areas across both the CPR and the buffer zone, particularly in the south-west of the study area and in the north. Coniferous forest is spread more evenly throughout, found primarily in the northern PRR and along the central corridor of the CEZ, as well as in the western and eastern buffer zones neighbouring the Dnipro River. Coniferous and Deciduous forests appear spatially intertwined in the western part of the study area. Although less represented than Coniferous, Deciduous forest is present across most of the area, predominantly in the CPR and the western buffer. Grassland forms a substantial continuous mass concentrated along the Pripyat River floodplain and is widely spread within the CPR, where it constitutes a major class. Panels C–D illustrate the river lowland landscape of the buffer zone in 1986, where Grassland is the dominant class associated with water bodies. Panels A–B show the central CEZ area around the Chernobyl nuclear plant and the city of Pripyat, where Urban/Disturbed pixels are concentrated. More generally, Shrub/Open is present but spatially limited in 1986, mostly contiguous with Coniferous forest. The Chernobyl reservoir and associated water bodies are clearly delineated in the south-central area.

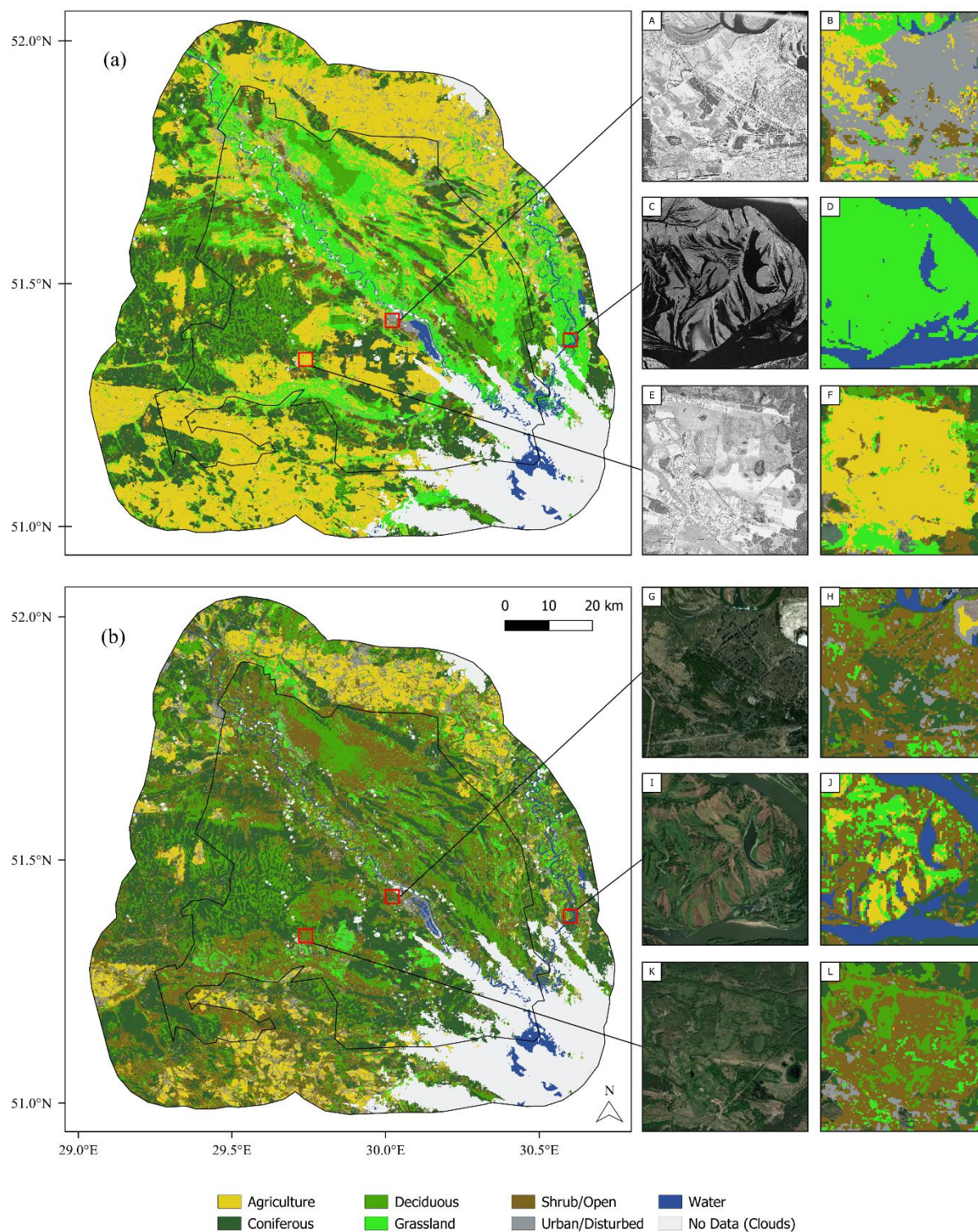


Figure 2. Random Forest classification outputs for 1986 (a) and 2018 (b). The right panel displays illustrations of three different types of landscapes: the northern part of Pripyat city less than 4 km away from the Chernobyl reactor (A, B, G, H); a riparian ecosystem alongside Dnipro river (C, D, I, J); and a former rural settlement with agriculture fields (E, F, K, L). KH-9 images (A, C, E) and ESRI images (G, I, K) are shown against their respective classifications.

By 2018 (Figure 2b), the spatial structure of the classification has changed substantially. Agriculture has retreated almost entirely from the CPR, while Shrub/Open has expanded considerably, forming large continuous patches across the reserve where agricultural land previously dominated. Coniferous and Deciduous forest cover has intensified across the northern reserve zones at the expense of Grassland, while Grassland now remains continuous only in the south of the reserve. The river floodplains are characterised by a mixture of Grassland and Shrub/Open with scattered forested areas. The contrast between the reserve interior and the buffer periphery is now marked, with Agriculture remaining the dominant class across the northern and southern buffer regions and notable in the western buffer. The zoom panels reflect these dynamics: panels G–H show the Pripjat city area in 2018, where Urban/Disturbed and Agriculture pixels visible in panels A–B are now largely absent, replaced by forest and shrubs. Panels I–J illustrate the same river lowland of the buffer zone, where Grassland cover has partially given way to Shrub/Open relative to 1986. Panels K–L capture a former agricultural landscape in the CPR now occupied by a mosaic of Shrub/Open, Coniferous and Deciduous cover. Water bodies, including the Chernobyl reservoir in the centre and the Kyiv reservoir in the south, remain spatially stable between the two dates. In both dates, the bulk of the Kyiv reservoir in the south-east is largely obscured by No Data values due to cloud and shadow masking.

The proportional composition of each restriction level across both dates, summarised in Figure 3, confirms and quantifies these spatial patterns.

6.3. Distribution of land classes

At the total study area level (Figure 3a and 3b), Agriculture was the largest class in 1986, occupying 34.6% of the total study area, followed by Grassland (19.7%) and Coniferous forest (18.5%). Shrub/Open represented less than 10% of the total area while Urban/Disturbed (4.0%) and Water (2.1%) were the most marginal classes. By 2018, this composition had shifted substantially: Shrub/Open became the dominant class at 32.1%, while Agriculture declined sharply (9.7%) and Grassland contracted significantly (7.7%). Coniferous and Deciduous forest both increased, reaching 26.4% and 15.0% respectively, and Urban/Disturbed (6.7%) and Water (2.4%) increased too while remaining the smallest classes.

This landscape shift was considerably more pronounced in the CPR than in the buffer zone. In the CPR, Agriculture declined from 25.9% in 1986 to a mere 1.8% in 2018, while Shrub/Open expanded from 11.4% to 36.9%, becoming the largest class in the reserve by 2018. Grassland contracted from 25.8% to 8.9%, and Coniferous forest increased from 17.3% to 28.7%, while Deciduous showed a less dramatic increase from 13.9% to 18.0%. Urban/Disturbed remained effectively stable at 3.8% across both dates, as did Water (1.9% to 2.0%).

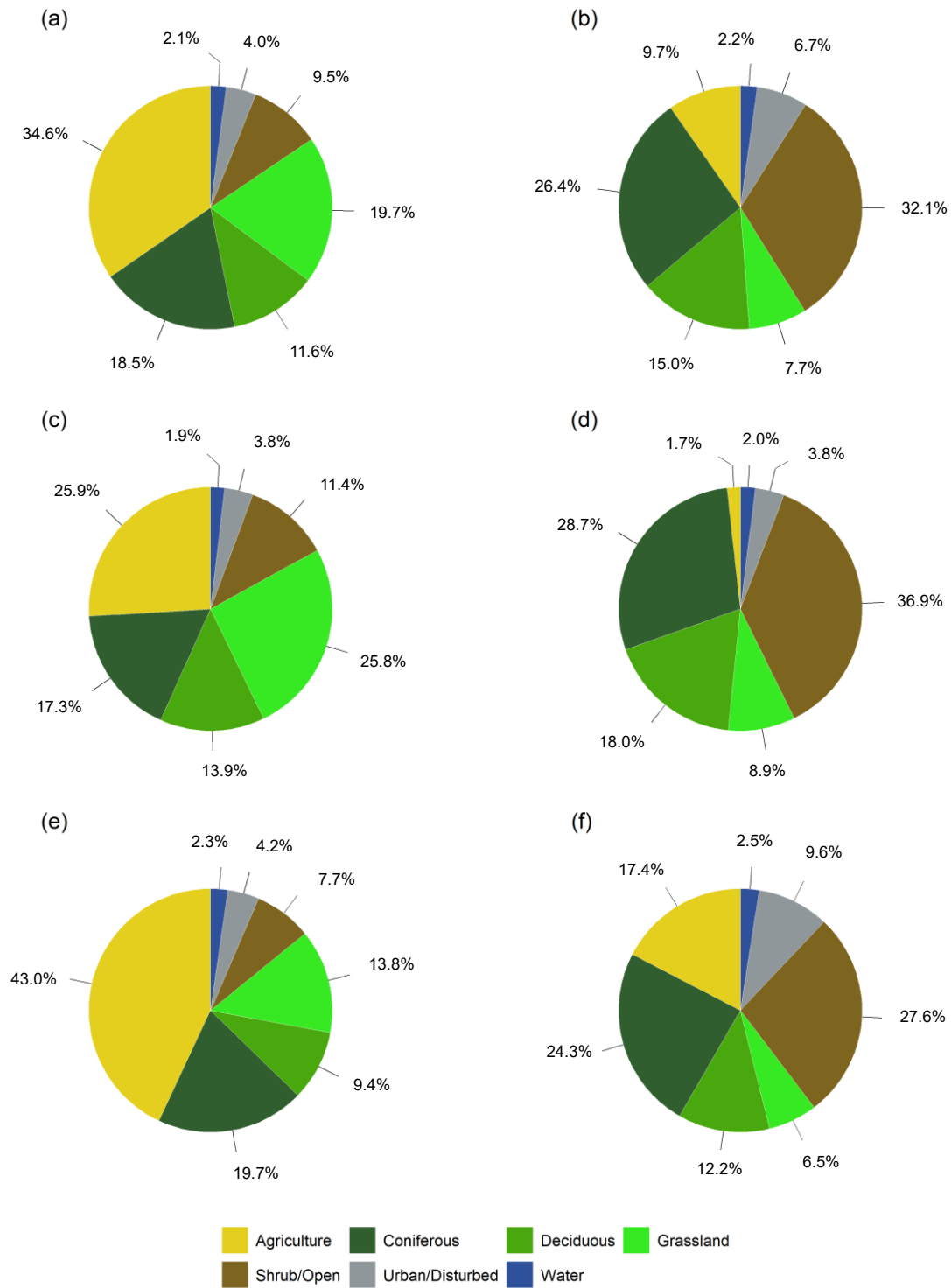


Figure 3. Land cover class proportions across the total study area (a, b), the Chernobyl-Palieski Reserve (c, d) and the 15km buffer zone (e, f) in 1986 (a, c, e) and 2018 (b, d, f), derived from Random Forest classification.

In the buffer zone, Agriculture also declined markedly from 43.0% to 17.4%, and Shrub/Open expanded from 7.7% to 27.6%, though both changes were less extreme than in the CPR. Grassland diminished from 13.8% to 6.5% while forest cover increased for both Coniferous

(19.7% to 24.3%) and Deciduous (9.4% to 12.2%). Notably, Urban/Disturbed increased from 4.2% to 9.6% in the buffer, a trend absent within the reserve, reflecting continued human land use development outside the exclusion boundary.

6.4. Cloud and shadow masking

After application of the union master mask described in the Methods as a combination of masks for all four scenes, results per subregions are reported here. For the entire study area, combining the reserve and the buffer, 11.6% was removed from analysis due to clouds and shadows. The buffer zone saw 15.4% of its surface masked while the CPR only lost 7.3% of its available pixels. The regional buffer zones however differed substantially, with 25.4% masked in the Ukrainian buffer against only 3.3% in the Belarusian buffer. A comparable contrast was observed within the CPR, where the CEZ reached 12.2% against 1.4% in the PRR. This spatial pattern reflects the persistent cloud cover affecting the south-eastern portion of the study area, most notably the Kyiv reservoir region. It should be noted that these masked areas apply consistently across the classification maps, land cover change analysis and EVI2 productivity assessment, but not the cross-product comparison.

6.5. Cross-product comparison of local and global classifications

Cross-product comparison between the RF classification and GLC-FCS30D (GLC) is summarised in Figure 4 for both 1986 and 2018.

In 1986, Agriculture extent was comparable between products, with the RF classification mapping 489 138 ha against 521 258 ha in the GLC. Water showed close agreement across both products (46 158 ha and 44 074 ha respectively). Coniferous forest area was nearly halved in the RF classification (299 996 ha) compared to the GLC (535 277 ha), and Deciduous forest cover was also smaller in the RF classification (177 912 ha vs 270 623 ha). The most pronounced divergence occurred in the Shrub/Open and Grassland classes. The RF classification mapped 140 750 ha of Shrub/Open in 1986, while the GLC recorded a near-absence (30 ha) for this class. Similarly, the RF classification assigned substantially more area to Grassland (247 029 ha) than the GLC (71 515 ha). The RF classifier also showed more Urban/Disturbed pixels than the GLC (55 406 ha and 13 613 ha respectively).

In 2018, divergence between products was more pronounced across several classes. Agriculture showed the largest absolute discrepancy, with the RF classification mapping 161 236 ha compared to 564 209 ha in GLC-FCS30D. The Shrub/Open pattern observed in 1986 intensified markedly, with the RF classification recording 434 304 ha while GLC-FCS30D assigned only 4 898 ha. Grassland extent remained higher in the RF classification though less markedly than in 1986 (93 549 ha vs 58 209 ha).

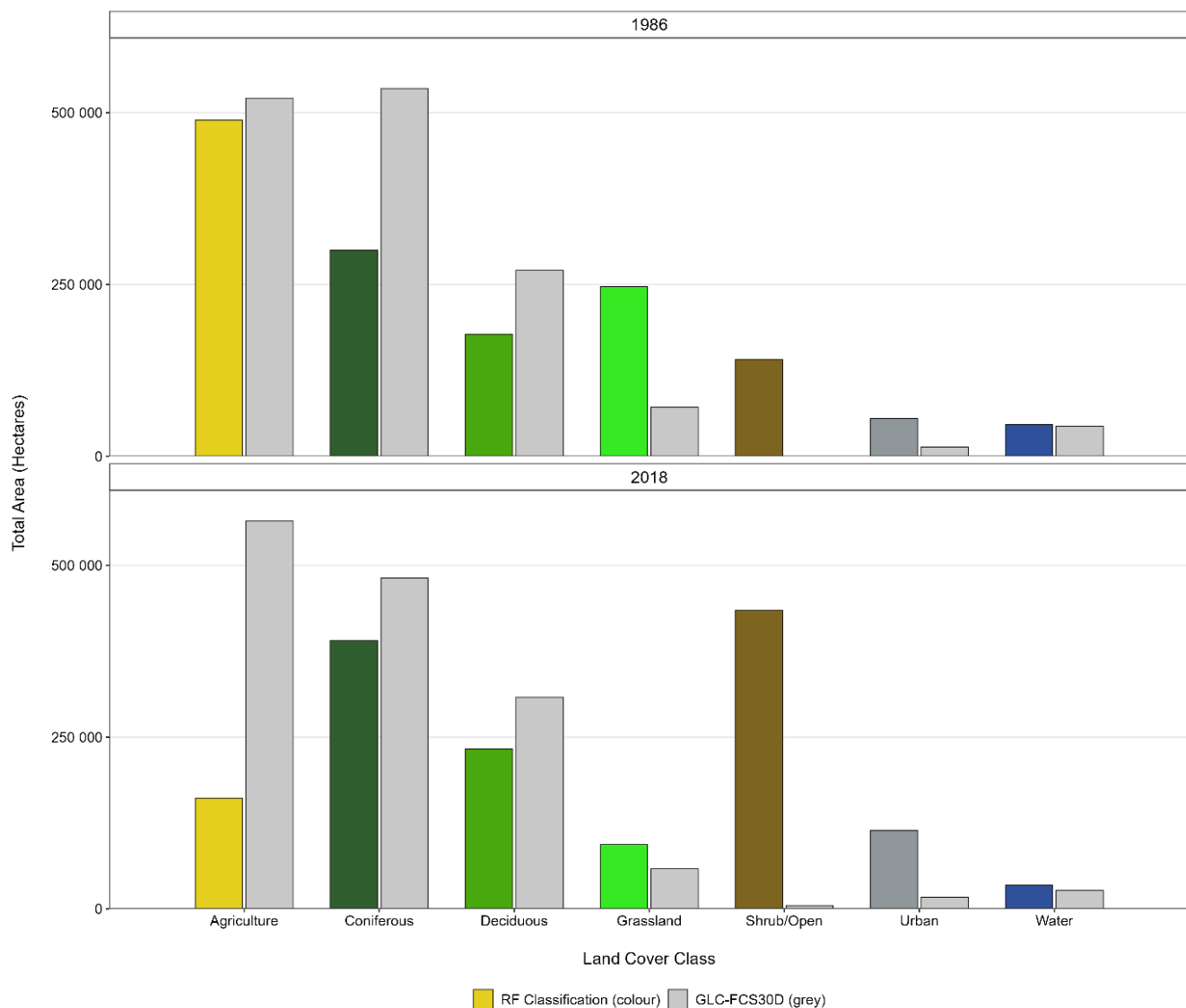


Figure 4. Per-class area estimates in hectares derived from the local Random Forest classification and the Global Land Cover Fine Classification System 30m (GLC-FCS30D) global product for 1986 (top) and 2018 (bottom), across the seven land cover classes of the study area. Coloured bars represent the Random Forest classification and grey bars represent GLC-FCS30D. Divergence between the two products is particularly pronounced for the Shrub/Open class in 2018.

Urban/Disturbed increased substantially in the RF classification relative to 1986 (114 235 ha), while the GLC figure remained stable (17 094 ha). Coniferous and Deciduous forest areas were broadly comparable between products, with the RF classification consistently lower (390 207 ha and 232 674 ha respectively, against 481 525 ha and 307 957 ha in GLC-FCS30D). Water extent was again closely matched (34 510 ha vs 26 796 ha).

This highlights a systematic divergence in classification behaviour between the two products, particularly for transitional land cover classes, which will be explored further in the Discussion.

6.6. Land Cover Change Analysis

Land cover transitions between 1986 and 2018 across four study zones (CEZ, PRR, Buffer Ukraine and Buffer Belarus) are summarised in the Sankey diagram matrix (Figure 5), with colour coding following the classification maps (Figure 2). Across all four zones, Agriculture to Shrub/Open was the dominant transition, representing the largest single change flow in each case: 36 222 ha in the CEZ, 35 738 ha in the PRR, 42 784 ha in the Ukraine Buffer, and 25 230 ha in the Belarus Buffer.

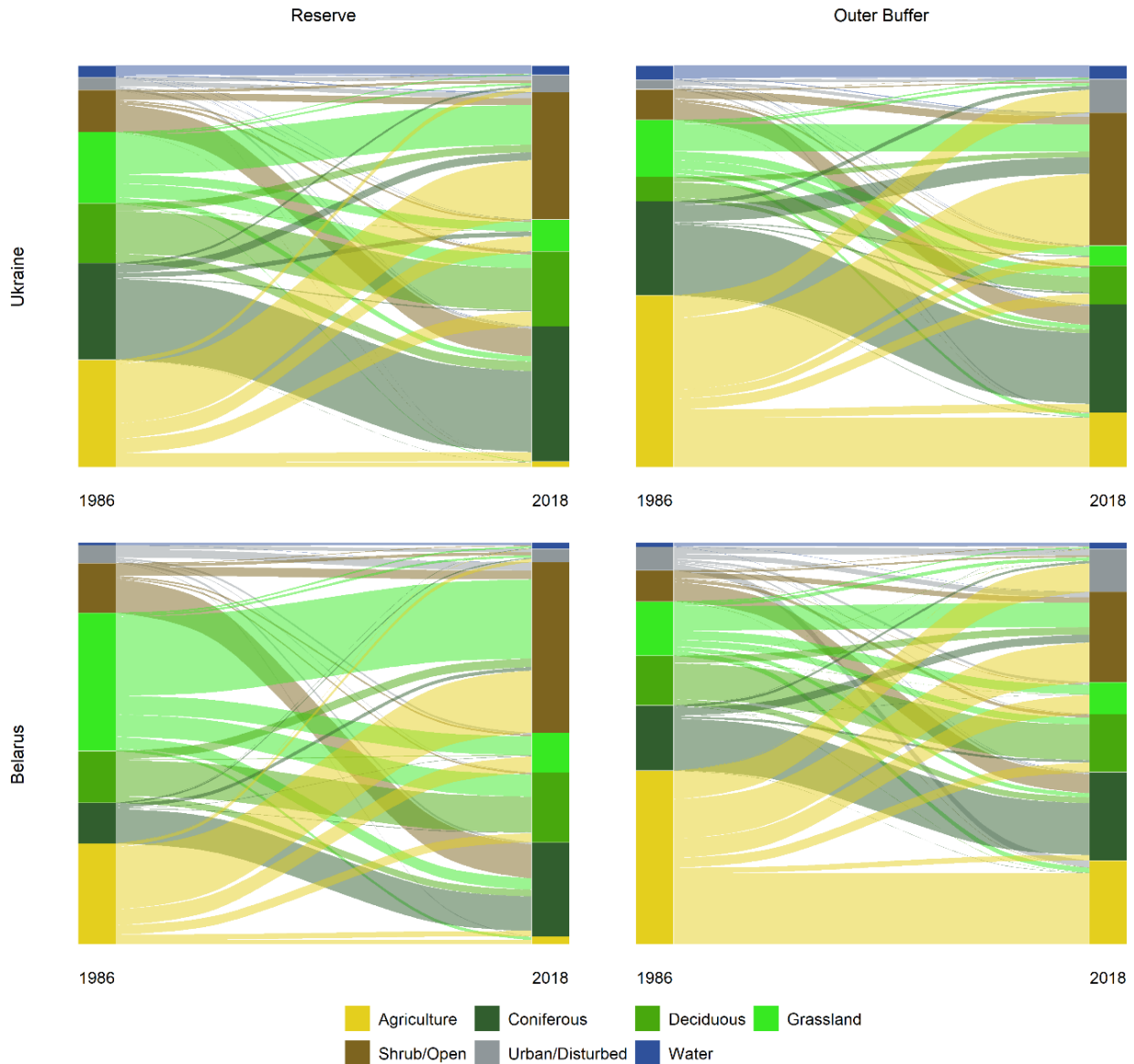


Figure 5. Land cover transitions between the 1986 and 2018 Random Forest classifications presented as a 2×2 Sankey diagram matrix, organised by governance zone (Reserve / Outer Buffer) and country (Ukraine / Belarus), covering the Chernobyl Exclusion Zone (Reserve-Ukraine), the Palieski Radioecological Reserve (Reserve-Belarus), the Ukraine Buffer (Outer Buffer-Ukraine) and the Belarus Buffer (Outer Buffer-Belarus).

Grassland to Shrub/Open constituted the second most important transition within the reserve zones, involving 24 215 ha in the CEZ and 45 412 ha in the PRR (the largest individual transition recorded across all classes and zones). A consistent successional signal was observed across all zones, with Shrub/Open converting to Coniferous at a scale ranging from 10 923 ha in the Ukraine Buffer to 19 484 ha in the PRR, indicating ongoing progression toward closed canopy forest within the study period. The fate of 1986 Shrub/Open pixels reinforces this successional reading. Between 60 and 68% of all shrubland present in 1986 had transitioned to Coniferous forest by 2018, while only 17 to 25% remained as Shrub/Open. Direct conversion of shrubland to Deciduous forest was also recorded, ranging from 3.0% in the PRR to 10.2% in the Belarus Buffer. A small back-flow from Coniferous and Deciduous toward Shrub/Open was observed across all zones.

Grassland dynamics present a more nuanced picture. Across three of the four zones, newly formed Grassland in 2018 originated more from converted agricultural land than from persistent 1986 Grassland. In the CEZ, Agriculture contributed 47.1% of total 2018 Grassland area compared to 28.7% from stable 1986 Grassland. The pattern was similar in the Ukraine Buffer (43.7% from Agriculture vs 43.1% stable) and most pronounced in the Belarus Buffer, where 60.0% of 2018 Grassland originated from former agricultural land against only 29.1% from persistent Grassland. The PRR is the exception, where stable 1986 Grassland contributed the largest share of 2018 Grassland (47.0%) against 40.4% from Agriculture, suggesting greater pre-existing grassland persistence on the Belarusian side of the reserve. Coniferous forest was the most spatially stable class across all zones, with stable areas of 49 346 ha in the CEZ, 42 007 ha in the Ukraine Buffer, 32 952 ha in the Belarus Buffer, and 19 827 ha in the PRR. Agriculture stability differed markedly between restriction levels. Within the reserves, only 4.3% of 1986 agricultural area remained stable in the CEZ (2 784 ha) and 4.4% in the PRR (2 547 ha). In contrast, 28.6% remained stable in the Ukraine Buffer (29 257 ha) and 40.9% in the Belarus Buffer (45 262 ha).

The buffer zones exhibited a transition pattern partially distinct from the reserve zones. Agriculture to Urban/Disturbed flows of 13 573 ha in the Ukraine Buffer and 18 139 ha in the Belarus Buffer represent the second largest change transition in both buffer zones, while this transition was nearly absent within the reserves. Direct transitions from Agriculture to Deciduous forest were also recorded in both reserve zones (8 845 ha in the CEZ and 5 297 ha in the PRR), representing direct conversion from cultivated land to woody cover without an intermediate shrubland stage.

These transition patterns evolve into a greening map (Figure 6), which reclassifies the classes into four categories of vegetation dynamics, allowing the net rewilding signal to be visualised spatially within the study area.

6.7. Rewilding signal across the exclusion zone

The greening map displays the spatial distribution of vegetation change categories across the study area between 1986 and 2018 (Table 9).

Persistent Vegetation is the dominant trend in the Chernobyl-Palieski Reserve (CPR), with 67.1% of the CEZ and 67.8% of the PRR belonging to this class. The second most represented vegetation change category in the CPR is the Rewilding Signal, accounting for 27.3% in the Ukrainian reserve and 26.7% in the Belarusian reserve. Together, these two categories account for the vast majority of the CPR at over 94%, while Persistent Non-Vegetation is nearly absent across both reserves (3.5% and 3.0%). This limited residual non-green cover within the CPR is spatially concentrated along zone edges and in the vicinity of Chernobyl city, near the water reservoir.

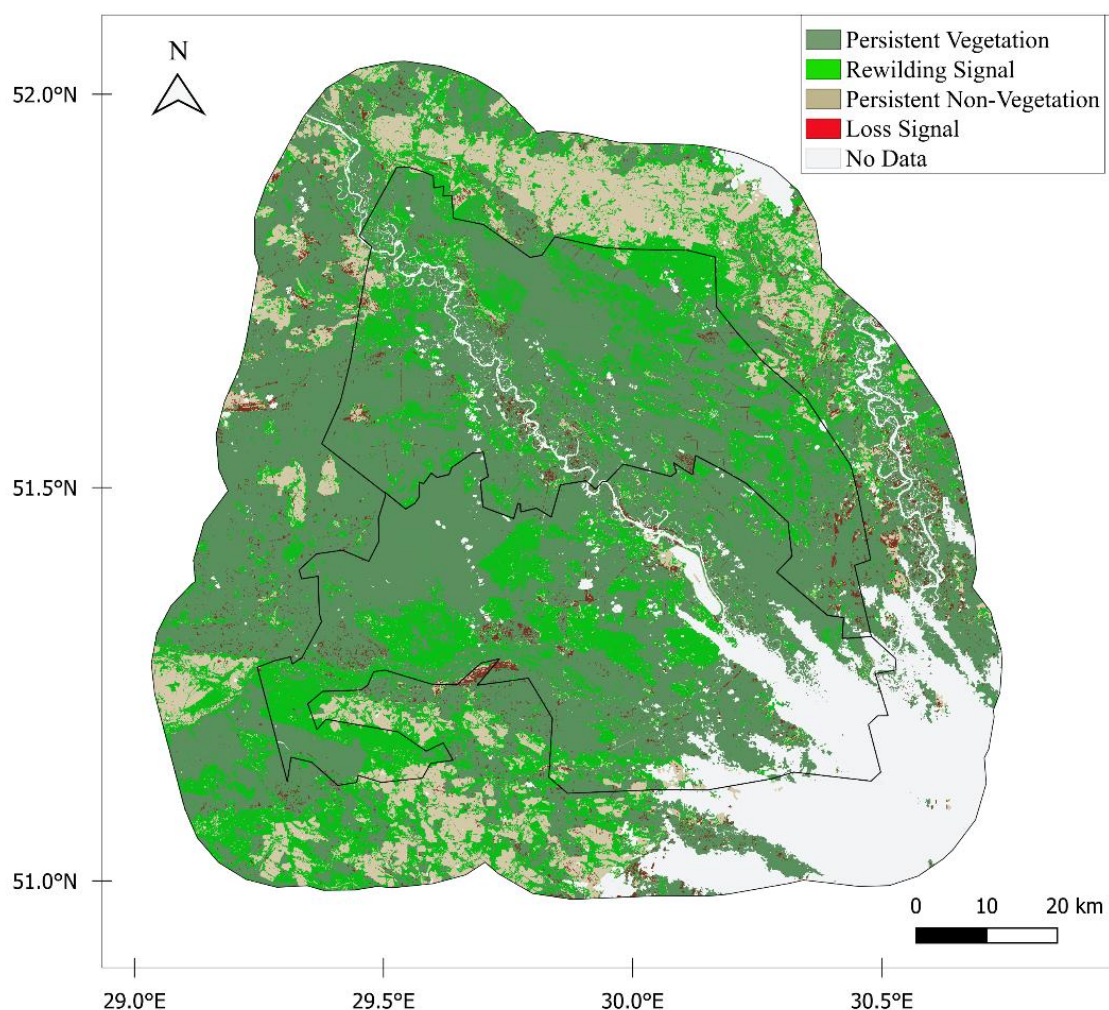


Figure 6. Vegetation change across the study area between 1986 and 2018. Land cover classes were reclassified into two categories: Vegetation (Coniferous, Deciduous, Shrub/Open and Grassland) and Non-Vegetation (Agriculture and Urban/Disturbed). Water and clouds were reclassified as No Data (NA). Four change categories are defined as follows: Persistent Vegetation represents pixels classified as Vegetation in both dates; Rewilding Signal represents pixels classified as Non-Vegetation in 1986 and Vegetation in 2018; Persistent Non-Vegetation represents pixels classified as Non-Vegetation in both dates; and Loss Signal represents pixels classified as Vegetation in 1986 and Non-Vegetation in 2018.

In contrast, Persistent Non-Vegetation is substantial in the non-restricted zones, reaching 19.6% in the Ukraine Buffer and 28.6% in the Belarus Buffer, reflecting the continuation of human

activities outside the exclusion boundary. The Rewilding Signal is nonetheless considerable in the buffer zones too, with 27.3% in Ukraine and 21.2% in Belarus. The Loss Signal is spatially dispersed across all four zones and limited in extent, ranging from 2.1% in the CEZ to 3.5% in the Belarus Buffer.

Table 9. Area in hectares (ha) and proportional cover (%) of vegetation change categories across the four study zones between 1986 and 2018.

	CEZ		PRR		Ukraine Buffer		Belarus Buffer	
	ha	%	ha	%	ha	%	ha	%
Persistent Vegetation	159 049	67.1	154 172	67.8	114 533	49.9	117 242	46.7
Rewilding Signal	64 789	27.3	60 837	26.7	62 798	27.3	53 241	21.2
Persistent Non-Vegetation	8 233	3.5	6 908	3.0	45 009	19.6	71 919	28.6
Loss Signal	4 934	2.1	5 569	2.4	7 391	3.2	8 741	3.5

Of the 140,767 ha classified as non-green within the CPR in 1986, 125,626 ha had transitioned to green cover by 2018, corresponding to a rewilding rate of 89.2%. The equivalent figure for the buffer zones was 49.8%, representing 116,039 ha of 232,968 ha originally classified as non-green.

6.8. Productivity analysis

EVI2 distributions for May 1986 and May 2018 are presented in Figure 7 at the restriction level (reserve against buffer). Mean EVI2 increased across both zones between the two dates, rising from 0.361 to 0.410 in the buffer zone (+13.6%) and from 0.359 to 0.414 in the CP Reserve (+15.3%), reflecting a moderate increase across both zones, with the CPR showing a slightly larger mean EVI2 increase relative to the buffer. Median values followed the same pattern, increasing from 0.347 to 0.403 in the buffer and from 0.343 to 0.408 in the reserve. The 2018 distributions were more dispersed than those of 1986 in both zones, with IQR values increasing from 0.184 to 0.211 in the buffer and from 0.189 to 0.211 in the reserve.

This broadening of the distribution is reflected in the upper quartile values, with Q75 rising from 0.449 to 0.516 in the buffer and from 0.449 to 0.520 in the reserve, indicating a greater proportion of high-productivity pixels in 2018. Similarly, the lower quartile Q25 saw an increase across the two dates for both regions (from 0.265 to 0.305 in the buffer and from 0.260 to 0.309 in the CPR). Pixel counts were consistent across dates within each zone, with approximately 5.3 million valid pixels in the buffer and 5.2 million in the reserve for both years.

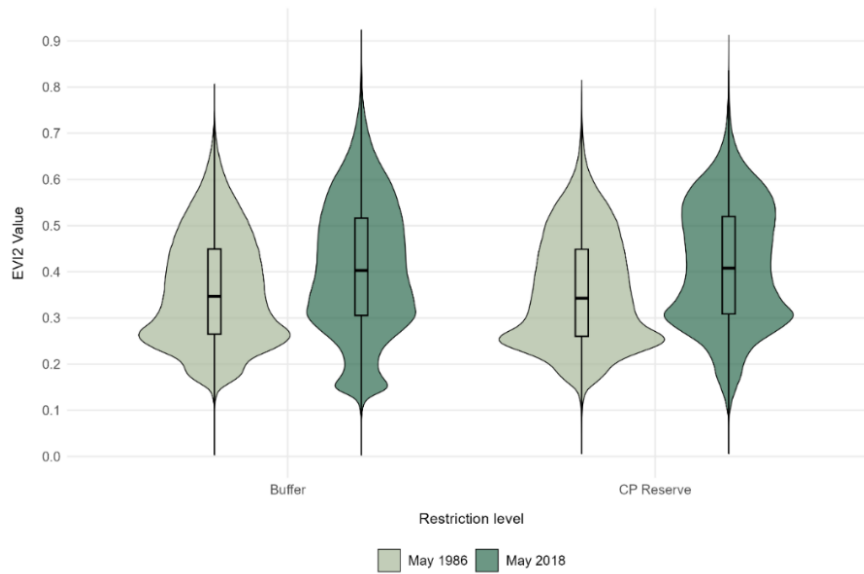


Figure 7. Distribution of EVI2 values across the Chernobyl-Palieski Reserve and the 15km buffer zone for 31 May 1986 and 23 May 2018. Violin plots represent the frequency distribution of pixel-level EVI2 values, with internal boxplots indicating the median and interquartile range.

Per-class EVI2 distributions for all six non-water land cover classes are shown in Figure 8. Mean EVI2 increased across all classes between May 1986 and May 2018. Deciduous forest recorded the highest mean EVI2 values in both dates (0.486 in 1986, 0.556 in 2018, +14.4%), while Urban/Disturbed consistently returned the lowest per date despite a notable relative increase (0.194 in 1986, 0.265 in 2018, +36.6%).

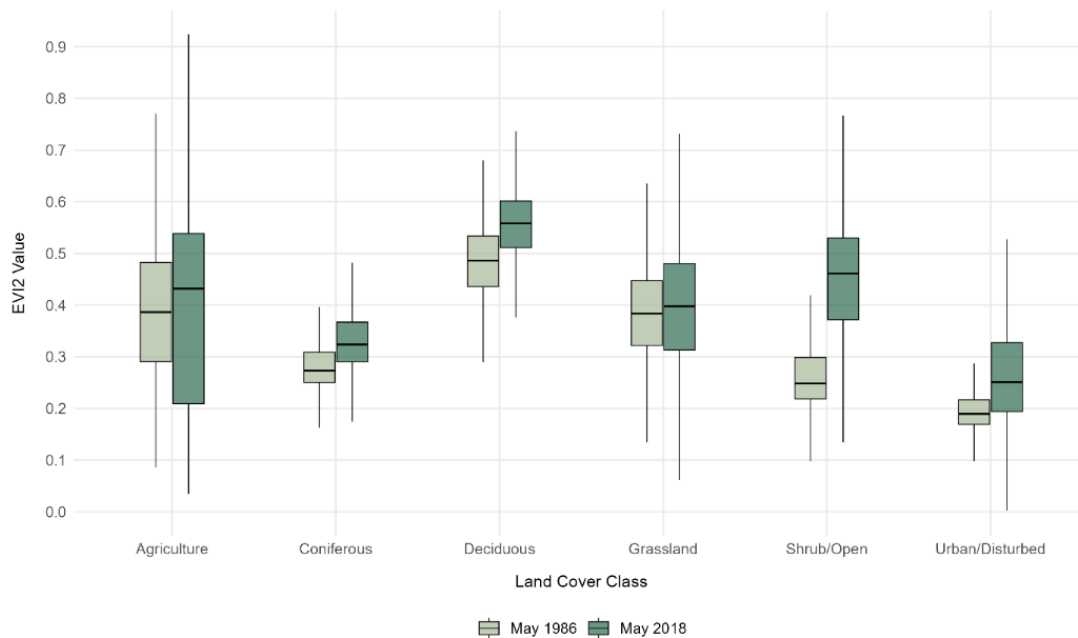


Figure 8. Distribution of EVI2 values by land cover class for 31 May 1986 and 23 May 2018 across the total study area. Paired boxplots show the median, interquartile range (IQR) and whiskers extending to $1.5 \times \text{IQR}$ for each class, excluding water.

The largest relative increase was recorded for Shrub/Open, with mean EVI2 rising from 0.264 to 0.448 (+69.7%). Agriculture and Grassland recorded the smallest relative increases, with mean EVI2 rising from 0.390 to 0.404 (+3.6%) and from 0.387 to 0.402 (+3.9%) respectively. Coniferous forest showed a moderate increase from 0.282 to 0.328 (+16.3%), consistent with its narrow IQR in both dates (0.058 and 0.077 respectively), reflecting limited within-class productivity variability.

7. Discussion

This study set out to quantify land cover change and vegetation productivity dynamics across the Chernobyl-Palieski Reserve and its surrounding buffer zones between 1986 and 2018, and to assess the extent to which observed changes reflect spontaneous ecological succession consistent with passive rewilding. The results illustrate large-scale vegetation gain across the study area, with marked differences between restricted reserves and areas where human activities continued. The following discussion interprets these findings ecologically, qualifies them methodologically and addresses limits to what conclusions can be drawn, and considers their implications for remote sensing of rewilding and for conservation policy.

7.1. Implication of results

The forced evacuation of the Chernobyl region in 1986 removed the primary driver shaping the local landscape: human land use. At that point in history, a mosaic of arable land, managed grasslands, forest cover and urban infrastructure associated with nuclear power activity was left behind (Hostert et al., 2011). Thirty-two years later, this landscape had shifted considerably. Within the CPR, 89.2% of pixels classified as non-vegetated in 1986 had transitioned to vegetated cover by 2018 through spontaneous ecological succession. No human planning, afforestation or deliberate restoration was at the origin of this greening. In comparison, even though the surrounding buffer areas shared similar environmental conditions, only 49.8% of the area underwent a similar transition, suggesting that a fundamental decrease in the pressure exerted by humans on the ecosystem was the primary factor enabling this vegetation transition. This is precisely what passive rewilding describes: a hands-off approach allowing for the natural occurrence of ecological succession through the limitation or restriction of human intervention (Perino et al., 2019; Gillson et al., 2011). What the IUCN-CEM envisions as the ideal outcome of rewilding appears to have unfolded in the surroundings of Chernobyl as an unintended consequence of forced human withdrawal (Perino et al., 2019; Carver et al., 2021). The CPR may therefore represent one of the most extensive and long-running empirical demonstrations of passive rewilding documented to date.

The most striking change in land cover within the CPR is the dramatic collapse of agriculture from 25.9% in 1986 to 1.7% in 2018. This reflects the sustained cessation of agricultural activities over 32 years of human exclusion (Hostert et al., 2011; Matsala et al., 2021). A similar though less marked trend is visible in the buffer zones, where agriculture fell from

43.0% to 17.4%. The dominant transition across all four study zones is the change from Agriculture to Shrub/Open, consistent with the spontaneous woody colonisation of abandoned agricultural land documented in post-Soviet landscapes of the region (Hostert et al., 2011). The occurrence of this transition in the buffer zones as well as the reserves suggests that factors beyond strict human exclusion have contributed to vegetation change across the broader study area. The 49.8% rewilding rate in the buffer zones may partly reflect the post-Soviet agricultural abandonment that followed the collapse of the Soviet Union in 1991, which affected land use trajectories across Ukraine and Belarus (Hostert et al., 2011). The cross-border contrast in agricultural stability supports this: only 28.6% of 1986 agricultural area remained stable in the Ukraine buffer compared to 40.9% in the Belarus buffer, consistent with Hostert et al.'s (2011) finding that post-Soviet land abandonment affected Ukraine at approximately twice the rate of Belarus, reflecting differences in post-independence agricultural policies. Whether buffer greening reflects primarily post-Soviet abandonment dynamics, proximity to the exclusion zone and its potential influence on land use behaviour, or a combination of both, cannot be resolved from remote sensing data alone and warrants further investigation.

However, the reserve shows transition not only towards Shrub/Open but from Shrub/Open to other classes, identifying a clear successional trajectory (Figure 5). Indeed, between 60 and 68% of all Shrub/Open across all four zones in 1986 had been replaced by Coniferous forest by 2018, suggesting that the existing Shrub/Open in 2018 is trending toward a dense canopy forest mainly composed of Coniferous. When combining Coniferous with Deciduous forest, we observe an increase from 31.2% to 46.7% across the CPR, which independently corroborates the 1.5-fold forest increase found by Matsala et al. (2021), although covering a different extent and with a distinct methodology. The fact that coniferous gain (+11.4%) is larger than the Deciduous increase (+4.1%) is consistent with a prevalence of Scots pine in the exclusion zone. Matsala et al. (2021) also note that silver birch and common aspen are commonly found as pioneer species on former farmlands, which may explain why grassland pixels converted proportionally more often to deciduous forest while shrubland pixels converted preferentially to coniferous forest, a divergence likely reflecting differences in soil conditions and seed bank legacy (Didukh et al., 2023). That study further documents a two-stage dynamic, with shrubland expansion unfolding during the first decade after abandonment followed by a densification of woodland into forest cover, as shown across a three-date Sankey of land cover transitions for 1986, 2000 and 2018, consistent with what is observed here. Most grassland-to-forest transitions within the CEZ only occurred after 2000, which Matsala et al. (2021) attribute in part to the relatively lower growth rate of Scots pine compared to pioneer broadleaved species. Field studies however allow for a more nuanced understanding of this process: Didukh et al. (2023) found that after 35 years, succession in the CEZ is slower and less linear than expected, with grass communities actively inhibiting colonisation by young trees in several areas. It should also be noted that part of the apparent Shrub/Open to Coniferous transition may reflect canopy densification of open woodland pixels already near the 50% cover threshold in 1986, rather than entirely new successional colonisation, a distinction that two-date classification cannot resolve. Despite its importance,

the landscape-scale signal captured by remote sensing data likely conceals considerable spatial heterogeneity in successional stages.

This pathway divergence is further complicated by the nature of the 1986 grassland class itself. Our results reveal that a large share of 2018 Grassland evolved from former agricultural land rather than from persistent natural grassland. This transition represents 47.1% in the CEZ, 43.7% in the Ukraine buffer, and 60.0% in the Belarus buffer, while 28.7%, 43.1%, and 29.1% of 1986 grassland was maintained respectively. The only exception is the PRR where stable grassland contributed the largest share of Grassland in 2018 (47.0%), suggesting greater pre-existing grassland persistence on the Belarusian side of the reserve, although this may partly reflect the large initial extent of grassland in this area. The pattern illustrated here suggests a baseline of managed pasture rather than natural grassland. Indeed, Hostert et al. (2011) document the importance of dairy and meat production in this region during the Soviet period, with cattle accounting for around 80-85% of total agricultural production and relying on substantial areas of managed grassland. While natural grassland communities would be expected to persist after 32 years without human management, previously managed pasture can likely undergo colonisation by woody vegetation, which aligns with what we find in this study. If this interpretation is correct, the binary reclassification of 1986 grassland as green vegetation in the greening map may underestimate the rewilding signal, as a portion of what was coded as Persistent Vegetation may in fact represent managed pasture that would more accurately be classified as a human land use signal.

Vegetation productivity increased across all land cover classes between 1986 and 2018, with Shrub/Open recording the largest relative gain of any class (+69.7% in mean EVI2). This figure must however be interpreted carefully: the pixel count for Shrub/Open increased from approximately 1.0 million to 3.4 million between dates. As illustrated above, the 2018 Shrub/Open class contains pixels that were predominantly Agriculture in 1986, but Grassland, Coniferous and Deciduous originating pixels are also found within it. While Agriculture and Grassland represent an expected transition, Coniferous and Deciduous pixels are unlikely to have actually transitioned to more open woody vegetation in a context of strict human restriction, and likely reflect misclassification. The per-pixel EVI2 increase therefore reflects a wide spectrum of values due to this compositional complexity rather than pure within-class productivity gain.

At the regional scale and across all classes, mean EVI2 increased in both the CPR and the buffer zone, with the reserve showing a slightly larger increase than the buffer (+15.3% vs +13.6%). This is consistent with the collapse of human footprint as a primary driver of productivity gain, supported by Gemitzi (2020) who documented higher NDVI greening trends within the exclusion zone compared to surrounding areas where human activities continued. The greater productivity increase observed in the reserve relative to the buffer suggests that the near-complete withdrawal of human activity enabled a more pronounced vegetation response than in areas where land use, though reduced, continued. EVI2 productivity dynamics are best understood as a combined effect of land abandonment alongside regional factors including climate trends and post-Soviet land use change, rather than as the product of a single driver.

Despite the fact that radiation effects subsequent to the Chernobyl accident are indisputable in the CPR both to human and non-human life (Møller & Mousseau, 2006), the landscape-scale evidence does not support radiation as the primary ecological driver of the vegetation dynamics observed. Large mammal populations have been recorded at comparable or higher rates inside the zone than in surrounding uncontaminated reserves (Deryabina et al., 2015), suggesting that at the population level the effects of human withdrawal outweigh those of chronic radiation exposure. The dramatic land cover transition documented here, supported by an increase in vegetation productivity following the accident, further reinforces this interpretation. However, the role of naturally occurring or introduced wildlife in shaping these vegetation dynamics cannot be assessed within the remote sensing framework applied here, and its contribution to vegetation structure and successional trajectories remains an open question addressed further in section 5.

7.2. Methodological Considerations

All results presented in this study flow from two independent post-classification maps based on independently drawn training data. The choice of a post-classification approach was driven primarily by the assumption that after 32 years of ecological succession, compositional changes in vegetation and canopy densification would produce significantly different spectral values for pixels of similar classes, making a direct spectral comparison unreliable. Furthermore, post-classification comparison facilitates the workflow since cross-sensor radiometric harmonisation between Landsat 5 TM and Landsat 8 OLI is not required (Coppin et al., 2004). However, it is important to note that this places greater analytical weight on the accuracy of each independent classification, since any error propagates directly into any subsequent result. Although overall accuracy increased from 0.941 in 1986 to 0.978 in 2018, this likely reflects differences in imagery quality and availability between the two dates rather than a genuine improvement in classification performance: the narrower panchromatic band of the KH-9 imagery used for the 1986 classification limits the visual detail available compared to modern Google satellite imagery, constraining the confidence with which training polygons could be drawn.

The weakest per-class result, and the one with the most consequential implications, was Grassland in 1986 with an F1 score of 0.542, notably driven by a commission error of 0.588. The interpretation of this number is that during validation of the model, over half of the tested pixels originally identified as Grassland in fact belonged to other classes. This is likely due to the spectral overlap of Grassland with other vegetated classes or agriculture that the added texture metrics could not overcome. A direct consequence is that class transitions from Grassland to other vegetation categories may therefore reflect misclassification in 1986 rather than genuine land cover change, and the grassland EVI2 distribution may be expanded by the presence of more woody pixels. This observation is limited to 1986 since Grassland accuracy improved significantly in 2018 ($F1 = 0.863$).

Although showing an F1 score consistently above 0.80, Shrub/Open holds the second lowest accuracy across all classes after Grassland. This is driven by a substantial commission error

across both dates, with 0.189 in 1986 and an increase to 0.251 in 2018. This is particularly relevant as the substantial expansion of the Shrub/Open class between 1986 and 2018 was among the most important findings of the results section, and suggests that this class is relatively inflated compared to its true extent. Beyond classification error, the interpretation of transitions out of Shrub/Open is further complicated by the nature of the successional process itself. Indeed, as some 1986 Shrub/Open pixels were classified near the 50% cover threshold, some of the Shrub/Open to Coniferous transition may represent a densification of open woodlands rather than actual successional colonisation.

The limitations of the analytical framework extend beyond classification uncertainty to include constraints on the temporal and sensor design of the study, which are considered in the following section.

7.3. Limitations

Because the analysis performed in this study is based on the classification of two scenes rather than a set of continuous data, the observed successional trajectory is limited to a starting and ending point across the 32 years. As a consequence, interannual variability of the land cover due to external factors like climate or fire regimes is inaccessible to the study's framework. The succession narrative presented here therefore reflects the net result of over three decades of change, where intermediate states, including the shrubland establishment in the first decade after abandonment, can only be inferred from previous work (Matsala et al., 2021) and are not directly observed.

The cross-sensor bias between Landsat 5 and Landsat 8 products, which is described in the Methods, has important implications for the EVI2 analysis used as a proxy for vegetation productivity. Because EVI values derived from Landsat 8 OLI have been found to be lower than those from Landsat 5 TM for similar surfaces (Zhu et al., 2016), the 2018 EVI2 values found in this study are likely slightly underestimated compared to what a consistent sensor would have recorded, and the observed increases of 13.6% and 15.3% in the buffer and CPR respectively should be understood as conservative estimates. However, further empirical work on the direction and magnitude of the EVI2 bias between these two sensors are required to confirm this assertion. Regarding the spatial comparison, since both the CPR and the buffer were measured using the same sensor for each date, the interpretation is direct and there are no concerns regarding a potential bias.

Although the two scenes were selected for their close dates (May 31st for 1986 and May 23rd for 2018), climatic variability may have influenced the phenological response of the vegetation between the two years. If May 2018 was systematically warmer or wetter than May 1986, EVI2 values could be elevated independently of land cover change. This represents a source of uncertainty that this thesis did not bridge as the climate component was not investigated. Future studies combining multitemporal productivity analysis alongside climate observations would be better positioned to isolate the land cover signal from interannual climatic variability across the study period.

Finally, the cloud and shadow masking applied to both scenes reduced the area available for analysis, most notably in the south-east where the Kyiv reservoir region is substantially impacted, as illustrated by the fact that up to a quarter of the Ukrainian buffer was removed from analysis for this reason. Although a large area covered by no-data values is in fact water, which would not have meaningfully affected results, the patterns observed should be interpreted with the limited spatial extent of the Ukrainian buffer in mind relative to the other regions.

Despite these limitations, the findings carry implications for how rewilding is monitored at global scale, which are considered in the following section.

7.4. Implications for Remote Sensing of Rewilding

The reclassification of GLC-FCS30D under our seven-class schema revealed a dramatic difference in sensitivity between both models for the Shrub/Open class. In 1986, the GLC found a near-total absence of this class (30 ha) against 140,750 ha in the RF model, increasing in 2018 to 4,898 ha against 434,304 ha respectively. Such a difference may reflect an underestimation from the GLC or an overestimation from the RF model. Three converging lines of evidence suggest the actual extent of the Shrub/Open class is closer to the RF estimate. First, visual inspection of the CEZ with contemporary imagery such as Google Satellite contradicts the GLC figure of 564,209 ha for Agriculture in 2018, a class documented and supported by this study to be almost gone from the reserve, having been replaced by grasses, shrubs and trees over the 32 years covered by this thesis (Matsala et al., 2021; Didukh et al., 2023). Second, Matsala et al. (2021) showed that global forest change products underestimate forest gain in the CEZ by a factor of 6.3, suggesting systemic insensitivity of global products to successional vegetation in this landscape. Third, Zhang et al. (2024) themselves report that shrubland achieved the lowest user's accuracy of their entire classification system, explicitly attributing this to the heterogeneous spectral characteristics of transitional land cover classes.

However, it is acknowledged that the RF commission error for Shrub/Open (0.189 in 1986, 0.251 in 2018) means the RF tends to slightly overestimate this class, and the true representation of it likely lies between the estimates of the two models. Nevertheless, the scale of the divergence, a factor of approximately 4,700 in 1986, suggests that global product insensitivity is the dominant source of disagreement. If spontaneous vegetation succession consistently passes through a shrubland stage before reaching closed canopy forest, as the successional narrative presented here suggests, global monitoring frameworks that cannot detect this stage will systematically underestimate the extent and rate of passive rewilding occurring across abandoned landscapes globally. Building on Matsala et al. (2021), the two studies together construct a two-stage argument: global products fail to capture not only forest gain but the entire pre-forest successional stage that precedes it.

At 32 years and approximately 10,000 km², this study contributes an additional independent case to the emerging body of remote sensing evidence for passive rewilding, complementing the Knepp estate study (20 years, Schulte to Bühne et al., 2022) and the Greater C  a Valley

study (15 years, Elphick et al., 2024) at a spatial and temporal scale not previously documented within this framework. Together, these three studies suggest that multispectral satellite data can consistently capture land cover and productivity signals of rewilding at landscape scale, though the extent to which findings generalise across ecological contexts and successional stages remains to be established through further cases. The inclusion of declassified KH-9 reconnaissance imagery from 1982 provided a high resolution pre-disturbance visual reference unachievable from any other freely available source for this landscape and period and proves the importance of historical declassified data for long term landscape monitoring, adapted to rewilding research. Whether a globally trained product can reliably substitute for such local classification in rewilding monitoring contexts, particularly for transitional vegetation classes, remains an open question that systematic comparisons across rewilding sites would be well positioned to address.

The remote sensing contribution documented here also raises broader questions about what these findings mean for conservation practice and policy, which the final section addresses.

7.5. Conservation and Policy Implications

This thesis reveals that sustained human withdrawal alone and without any management forms a case of passive rewilding that can drive large-scale land cover transitions. Although vegetation productivity increased and the landscape transitioned towards vegetated classes over 32 years, the rewilding signal documented here should be interpreted with caution in light of the ecological and radiological complexity specific to this area. The expansion of woody vegetation stimulates the accumulation of radionuclides in forest biomass, increasing the risk of radioactivity spread during wildfire events (Matsala et al., 2021). Dense closed-canopy forest represents a continuous flammable structure that may increase the risk of wildfire and subsequent spread of radionuclides in the atmosphere under increasingly extreme climate conditions (Ager et al., 2019). Therefore, passive rewilding alone in the CEZ context and without the full restoration of ecological processes may carry risks that a more complete rewilding trajectory could help mitigate.

In this regard, a complete rewilding including the full recovery of ecological functions through trophic rewilding should gain attention. The documented recovery of large herbivore populations within the CPR likely represents an outcome of decreased human pressure but may also add a functional mechanism for managing the landscape that passive succession alone cannot provide. Indeed, it has been documented that large herbivores represent an ecological disturbance that tends to spatially reduce tree cover while increasing spatial heterogeneity in vegetation structure, whereas fire reduces both tree cover and heterogeneity, suggesting that these two disturbance regimes shape the landscape differently (Wang et al., 2023a). In the CEZ context, where the densification of woody vegetation towards closed-canopy forest has been identified as a primary driver of fire severity (Ager et al., 2019), the increasing populations of large herbivores may contribute to a more open and heterogeneous vegetation mosaic. Therefore, the restoration of large herbivore assemblages could represent a complementary and cost-effective pathway to active fuel management, one that is ecologically

self-sustaining and consistent with the rewilding trajectory already underway in the exclusion zone.

Approximately 117 million hectares have been identified across Europe as having rewilding potential (Araujo & Alagador, 2024), and the ongoing land abandonment related to agriculture dynamics is offering opportunities for passive rewilding to occur spontaneously. Building on this, passive rewilding on abandoned land has been shown to represent a more cost-effective and ecologically meaningful pathway toward large-scale ecosystem transition than active restoration approaches such as afforestation (Wang et al., 2023b; Perino et al., 2019). This study, alongside the Knepp estate and the Côa Valley, represents an empirical case that can provide substantial information for possible future planned rewilding on former agricultural stands.

The findings of this study and previous work on the area converge on the fact that rewilding has occurred across the CPR, and the question posed is now less whether rewilding is occurring, but what kind of rewilding is most ecologically desirable and radiologically safe. Continuous satellite-based monitoring integrated with field assessment of wildlife populations and radionuclide dynamics would provide the evidence base needed to guide adaptive management of this unique region and scientific case. Additionally, where rewilding is implemented deliberately as a conservation strategy, integrating remote sensing monitoring frameworks would provide the evidence base currently lacking across most rewilding initiatives (Pettorelli & Schulte to Bühne, 2022). The scientific and policy communities have much still to learn from Chernobyl, not only about the ecological consequences of human absence, but about how to monitor, plan and govern the rewilding of Europe's abandoned landscapes.

8. Conclusion

This thesis aimed to quantify and contextualize land cover change and the vegetation productivity net outcome for the Chernobyl-Palieski reserve and its surroundings between 1986 and 2018, and to assess whether observed changes correspond to passive rewilding through ecological succession. The results provide clear and consistent answers to the four research questions that framed this aim. The CPR witnessed a dramatic land cover change with a near-collapse of agriculture accompanied by a transition towards shrubland and forest while the buffer transition was comparable but less marked. Shrub/Open emerged as the class carrying the strongest rewilding signal in both its expansion across the study area and its productivity gain. Vegetation productivity increased across both zones, with the CPR showing a slightly larger gain, consistent with human exclusion as the primary enabling condition for vegetation transition. These findings support the view that the ecological changes documented here are primarily a consequence of the near-total and long-lasting withdrawal of human activity, with no deliberate restoration or afforestation at causing this rewilding. Further comparison between products suggests that global monitoring frameworks could be insensitive to transitional vegetation classes although such stages are crucial to analyse

ecological succession, and this may have significant implications for how rewilding is monitored at the global scale.

Looking forward, the question for the Chernobyl region is no longer whether rewilding is occurring, but what level of rewilding is most ecologically desirable and radiologically safe. The scientific and policy communities have much still to learn from Chernobyl, not only about the ecological consequences of human absence, but about how to monitor, plan and govern the rewilding of Europe's abandoned landscapes.

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Appendix

Table S1. Satellite and elevation datasets used for land cover change and vegetation productivity analysis across the Chernobyl-Palieski Reserve (CEZ and PRR) and its 15 km buffer zone in Ukraine and Belarus. For each dataset, the product identifier and spatial coverage are listed. KH-9 tile references (f, g, h, i) correspond to adjacent panchromatic tiles from scene D3C1217-100073A012, covering the CEZ from east to west at 0.6–1.2 m resolution. Sentinel-2B tile names follow the Military Grid Reference System (MGRS). Landsat path/row notation (Path 182, Row 024) refers to the Worldwide Reference System-2 (WRS-2). SRTM tile names follow standard 1-arc-second geographic grid notation. Full dataset descriptions including sensor type, spectral bands, resolution, and acquisition dates are provided in Table 1.

Datasets	Product ID	Tile name/ coverage
KH-9	D3C1217-100073A012	f, g, h, i
Sentinel- 2B	S2B_MSIL2A_20180526T091019_N0500_R050	T35UPS, T35UPT, T35UQS, T35UQT
L4 MSS (Level-1)	LM04_L1TP_182024_19830515_20210902_02_T2	Path: 182/ Row: 024
L5 TM (Level-2)	LT05_L2SP_182024_19860531_20200917_02_T1	Path: 182/ Row: 024
L5 TM (Level-2)	LT05_L2SP_182024_19851003_20200918_02_T2	Path: 182/ Row: 024
L8 OLI (Level-2)	LC08_L2SP_182024_20180523_20200901_02_T1	Path: 182/ Row: 024
L8 OLI (Level-2)	LC08_L2SP_182024_20181014_20200830_02_T1	Path: 182/ Row: 024
SRTM	SRTM_1ARC_V3	N50E029, N50E030, N51E029, N51E030, N52E029