

FROM SOIL TO SATELLITE: WILDFIRE DETECTION AND VEGETATION RECOVERY MONITORING

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Samenvatting

Deze thesis onderzoekt de ecologische gevolgen van de bosbrand van 23 maart 2025 in de Clingse Bossen en evalueert het gebruik van satellietbeelden voor de detectie van verbrande gebieden en de monitoring van vegetatieherstel. De brand in Clinge vond plaats in een ecosysteem dat reeds onder druk stond door een grootschalige fijnsparsterfte (*Picea abies*) als gevolg van aantastingen door de letterzetter (*Ips typographus*). De resultaten tonen aan dat de brand, ondanks haar relatief lage intensiteit, duidelijke effecten had op zowel de bodem als de vegetatie. Verbrande bodems vertoonden veranderingen in waterafstotendheid, bulkdichtheid en pH. Zowel de vegetatiebedekking als het aantal soorten namen toe tijdens het eerste jaar na de brand, maar het herstel werd sterk gedomineerd door schapenzuring (*Rumex acetosella*), een pionierssoort die goed aangepast is aan droge, voedselarme en verstoorde zandgronden.

Daarnaast werd onderzocht hoe verschillende spectrale indices op basis van Sentinel-2 kunnen worden ingezet voor branddetectie en post-brandmonitoring. Hiervoor werden brandlocaties in Clinge, Arlon, Maasmechelen en Houffalize geanalyseerd. Indices zoals NDVI, NDVI red edge, NBR, NBR+, NBR2, NDSWIR en BAI werden vergeleken voor het detecteren van verbrande zones, waarbij NBR over het algemeen de beste resultaten opleverde. Daarnaast werd de Post-Fire Stability Index (PFSI), gebaseerd op NBR2, gebruikt om vegetatieherstel doorheen de tijd op te volgen. De resultaten tonen aan dat Sentinel-2 en afgeleide indices waardevolle instrumenten zijn voor het detecteren van natuurbranden en het monitoren van herstelprocessen in België.

Summary

This thesis investigates the ecological consequences of the forest fire of 23 March 2025 in the Clingse Bossen and evaluates the use of satellite imagery for the detection of burned areas and the monitoring of vegetation recovery. The fire in Clinge occurred in an ecosystem that was already under pressure due to large-scale Norway spruce (*Picea abies*) mortality caused by infestations of the European spruce bark beetle (*Ips typographus*). The results show that, despite its relatively low intensity, the fire had clear effects on both soil and vegetation. Burned soils showed changes in water repellency, bulk density, and pH. Both vegetation coverage and species richness increased during the first year after the fire, but recovery was strongly dominated by sheep sorrel (*Rumex acetosella*), a pioneer species well adapted to dry, nutrient-poor, and disturbed sandy soils.

In addition, this thesis examined how different spectral indices based on Sentinel-2 can be used for fire detection and post-fire monitoring. For this purpose, fire locations in Clinge, Arlon, Maasmechelen, and Houffalize were analysed. Indices such as NDVI, NDVI red edge, NBR, NBR+, NBR2, NDSWIR, and BAI were compared for the detection of burned areas, with NBR generally producing the best results. In addition, the Post-Fire Stability Index (PFSI), based on NBR2, was used to monitor vegetation recovery over time. The results show that Sentinel-2 and derived indices are valuable tools for detecting wildfires and monitoring recovery processes in Belgium.

Introduction

According to the European Commission, Civil Protection Humanitarian Aid Operations (2025), a wildfire is an uncontrolled fire that spreads in natural areas or in zones where urban development meets wildland, commonly referred to as the wildland–urban interface (WUI). To understand how such fires ignite and spread, the fire triangle provides a useful conceptual framework (Yakubu et al., 2015). It states that three elements must be present for combustion to occur: heat, fuel, and oxygen. Heat raises the temperature of potential fuels to their ignition point, fuel supplies the combustible material required to sustain the fire, and oxygen enables the chemical reactions of combustion. When these three components are present in a favourable balance, a fire can ignite and spread rapidly.

Fuel availability is a key factor controlling wildfire risk because it determines how easily an ignition can develop into a spreading fire. In many forest ecosystems, management strategies have aimed to suppress fires as quickly as possible in order to protect human infrastructure. While this approach reduces immediate fire damage, long-term fire suppression can lead to the accumulation of combustible vegetation, dead wood, and litter, thereby increasing fuel loads within forest stands (Millar and Stephenson, 2015; Teale and Castello, 2011). As a result, ignition events may develop into larger or more severe wildfires.

Although fire is a natural ecological process in many ecosystems, wildfires are increasingly studied in the context of climate change and changing disturbance regimes (Millar and Stephenson, 2015). In that broader context, wildfires should not only be viewed as isolated events but also as disturbances that can trigger cascading changes in soils, vegetation structure, and ecosystem functioning (Teale and Castello, 2011; Neary et al., 1999; Agbeshie et al., 2022). Understanding these effects is particularly relevant in temperate regions, where fire has historically received less attention than in more fire-prone Mediterranean or boreal ecosystems.

Despite the historically limited role of wildfires in Belgium, increasing drought, heat stress, and forest degradation are expected to raise future wildfire risk (CERAC et al., 2025; Baetens et al., 2026). At the same time, our understanding of post-fire ecological responses in Belgian ecosystems remains limited. The CERAC assessment identified important research gaps regarding wildfire impacts on forest subsystems, including soils, understory vegetation, regeneration processes, and post-fire recovery dynamics (CERAC et al., 2025).

This thesis therefore examines wildfires from both an ecological and a remote sensing perspective. First, it reviews how wildfires affect soil properties, including changes in soil water repellency, bulk density, soil organic matter, nutrient dynamics, and pH. It also discusses wildfire effects on vegetation, with a focus on post-fire recovery processes. These ecological changes are directly relevant for remote sensing, as fire-induced alterations in vegetation structure, soil exposure, moisture conditions, and ash cover influence spectral reflectance. Building on this ecological foundation, the thesis then evaluates remote sensing approaches for burned area detection and post-fire vegetation recovery monitoring.

A specific focus of this study is the Clingse Bossen, which form part of the Waterwinbossen in the southwest of the Netherlands near the Belgian border. On 23 March 2025, a wildfire affected approximately 2.4 ha of this area, burning mainly stands of already dead *Picea abies* (Norway spruce) (Stichting Het Zeeuwse Landschap, 2025). Because the site combines a recent wildfire with ongoing post-fire recovery, it provides a valuable field setting for investigating soil and vegetation responses to fire. In addition, the wildfire detection analyses were performed for the Clingse Bossen and three other Belgian wildfire sites in Arlon, Maasmechelen, and Houffalize, enabling the evaluation of burned area detection and vegetation recovery monitoring across a broader range of vegetation types.

1. Wildfire impacts and detection

This chapter provides an overview of wildfire effects on soil and vegetation, followed by an introduction to remote sensing approaches for wildfire detection and post-fire recovery monitoring. Together, these components form the foundation for understanding how fire-induced changes can be analysed in this study.

1.1 Effects of wildfires on soil

Wildfires can induce profound changes in soils by altering physical structure and chemical composition, which in turn influence vegetation recovery and ecosystem functioning (Neary et al., 1999; Agbeshie et al., 2022). Heat exposure, organic matter combustion, ash deposition, and so on, influence how soils function and recover after fire events (Agbeshie et al., 2022). To understand these impacts, this section examines both physical and chemical soil properties that are known to be sensitive to fire disturbance.

The effects of wildfire on soil properties are strongly controlled by fire severity and intensity, as the amount of heat transferred to the soil largely determines the magnitude of physical and chemical changes (Agbeshie et al., 2022). Fire intensity refers to the physical combustion process and is defined as the energy released during a fire. It can be described using several measures of energy output, including fireline intensity, temperature, heating duration (residence time), and radiant energy, although no single metric captures all aspects of fire energy (Keeley, 2009). Fire severity, in contrast, describes the degree to which fire-induced energy results in the loss or alteration of organic matter, both above- and belowground. In empirical studies, fire severity is commonly assessed using indicators such as vegetation consumption, loss of litter and soil organic layers, and ash characteristics. Importantly, fire severity is conceptually distinct from post-fire ecosystem responses, including vegetation recovery, erosion, or changes in hydrological processes (Keeley, 2009).

However, it is important to note that there is currently no universal consensus on how fire severity or intensity should be classified. Different studies apply different thresholds, terminology, and metrics, which complicates direct comparison between results.

Two temperature-based classification approaches are presented in Table 1.1. These examples are not exhaustive, but are included to illustrate how terminology for fire intensity and severity can vary across studies.

Table 1.1: Examples of fire intensity and severity classifications used in the literature (Caon et al., 2014; Neary et al., 1999)

Source	Fire class	Temperature
Caon et al. (2014)	Low intensity	< 100 °C
	Medium intensity	up to 250 °C
	High intensity	> 350 °C
Neary et al. (1999)	Light severity	~250 °C
	Moderate severity	~400 °C
	High severity	~675 °C

Caon et al. (2014) apply a temperature-based classification of fire intensity using relatively strict thermal thresholds. In contrast, Neary et al. (1999), based on the work of DeBano et al. (1998), do not define explicit temperature boundaries but associate light, moderate, and high fire severity with indicative soil surface temperatures, emphasizing ecological effects rather than fixed thermal limits. A different method was applied by Badía et al. (2014), who used the Composite Burn Index (CBI), a field-based burn severity rating developed to quantify the on-the-ground effects of fire on both vegetation and soil conditions. The CBI uses plot measurements of fire effects on multiple vegetation layers and substrates, assigning scores from 0.0 (no effect) to 3.0 (high severity) that are averaged to obtain an overall severity value, which can then be compared to satellite-derived burn severity metrics. These scores are derived through structured field observations and are primarily based on expert judgment, relying on visual estimation of fire effects relative to pre-fire conditions (Key and Benson, 2006).

Because these classifications are based on different conceptual frameworks and temperature ranges, caution is required when interpreting and comparing fire severity and intensity terms across studies. Keeley (2009) explicitly highlights that the terms fire intensity and fire severity are frequently used inconsistently in the scientific literature, often conflating physical fire processes with ecological effects. This inconsistent usage has led to substantial conceptual confusion in post-fire research.

To maintain consistency and avoid reinterpretation, the remainder of this study will, per section, adopt the terminology used in the papers cited within that section, each time applying the terms fire intensity and fire severity according to the definitions employed by the respective authors. With this terminological distinction in mind, the following subsections review how selected physical and chemical soil properties are influenced by wildfire.

1.1.1 Physical soil properties

1.1.1.1 Bulk density

Bulk density of soils is defined as the mass of dry soil per unit volume, where this volume includes both soil particles and pore spaces (Weil and Brady, 2017), whereas particle density refers to the mass per unit volume of the soil solids only, and therefore excludes the pore spaces between particles (Weil and Brady, 2017).

Sandy soils tend to have higher bulk densities than silt loams and clay loams because their solid particles are less likely to form aggregates. As a result, fewer micropores are created and the total pore space is lower. The bulk density of loose to tightly packed sand typically ranges between 1.38 and 1.99 g/cm³, assuming the grains consist primarily of quartz (Weil and Brady, 2017).

Meira-Castro et al. (2015) and Goberna et al. (2007) reported no impact on bulk density following low-severity fires. In contrast, Heydari et al. (2016) and Jordán et al. (2013) observed increased bulk density after high-severity fires. Downing et al. (2017) found a decrease in bulk density 3 years after a high-intensity fire.

1.1.1.2 Soil water repellency

Soil water repellency is a soil property characterized by a reduced affinity for water, resulting in delayed infiltration and uneven wetting. It arises from hydrophobic organic compounds coating soil particles (Dekker and Ritsema, 2009). According to Neary et al. (1999) a hydrophobic layer parallel to the soil surface can be formed because of wildfires. This layer can strongly reduce infiltration and promote surface runoff and erosion, particularly on sloping terrain.

Several studies have examined how soil water repellency responds to fire. Granged et al. (2011) found an increased soil water repellency after a mixed-intensities fire, while no impact was found by Scharenbroch et al. (2012) after a low-intensity prescribed fire. Inbar et al. (2014) and Varela et al. (2015) observed decreased soil water repellency after low- to moderate-severity fires.

In addition, Stoof et al. (2011) showed that soil water repellency is not solely fire-induced, but a persistent and dynamic soil property strongly influenced by environmental conditions. Repellency was already present before fire and remained within the natural range after burning. Their study found a strong inverse relationship between soil moisture and repellency persistence: drier soils were more repellent, whereas wetter soils were more likely to be wettable.

Furthermore, Stoof et al. (2011) highlighted the important role of vegetation in modulating soil water repellency. Vegetation removal, whether by fire or mechanical clipping, altered the development and breakdown of repellency by increasing soil exposure to rainfall and evaporation, thereby accelerating wetting–drying cycles. Although burning slightly increased repellency persistence, vegetation removal had particularly strong effects at the soil surface and in the litter layer, where repellency responded rapidly to environmental conditions.

1.1.2 Chemical soil properties

1.1.2.1 Soil organic matter and soil organic carbon

Soil organic matter (SOM) includes all organic components present in the soil. This comprises living biomass such as intact plant and animal tissues, microorganisms, plant litter and residues including dead roots and other plant materials at different stages of decomposition, and dissolved organic biomolecules ranging from plant-derived amino acids to microbial enzymes. It also encompasses complex assemblages of biomolecules associated with mineral particle surfaces, microscopic fragments of no longer identifiable organic tissue protected within soil microaggregates, and plant material that has been blackened or charred by fire (Weil and Brady, 2017)

Soil organic carbon (SOC) represents the carbon component of SOM. Because carbon constitutes a relatively stable proportion of SOM, SOC is commonly used as a proxy to estimate SOM. A widely applied conversion factor assumes that organic matter contains approximately 50% carbon, allowing SOM to be estimated from SOC measurements (Weil and Brady, 2017).

$$\text{SOM} = 2 \times \text{SOC} \quad (1.1)$$

Reported effects of fire on soil organic matter and carbon are variable across studies. Meira-Castro et al. (2015) reported no significant changes in SOM following a prescribed fire. Similarly, Downing et al. (2017) observed no significant effect on SOC three years after a high-intensity fire. In contrast, Badía et al. (2014) found a decrease in SOC one week after a moderate- to high-intensity fire, although SOC levels had recovered within one year.

1.1.2.2 Soil total nitrogen

Total nitrogen represents the sum of all nitrogen forms present in the soil, including organic nitrogen bound in soil organic matter and inorganic forms such as ammonium and nitrate (Weil and Brady, 2017).

Wildfires can strongly affect soil nitrogen pools because nitrogen-containing compounds are highly sensitive to heat. During combustion, organic nitrogen may be volatilized and lost to the atmosphere, particularly at high fire intensities. At lower fire intensities, inorganic nitrogen availability may temporarily increase in the soil through the mineralization of organic nitrogen to ammonium, although this effect is generally short-lived (Neary et al., 1999).

Badía et al. (2014) reported an increase in soil NO_3^- and NH_4^+ concentrations following a moderate- to high-severity wildfire, attributed to the transformation of organic nitrogen into mineral forms. In contrast, Akburak et al. (2017) observed no significant effect on total soil nitrogen after a low-intensity burning. A decrease in total nitrogen following a high-severity wildfire was documented by Dzwonko et al. (2015), which was explained by nitrogen losses through volatilization.

1.1.2.3 Cation exchange capacity

Cation exchange capacity (CEC) is the total amount of positively charged ions (cations) that a soil can adsorb and hold on exchange sites of clay minerals and organic matter. It reflects the soil's ability to retain essential nutrients and buffer changes in soil chemistry (Weil and Brady, 2017). Clay minerals carry a net negative charge on both their external and internal surfaces, which attracts cations from the soil solution. These cations form an ionic double layer consisting of adsorbed cations near the clay surface and a diffuse layer of ions in the surrounding soil solution. Exchangeable cations such as Ca^{2+} , Mg^{2+} , K^+ , and H^+ are weakly held and can be easily exchanged with other cations in solution.

Inbar et al. (2014) reported an increased CEC following a low- to moderate-severity wildfire, which they attributed to an increased SOM. Similarly, Downing et al. (2017) found an increased CEC despite relatively stable SOM contents, which they attributed to changes in the quality of the organic matter following fire. They suggested that the formation of black carbon or biochar through incomplete combustion increased the number of negatively charged exchange sites in the soil, thereby enhancing cation exchange capacity.

1.1.2.4 pH

Soil pH is a fundamental measure of soil acidity and is defined as the availability of H^+ ions on a logarithmic scale (Weil and Brady, 2017).

$$pH = -\log_{10}([H^+]) \quad (1.2)$$

where low pH indicates acidic conditions and high pH reflects alkaline conditions. Soil pH strongly influences the solubility of nutrients and chemical compounds in the soil solution, and therefore determines their availability to plants. Changes in pH can have significant consequences for vegetation health and ecosystem functioning (Weil and Brady, 2017).

Inbar et al. (2014) found no significant change in pH after a low- to moderate-severity fire, Badía et al. (2014) reported no effect after moderate to high severity, and Alcañiz et al. (2016) similarly reported no significant change following prescribed low-intensity burning, whereas Muqaddas et al. (2015) observed an increase in soil pH after low-intensity prescribed fires carried out every two years, with a total of 17 burns, due to increased base cation concentrations. Dzwonko et al. (2015), Akburak et al. (2017), and Heydari et al. (2016) all found an increased pH following high-severity, low-severity, and mixed-intensity fires.

1.1.3 Summary

Overall, the effects of wildfire on soil properties are strongly dependent on fire severity and intensity, frequency, and management context. As synthesized by Neary et al. (1999), low-impact fires may induce short-term beneficial effects, such as increased nutrient availability, reduced pathogen pressure, and improved stand structure, thereby supporting ecosystem functioning. In contrast, moderate- to high-severity fires often lead to substantial nutrient losses through volatilization, erosion, and leaching, as well as degradation of soil physical properties, altered hydrological functioning, and reductions in microbial activity, with consequences that may persist over the long term. Neary et al. (1999) further emphasize that frequent or repeated fires used as a management tool can produce inconclusive or even negative effects on belowground systems, particularly when combined with other disturbances.

In contrast, Agbeshie et al. (2022) highlight the potential benefits of prescribed burning as a fuel management strategy, emphasizing that low-intensity fires generally cause limited soil heating and are therefore less likely to induce severe soil degradation. However, Neary et al. (1999) also warn that burning contributes to the release of greenhouse gases, which may increase global warming and promote a positive feedback loop by increasing future fire frequency and intensity. This apparent contradiction illustrates that while prescribed burning can reduce the risk of high-severity wildfires at the local scale, it may simultaneously contribute to broader climate-driven feedback that increases wildfire frequency at larger spatial and temporal scales.

1.2 Effects of wildfires on vegetation

Fire severity plays a central role in determining post-fire vegetation recovery, ecosystem resilience, defined as the capacity of an ecosystem to recover from disturbances, and the potential for long-term structural changes in temperate forests, which occur in mid-latitude regions characterized by distinct seasonal climates. Empirical studies across different forest types demonstrate that recovery trajectories vary strongly with disturbance intensity, species traits, and post-fire environmental conditions (Adámek et al., 2016; Etchells et al., 2020).

1.2.1 *Pinus sylvestris*

Adámek et al. (2016) investigated post-fire succession in temperate *Pinus sylvestris* forests and showed that vegetation recovery is characterised by long-term changes in structure, species composition, and diversity, strongly shaped by fire severity. All vegetation layers responded to fire, but followed different recovery trajectories. The tree layer re-established within about two decades, although canopy cover remained lower than in unburned plots for up to 25–50 years after high-severity fires. Low-severity fires caused limited damage, whereas high-severity fires almost completely removed the tree layer, thereby initiating divergent successional pathways (i.e. different trajectories of vegetation recovery and forest development) (Adámek et al., 2016).

The shrub layer was highly vulnerable even to low-severity fires and was largely absent during the first post-fire phase, together with young trees and ground lichens. Species richness was higher in all post-fire age classes than in unburned plots, especially due to nutrient-demanding species and pioneer tree regeneration during early succession. Fire-induced changes in soil conditions, particularly the burning of organic and humus horizons, influenced early vegetation development and promoted tree regeneration for up to two decades. Despite these initial effects,

forest structure and species composition returned to a pre-disturbance-like state after about 140 years, indicating long-term resilience of Scots pine forests (Adámek et al., 2016).

1.2.2 *Eucalyptus diversicolor*

Similar severity-dependent recovery patterns were observed in karri forests (*Eucalyptus diversicolor*) in south-western Australia. Etchells et al. (2020) showed that, although karri forests are generally fire-adapted through thick bark and epicormic resprouting, i.e. the production of new shoots from dormant buds beneath the bark on trunks or branches, their resilience is limited under extreme fire severity. Based on vegetation and soil measurements 13 and 17 months after fire, mature tree mortality was much higher at high-severity sites ($\approx 47\%$) than at low-severity ($\approx 5\%$) and unburned sites ($\approx 7.5\%$). One extreme-severity site showed even stronger responses, including 43% higher tree mortality, 27% greater canopy loss, and more than twice the seedling growth compared with other high-severity sites. Seedling growth increased with canopy loss, indicating that light availability strongly drives regeneration (Etchells et al., 2020).

Understorey composition changed mainly through shifts in species dominance rather than species loss. Although species richness was higher in burnt sites, the dominant shrub *Trymalium odoratissimum* was absent from the extreme high-severity site 13–17 months after fire, suggesting tolerance thresholds for some understorey species. High-severity fires may therefore cause prolonged structural change and increase vulnerability to future disturbances, highlighting the importance of identifying fire severity thresholds for adaptive forest management (Etchells et al., 2020).

1.2.3 Limits of forest resilience under increasing disturbance pressure

A key aspect discussed by Millar and Stephenson (2015) is the shift in the conceptual understanding of forest health. Earlier views linked healthy forests with optimal tree growth and minimal disturbance, leading to widespread fire suppression and pest control. However, ecological theory has since recognized disturbance as an essential component of forest functioning (Teale and Castello, 2011). Under current climate change, the key question is no longer whether disturbance occurs, but how much disturbance forests can tolerate before crossing thresholds that lead to persistent changes in structure, composition, and ecosystem services (Millar and Stephenson, 2015).

1. Wildfire impacts and detection

A critical driver of emerging vulnerability is the interaction between climate warming and disturbance agents. Rising temperatures intensify drought stress and promote insect population outbreaks, which increase tree mortality and fuel accumulation. These processes, often reinforced by structurally homogeneous forest stands resulting from past management practices, enhance the likelihood of large and severe wildfires. As the occurrence of megafires increases, the potential for forests to transition to alternative forest types or non-forest vegetation states accelerates, threatening long-term ecosystem service provision (Millar and Stephenson, 2015).

Figure 1.1 presents a conceptual framework, developed by Millar and Stephenson (2015) based on a literature synthesis, describing how temperate forests respond to increasing disturbance pressure such as drought, heat, insects, and wildfire, and showing that forest ecosystems can pass through several response stages.

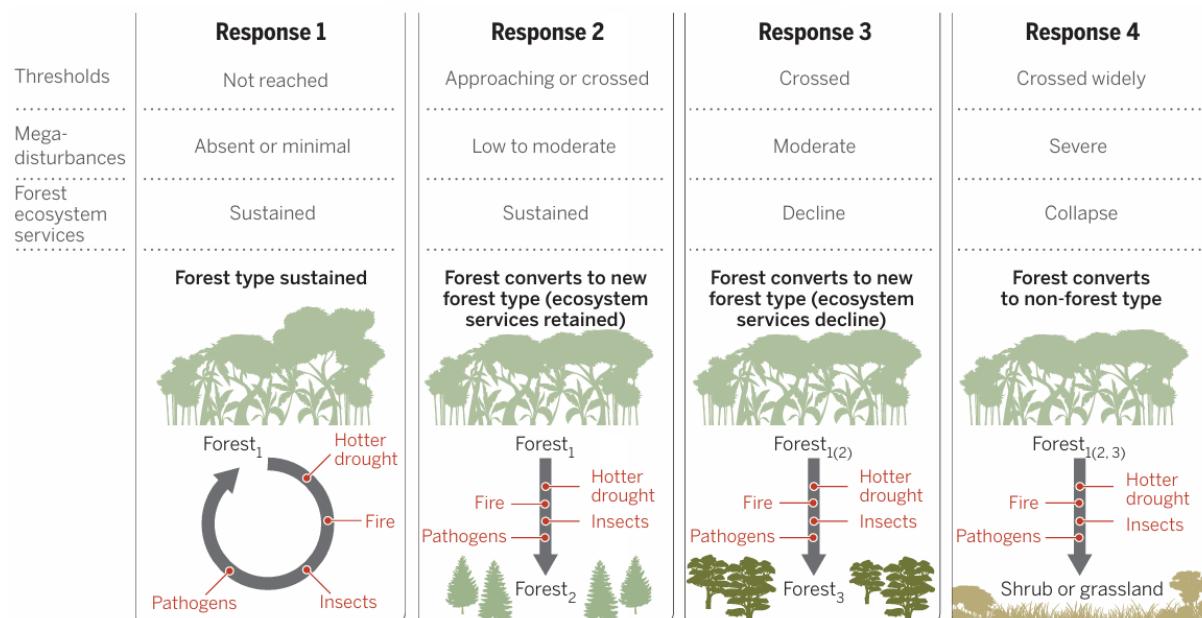


Figure 1.1: Temperate forest responses to 21st-century disturbances (Millar and Stephenson, 2015).

Four response stages are shown along a disturbance gradient. In Response 1, disturbance is minimal and ecological thresholds are not reached, allowing forest structure, species composition, and ecosystem services to be sustained. In Response 2, thresholds are approached or locally crossed, leading to shifts in species composition and conversion to a different forest type, while key ecosystem services are largely retained. Response 3 represents conditions where thresholds are exceeded, resulting in substantial structural change, loss of dominant species, and declining ecosystem services, although the system remains forested. In Response 4, thresholds are widely crossed, disturbances are severe and persistent, and forests transition to non-forest vegetation, accompanied by collapse of forest ecosystem services (Millar and Stephenson, 2015).

Overall, the figure emphasizes that forest resilience is finite and that increasing disturbance intensity can drive abrupt and potentially irreversible ecosystem transitions once critical thresholds are exceeded (Millar and Stephenson, 2015).

1.3 Wildfire detection

Vegetation and soil recovery after a wildfire are closely interconnected processes, as fire-induced changes in organic and humus horizons strongly influence post-fire vegetation regeneration and successional trajectories (Adámek et al., 2016). Post-fire spectral responses at the land surface are controlled by the combined effects of vegetation recovery and changes in soil exposure and moisture conditions, with these effects varying across vegetation types (Gitas et al., 2012; Schepers et al., 2014). A sound understanding of these ground-level processes is therefore essential for the correct interpretation of remotely sensed wildfire signals. Only by understanding how fire alters soil properties and vegetation structures is it possible to make well-informed choices in satellite data analysis, such as the selection of spectral bands and indices. Consequently, knowledge of post-fire soil-vegetation interactions provides a critical foundation for the effective use of remote sensing techniques in wildfire detection and monitoring. In addition, ground-truth information obtained through field spectroradiometric measurements is essential for validating the selection of representative image wavebands and ensuring the reliability of object-based classification approaches (Gitas et al., 2012).

1.3.1 Spectral properties of vegetation and fire-affected surfaces

Wildfire detection can be achieved through remote sensing techniques, which rely on spectral indices derived from electromagnetic radiation recorded by satellites. These indices are numerical values calculated by combining reflectance measurements from different spectral bands (Lillesand et al., 2015). The main types of electromagnetic waves are shown in Figure 1.2.

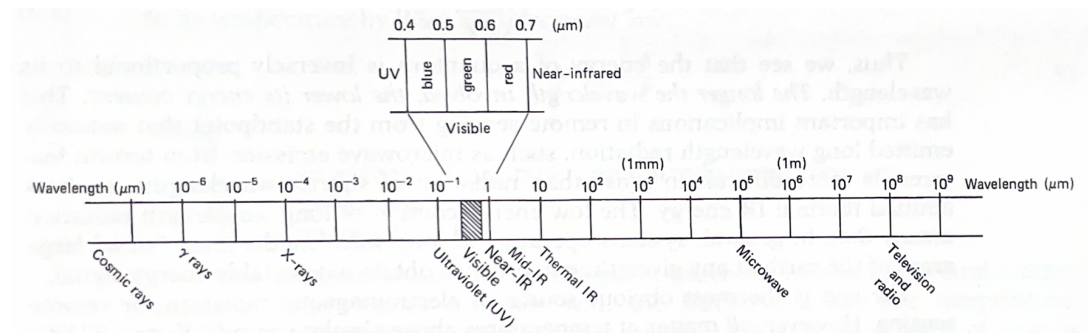


Figure 1.2: Electromagnetic spectrum (Lillesand et al., 2015).

1. Wildfire impacts and detection

To understand the behaviour of spectral indices, it is first necessary to examine how vegetation interacts with incoming solar radiation. It can react by reflecting, absorbing, and transmitting different portions of the electromagnetic spectrum. The spectral reflectance is defined as the ratio of reflected to incident radiation and provides valuable information about plant health. Healthy vegetation strongly absorbs radiation in the blue and red wavelengths because of chlorophyll, while reflecting more in the green region, giving plants their characteristic color (Lillesand et al., 2015; Silvestre, 2021). In the near-infrared region (NIR), healthy leaves exhibit high reflectance due to the internal structure of the mesophyll (Lillesand et al., 2015; Silvestre, 2021; Slaton et al., 2001). Vegetation has low reflectance in the short-wave infrared region (SWIR) due to water absorption (Lillesand et al., 2015).

After a fire, the destruction of vegetation causes a strong decrease in NIR reflectance, indicating the loss of canopy structure and internal leaf integrity (Alcaras et al., 2022; Korets et al., 2010). On the other hand, SWIR reflectance increases due to the removal of water in the vegetation and the resulting increase in landscape dryness (Alcaras et al., 2022). Consequently, as shown in Figure 1.3, recently burned areas typically show low NIR reflectance and high SWIR reflectance. The red region is also important for burned area mapping, as it is sensitive to changes in chlorophyll absorption. As tree mortality increases, chlorophyll concentration decreases, leading to reduced absorption in the red spectral band (Korets et al., 2010).

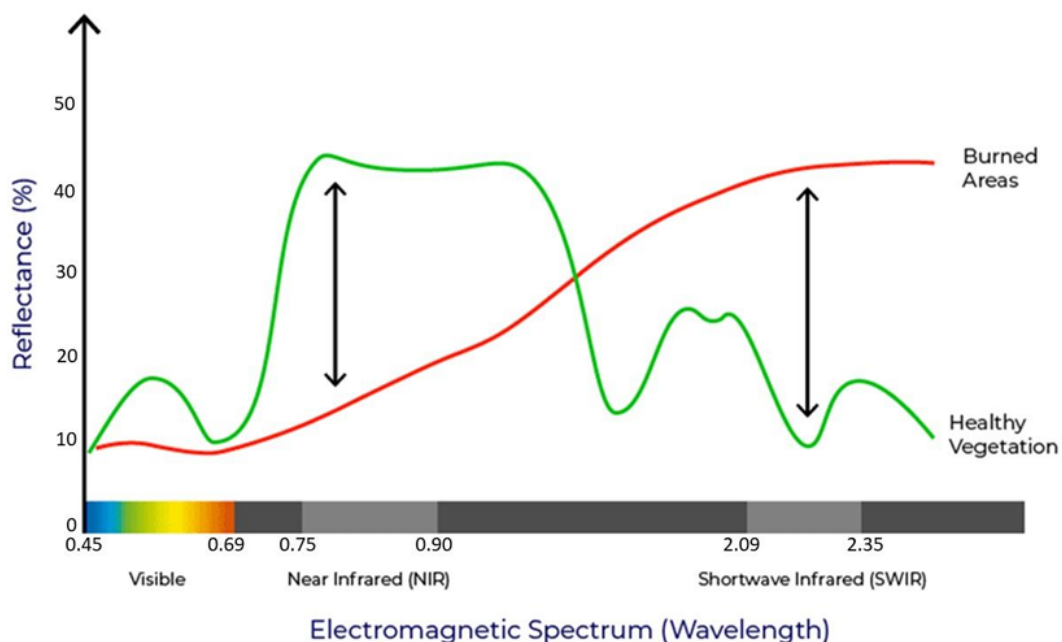


Figure 1.3: Spectral reflectance of burned areas versus healthy vegetation (Alcaras et al., 2022).

Although these general spectral responses are at the basis of most burned area detection methods, fire effects on surface reflectance are not always uniform. In particular, fire intensity can modify the expected spectral patterns. Roy and Landmann (2005) found that burned vegetation typically becomes darker and less reflective across most of the 350–2500 nm spectrum due to black ash and char. However, their results also demonstrate that very high-intensity fires can produce white ash with much higher reflectance than black ash, meaning that the expected decrease in reflectance may not occur and some burned areas may even appear brighter.

1.3.2 Synthetic Aperture Radar and Polarization

Synthetic Aperture Radar (SAR) is an active remote sensing technology that operates by transmitting microwave signals towards the Earth's surface and measuring the portion of the signal that is scattered back to the sensor. Unlike optical sensors, SAR systems do not rely on solar illumination and are therefore capable of acquiring data independently of daylight conditions. Furthermore, microwave signals penetrate clouds, smoke, and haze, which makes SAR particularly suitable for monitoring during or after wildfire events (Moreira et al., 2013; NASA Earthdata, 2024; Rokhmatuloh et al., 2022).

The intensity of the returned radar signal, commonly referred to as backscatter, depends on several surface properties, including surface roughness, moisture content, and vegetation structure. Changes in these properties, for instance due to vegetation loss caused by fire, directly affect the magnitude of the backscattered signal and can therefore be detected using SAR observations (Moreira et al., 2013; Rokhmatuloh et al., 2022).

A key characteristic of SAR systems is their ability to transmit and receive electromagnetic waves with specific polarization states. Polarization describes the orientation of the electric field of the radar wave and is typically defined as vertical (V) or horizontal (H). In dual-polarization SAR systems such as the Sentinel-1 satellite mission, commonly used polarization combinations include VV (vertical transmit, vertical receive) and VH (vertical transmit, horizontal receive) (Moreira et al., 2013).

Co-polarized backscatter (VV) is generally more sensitive to surface scattering and soil-related properties, while cross-polarized backscatter (VH) is primarily associated with volume scattering caused by vegetation elements such as leaves, branches, and stems. As a result, VH polarization is particularly sensitive to changes in vegetation structure, whereas VV polarization may respond more strongly to exposed soil surfaces following vegetation removal (Moreira et al., 2013). Rokhmatuloh et al. (2022) show that burned areas have lower backscatter values in both VV and VH polarization, with the strongest differences observed in the VH channel.

1.3.3 Wildfire indices

1.3.3.1 Burned area indices

For the purposes of this study, the relevant spectral regions sensitive to fire-related changes are the visible, red edge, NIR, and SWIR portions of the spectrum, each capturing different aspects of chlorophyll loss, structural damage, moisture depletion, or ash deposition. The combined use of these regions in spectral indices provides a clearer separation between burned and unburned surfaces (Bastarrika et al., 2014).

The **Normalized Difference Vegetation Index** (NDVI), defined by

$$\text{NDVI} = \frac{\text{NIR} - R}{\text{NIR} + R} \quad (1.3)$$

measures vegetation greenness and density by comparing reflectance in the NIR and red (R) spectral bands. Healthy vegetation strongly reflects in NIR and absorbs R, so NDVI values are high for dense vegetation and low (or negative) for bare soil or burned surfaces (Mpakairi et al., 2020).

Research has shown that replacing the red band with red edge wavelengths improves the sensitivity of vegetation indices to burn severity and post-fire vegetation condition (Fernández-Manso et al., 2016; Korets et al., 2010). The red edge is the sharp increase in vegetation reflectance between approximately 0.68 and 0.75 μm , where strong chlorophyll absorption in the red wavelengths transitions to high near-infrared reflectance controlled by leaf internal structure (Lillesand et al., 2015). Because this region is highly sensitive to chlorophyll content, red edge bands allow satellites to detect subtle changes in vegetation health, stress, nutrient status, and productivity more accurately (Clevers and Gitelson, 2013).

In burned areas, the destruction of chlorophyll and changes in leaf structure cause clear spectral changes in the red edge region, making red edge-based indices more sensitive to post-fire damage than traditional NDVI. Fernández-Manso et al. (2016) confirmed that Sentinel-2's red edge bands are effective for discriminating burn severity, while Korets et al. (2010) showed that post-fire reductions in chlorophyll shift the red edge toward shorter wavelengths and correspond with increasing tree mortality. Together, these findings indicate that red edge-based indices can outperform red-based indices in detecting subtle fire-induced vegetation stress and burn severity.

The **Normalized Burn Ratio** (NBR), given by

$$NBR = \frac{NIR - SWIR}{NIR + SWIR} \quad (1.4)$$

replaces the red band in NDVI with a SWIR band, which is more sensitive to water content and charcoal. Burned areas typically show decreased NIR reflectance and increased SWIR reflectance. Therefore, NBR is more effective than NDVI in distinguishing burned from unburned vegetation (Mpakairi et al., 2020).

The standard NBR index works well for burned area detection but is sensitive to misclassifications when water bodies or clouds are present in the scene. These features often produce reflectance patterns similar to those of burned areas in the NIR–SWIR domain, leading to false positives. To address this limitation, Alcaras et al. (2022) developed an enhanced version of NBR, called the **Normalized Burn Ratio Plus** (NBR+):

$$NBR+ = \frac{SWIR - NIR - G - B}{SWIR + NIR + G + B} \quad (1.5)$$

This index modifies the original NBR formula by incorporating the blue (B) and green (G) bands. The inclusion of visible bands reduces the reflectance values of water bodies and clouds, making them appear with low (often negative) NBR+ values. Burned areas, on the contrary, remain highlighted with high values. As a result, NBR+ significantly reduces commission errors compared to NBR, particularly in coastal or cloud-affected regions (Alcaras et al., 2022).

The **Burned Area Index** (BAI), i.e.

$$BAI = \frac{1}{(0.1 - R)^2 + (0.06 - NIR)^2} \quad (1.6)$$

quantifies the spectral distance between a pixel's red and NIR reflectance values and a reference point ($R = 0.1$ and $NIR = 0.06$) representative of burned surfaces. Burned areas typically exhibit low reflectance in both bands due to charcoal, ash, and vegetation loss, resulting in high BAI values when pixels approach this reference in spectral space (Martín Isabel and Chuvieco Salinero, 1998).

This spectral-distance approach makes the index effective for detecting burned areas, even in sparsely vegetated or slowly recovering environments (Martín Isabel and Chuvieco Salinero, 1998; Mpakairi et al., 2020). However, because BAI is based on absolute reflectance rather than band ratios, it is sensitive to atmospheric and illumination variability and should be applied with caution in temporal analyses (Martín Isabel and Chuvieco Salinero, 1998).

Normalized Burn Ratio 2 (NBR2) assesses post-fire changes in vegetation structure, moisture content, and soil conditions using the normalized difference between the two short-wave infrared bands:

$$\text{NBR2} = \frac{\text{SWIR1} - \text{SWIR2}}{\text{SWIR1} + \text{SWIR2}}. \quad (1.7)$$

Pérez et al. (2022) found that NBR2 was generally the second-best performing index for burned area discrimination, although it outperformed all other indices in specific cases such as grassland, where it showed the highest separability. Gibson et al. (2022) showed that when incorporated into the post-fire stability index, NBR2 provides the best performance for monitoring post-fire vegetation recovery. The formulation and underlying principles of the post-fire stability index are discussed in Section 1.3.3.3.

Building on the work of Gerard et al. (2003), Alcaras et al. (2022) also evaluated the **NDSWIR** formulation for burned area detection. The index is defined as:

$$\text{NDSWIR} = \frac{\text{SWIR}_1 - \text{NIR}_{\text{narrow}}}{\text{SWIR}_1 + \text{NIR}_{\text{narrow}}} \quad (1.8)$$

This formulation enhances the contrast between burned and unburned surfaces by combining the sensitivity of SWIR to vegetation moisture and the sensitivity of NIR to canopy structure (Gerard et al., 2003).

According to Mpakairi et al. (2020) NDVI was less effective for burned area detection because it mainly tracks vegetation vigor, meaning the overall health, vitality and growth activity of plants, rather than burn characteristics. NBR performed better but still showed confusion in heterogeneous landscapes or when post-fire regrowth occurred. The BAI provided the highest accuracy among the indices tested, effectively isolating burned pixels and minimizing false positives. The authors concluded that fire-specific indices like BAI are more suitable than general vegetation indices (NDVI) for post-fire mapping in European ecosystems. Alcaras et al. (2022) report that while traditional indices such as NDVI and NBR capture the main spectral changes associated with burning, they still misclassify water bodies, clouds, and dark surfaces as burned areas. BAI performs somewhat better in isolating burned pixels but can still confuse dark non-burn features. In contrast, NBR+, which incorporates blue and green bands, substantially reduces these false positives and provides the highest overall accuracy for burned area mapping, particularly in coastal or atmospherically complex scenes.

1.3.3.2 Radar-based indices for burned area detection

Several radar-based indices derived from Sentinel-1 SAR data have been employed to enhance burned area detection by quantifying changes in radar backscatter between pre-fire and post-fire conditions using both VV and VH polarizations (Hosseini and Lim, 2023; Rokhmatuloh et al., 2022).

The **Radar Burn Difference** (RBD) quantifies the absolute change in backscatter between pre-fire and post-fire conditions and is defined as:

$$RBD_{VV} = \gamma_{VV, post}^0 - \gamma_{VV, pre}^0 \quad (1.9)$$

$$RBD_{VH} = \gamma_{VH, post}^0 - \gamma_{VH, pre}^0 \quad (1.10)$$

Rokhmatuloh et al. (2022) report that RBD values in burned areas typically range between -1.5 and -2 dB, whereas unburned areas show near-zero or slightly positive values, indicating that RBD provides strong separability between burned and unburned surfaces. Similarly, Hosseini and Lim (2023) demonstrate that RBD-based indices are among the most effective predictors for burned area classification.

In addition, the **Radar Burn Ratio** (RBR) expresses the relative change in backscatter by means of a ratio between post-fire and pre-fire observations:

$$RBR_{VV} = \frac{\gamma_{VV, post}^0}{\gamma_{VV, pre}^0} \quad (1.11)$$

$$RBR_{VH} = \frac{\gamma_{VH, post}^0}{\gamma_{VH, pre}^0} \quad (1.12)$$

Hosseini and Lim (2023) and Rokhmatuloh et al. (2022) indicate that RBR provides weaker discrimination between burned and unburned areas than RBD and contributes less to overall burned area classification performance, particularly in peatland and heterogeneous environments.

To further capture changes in vegetation structure, Hosseini and Lim (2023) also employed the **Radar Vegetation Index** (RVI), which combines both VV and VH polarizations:

$$RVI = \frac{4 \cdot \gamma_{VH}^0}{\gamma_{VV}^0 + \gamma_{VH}^0} \quad (1.13)$$

1. Wildfire impacts and detection

The temporal change in vegetation condition was then represented by the difference in RVI between post-fire and pre-fire situations:

$$\Delta RVI = RVI_{post} - RVI_{pre} \quad (1.14)$$

According to Hosseini and Lim (2023), ΔRVI provides complementary information by capturing changes in vegetation structure and enhances classification performance when combined with backscatter-based indices.

Overall, indices derived from VH polarization outperform their VV counterparts in discriminating burned from unburned surfaces, as cross-polarized SAR backscatter is more sensitive to fire-induced changes in vegetation structure and shows stronger negative responses over burned areas (Moreira et al., 2013; Rokhmatuloh et al., 2022). Misclassification was primarily observed in areas characterized as cropland (e.g., planted cereals and grasses), where backscatter characteristics may resemble post-fire surfaces, leading to classification confusion (Hosseini and Lim, 2023). Similarly, Rokhmatuloh et al. (2022) report increased classification noise at the boundaries of burned areas and in heterogeneous land cover types.

Although these SAR-derived indices have demonstrated promising results for burned area detection, their implementation and evaluation fall outside the scope of the present study and will therefore not be considered further due to time constraints.

1.3.3.3 Vegetation recovery indices

Beyond identifying suitable spectral indices for burned area detection, there is a clear need to analyse post-fire vegetation recovery, as plant communities may respond to wildfire in fundamentally different ways depending on vegetation type and disturbance severity (Adámek et al., 2016; Etchells et al., 2020; Millar and Stephenson, 2015). Remote sensing provides an effective means to assess these recovery processes at landscape scales, but its reliability depends on how well spectral signals can be linked to ecological responses.

Monitoring post-fire recovery is fundamental for understanding the drivers and dynamics of vegetation regeneration, identifying ecosystems vulnerable to long-term degradation, and prioritizing post-fire management interventions (Gitas et al., 2012). Gitas et al. (2012) emphasize that assessment of ecosystem resilience requires long-term post-fire monitoring, defined not by a fixed time span but by repeated observations over multiple years to decades, depending on ecosystem type and recovery rates. After the abrupt spectral changes induced by fire, vegetation recovery is characterised by more gradual, landscape-scale spectral changes driven by the disappearance of charcoal and ash, shifts in the proportion of exposed bare soil, and a progressive increase in vegetative cover (Gitas et al., 2012).

Schepers et al. (2014) analysed post-fire vegetation response in a heterogeneous heathland landscape using hyperspectral remote sensing combined with field-based burn severity measurements. A key focus of their study was the challenge that different vegetation types exhibit distinct spectral responses to fire and early recovery.

Airborne hyperspectral imagery acquired shortly after the fire was used to calculate spectral indices (NDVI, NBR, MIRBI, and CSI). Vegetation response was assessed in the field using a modified Geometrically Structured Composite Burn Index (GeoCBI) adapted to heathlands. Relationships between spectral indices and field measurements were analysed both across all vegetation types and per vegetation type. While pooled analyses showed weak relationships, vegetation-type-specific analyses revealed much stronger correlations, with different indices performing best for different vegetation communities (Schepers et al., 2014). These results indicate that no single spectral index reliably captures post-fire vegetation response across mixed landscapes, emphasizing the need for vegetation-type stratification.

Similarly, Hislop et al. (2018) evaluated the performance of multiple spectral indices for assessing wildfire disturbance and post-fire recovery in sclerophyll forests using a long-term time-series approach. Rather than relying on a single pre- and post-fire image comparison, they analysed annual composites over a 25-year period, allowing them to compare post-fire spectral trajectories against the natural variability observed during the ten years preceding fire disturbance. Their results showed that greenness-based indices, such as NDVI, were highly sensitive to immediate fire disturbance but returned to pre-fire levels relatively quickly, indicating the rapid recovery of photosynthetic activity. In contrast, SWIR-based wetness indices, such as NBR, NDMI, TCW, and NBR2, showed longer recovery trajectories because they are more sensitive to vegetation moisture and forest structure. This shows that greenness indices may overestimate post-fire recovery when structural forest impacts persist (Hislop et al., 2018).

An alternative approach is presented by Gibson et al. (2022), who introduce the **post-fire stability index** (PFSI). Rather than relying on comparisons with pre-fire baseline conditions, the PFSI quantifies year-to-year changes in spectral indices following fire, beginning with the post-fire period. By focusing on temporal change between consecutive post-fire years and by comparing burned areas with nearby unburned areas at the same point in time using fire severity maps, this approach avoids uncertainties associated with pre-fire variability and interannual climatic effects.

The PFSI is derived from the NBR2, which is sensitive to changes in canopy structure and moisture content. For a given year t , the PFSI is defined as:

$$\text{PFSI}_{\text{NBR2}}(t) = \frac{\text{NBR2}_t - \text{NBR2}_{t-1}}{\sqrt{|\text{NBR2}_{t-1}/1000|}}. \quad (1.15)$$

1. Wildfire impacts and detection

By relying on SWIR information, NBR2 captures changes in vegetation structure and moisture rather than short-term greenness, making it useful for monitoring post-fire recovery trajectories (Gibson et al., 2022). The post-fire stability index (PFSI) builds on the assumption that stable vegetation shows small year-to-year spectral changes, while disturbed or recovering systems show larger fluctuations. Through field validation with plot-level vegetation data and satellite indices, Gibson et al. (2022) demonstrated that PFSI provides a robust and scalable approach for monitoring vegetation recovery without requiring pre-fire baselines. Together with Schepers et al. (2014), this highlights the importance of accounting for both vegetation-type-specific responses and temporal dynamics in post-fire remote sensing.

1.3.4 Satellites

Given the wide range of Earth observation satellites currently available, we need to identify those most suitable for wildfire detection and monitoring. An overview, based on European Space Agency (2025a), of the selected optical and radar satellite platforms, together with their main technical characteristics, is provided in Appendix Tables A.1 and A.2.

In a Belgian context, wildfires are typically limited in spatial extent (the fire perimeters analysed in this study had a mean area of 9.9 ha), and forested areas are relatively small and fragmented. As a result, satellites with high spatial resolution are required to adequately capture fire-affected areas. In addition, Section 1.3.1 demonstrated that effective wildfire detection relies on the availability of visible, red edge, near-infrared, and short-wave infrared bands, which are sensitive to changes in vegetation structure, chlorophyll content, and moisture conditions caused by fire.

Taking these considerations into account, Sentinel-2 was selected for this study as it provides freely accessible data with suitable spatial, spectral and temporal characteristics for wildfire monitoring. As this thesis focuses exclusively on optical remote sensing approaches, Sentinel-1 SAR data were not included in the analysis.

The Sentinel-2 mission operates in a sun-synchronous orbit at a mean altitude of approximately 786 km, with an inclination of about 98.62°. A sun-synchronous orbit ensures that the satellites pass over the same location on Earth at a consistent local solar time, maintaining nearly constant illumination conditions for all observations. This is essential for reliable temporal analysis, as it minimizes variations in solar angle and shadow effects (Copernicus Sentinel Wiki, nd).

Each Sentinel-2 satellite follows a 10-day repeat cycle. However, the constellation is designed with multiple satellites phased along the same orbit, resulting in a combined revisit time of approximately 5 days at the equator (Copernicus Sentinel Wiki, nd).

Originally, the constellation consisted of Sentinel-2A and Sentinel-2B operating together. With the launch of Sentinel-2C, Sentinel-2A is being progressively replaced, while Sentinel-2B continues to operate. This renewal strategy ensures operational continuity while maintaining long-term data availability (Copernicus Sentinel Wiki, nd).

The Sentinel-2 mission provides systematic and consistent coverage of terrestrial and coastal environments between 56°S and 82.8°N. This includes continental land surfaces, inland water bodies, coastal waters up to 20 km from the shoreline, all islands larger than 100 km², all European Union islands regardless of size, and the Mediterranean Sea and other closed seas (Copernicus Sentinel Wiki, nd).

An overview of the Sentinel-2 MultiSpectral Instrument (MSI) bands, including their spectral characteristics, spatial resolution, and main applications, is provided in Appendix Table A.3.

The Scene Classification Layer (SCL) is a key component of the Sentinel-2 Level-2A processing chain within the Copernicus Programme. It is generated from Level-1C Top-Of-Atmosphere (TOA) reflectance data and provides a pixel-wise classification of surface and atmospheric conditions. The primary purpose of the SCL is to identify features such as clouds, cloud shadows, vegetation, bare soil, water, and snow or ice (Copernicus Sentinel Wiki, nd). The corresponding scene classification labels can be found in Appendix Table A.4.

2. Materials and methods

2.1 Study areas

Four recent wildfire events were selected as case studies: Arlon (18 March 2025; 10.77 ha), Clinge (23 March 2025; 2.4 ha), Houffalize (12 April 2025; 5.2 ha), and Maasmechelen (22 May 2025; 21.23 ha). At these four sites, satellite-based wildfire detection and vegetation recovery monitoring was carried out. Together, these study areas represent a range of environmental conditions, from heathlands in Maasmechelen to forested landscapes in Clinge, Houffalize, and Arlon. Soil properties and vegetation composition were only assessed in Clinge; therefore, this site is described in greater detail below.

The Clingse Bossen are a forested subarea of the Waterwinbossen in eastern Zeeuws-Vlaanderen (the Netherlands), located near the Dutch–Belgian border. The area consists primarily of mixed woodland (deciduous and declining coniferous stands), interspersed with small clearings and grasslands, and is intersected by infiltration canals. The area is owned by the drinking water company Evides, while a large part of the land is managed by Stichting Het Zeeuwse Landschap through a long-term lease agreement. The primary function of the area is drinking water extraction, while nature conservation and recreation are secondary and must not negatively affect water production. Geomorphologically, the area lies on a Pleistocene aeolian sand ridge, which is exceptional in the province of Zeeland. The soils are predominantly nutrient-poor, lime-free sandy soils. These soils originated from wind-deposited sands during the last glacial period and were further modified by historical agricultural practices (Calle et al., 2023).

2.1.1 2025 Wildfire Clinge

On 23 March, a forest fire affected approximately 2.4 hectares of the Clingse Bossen. The fire mainly burned already dead stands of *Picea abies* (Norway spruce). These trees had previously died due to drought stress and subsequent infestation by the bark beetle *Ips typographus* (Stichting Het Zeeuwse Landschap, 2025).

The fire was relatively low in intensity, as it moved rapidly through the study area and the visibly burned layer in the soil profile was mainly limited to the litter layer. Although the fire was eventually brought under control, local flare-ups and smouldering persisted afterwards (VRT NWS, 2025). Therefore, the classification of the fire as low intensity should be interpreted with caution, since prolonged smouldering may still have caused localized soil heating.

2.1.2 Sampling design and data collection

Vegetation surveys and soil sampling were conducted to monitor post-fire ecological dynamics within the study area. The spatial distribution of all sampling plots is shown in Figures 2.1 and 2.2.

Within the burned area, the sampling design followed two transects. The first transect extended from plot A towards plot C and was oriented approximately parallel to the main direction of fire spread, as the fire originated near plot A before spreading northward through the study area under the influence of strong winds. A second transect, extending from plot C towards plot E, was positioned approximately perpendicular to the main fire direction in order to capture spatial variability across the burned zone. Burned soil sampling locations were spaced at intervals of approximately 20 m.

Unburned soil samples were collected outside the fire perimeter in nearby areas where spruce vegetation was still present. These locations were selected to ensure soil and vegetation conditions that were as comparable as possible to those within the burned plots.

Figures 2.1 and 2.2 also distinguish different management zones within the study area. The red zone represents unmanaged areas where *Prunus serotina* was not removed. In the hatched zone, *Prunus serotina* had been removed as part of vegetation management. The blue zones indicate areas where new trees had already been replanted following the fire.

2.1.2.1 Vegetation surveys

Vegetation surveys were carried out on a monthly basis throughout the study period (Appendix Table A.5). During each survey, all plant species present within each plot were identified as accurately as possible to species level. In addition, the coverage of each species was visually estimated.

2.1.2.2 Soil sampling

Soil samples were collected on 18 April, 8 August, and 26 November 2025 to assess changes in soil properties following the fire. Six sampling locations were established within the burned area, complemented by three reference locations outside the fire perimeter (Figure 2.2). This design allowed direct comparisons between burned and unburned conditions, thereby facilitating the assessment of fire effects on vegetation and soil properties.

At each sampling location, six samples were collected just below the litter layer at an approximate depth of 7 cm, ensuring consistency across sampling events. These included three undisturbed soil samples, in which the natural soil structure was preserved during collection, and three disturbed soil samples. The undisturbed samples were used for the analysis of physical soil properties, whereas the disturbed samples were used for the analysis of chemical soil properties.

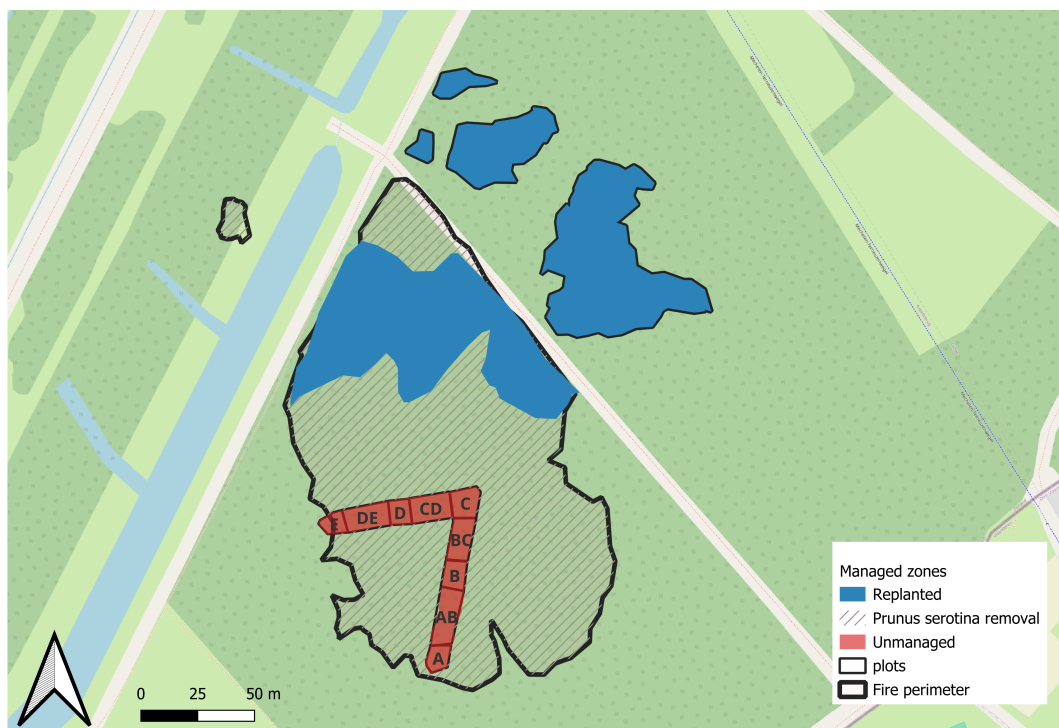


Figure 2.1: Overview of the study area in the Clingse Bossen, showing the fire perimeter, managed zones, and the spatial distribution of sampling plots.

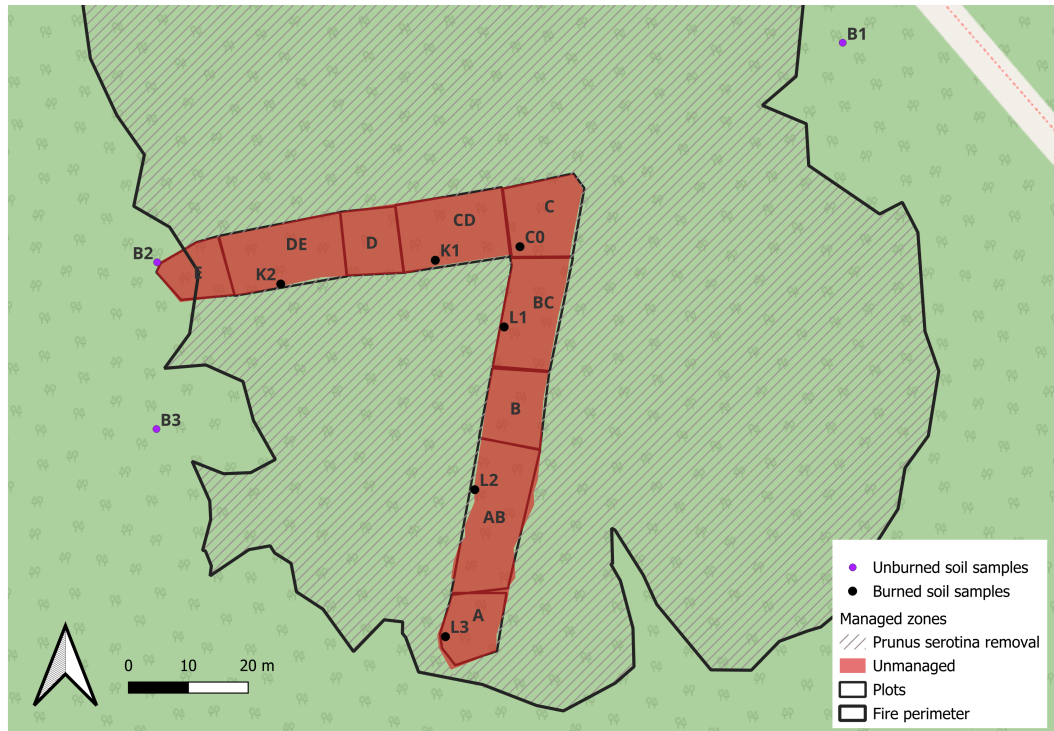


Figure 2.2: Detailed overview of sampling plots within the burned area, including locations of vegetation surveys and soil sampling points. Black dots indicate burned soil samples, while purple dots represent unburned reference samples.

2.2 Soil analysis

2.2.1 Physical properties

2.2.1.1 Bulk density & gravimetric soil moisture

Soil bulk density is determined by collecting a soil sample of known volume, drying it to remove all moisture, and weighing the resulting dry mass (Weil and Brady, 2017). For this purpose, Kopecky rings with a nominal volume of 100 cm³ were used. Because repeated use can slightly deform the rings, their exact volume was re-determined for each ring by measuring the height and diameter. Approximately 50 g of each soil sample was oven-dried at 105 °C for at least 12 hours. By comparing the mass before and after drying, gravimetric soil moisture content was calculated. Subsequently, the dry mass and the known ring volume were used to calculate the bulk density of the original soil sample.

2.2.1.2 Water repellency

Soil water repellency was assessed using the water drop penetration time (WDPT) test, following the methodology described by Dekker and Ritsema (2009). Undisturbed soil samples were collected in the field and subsequently brought to field capacity under laboratory conditions, corresponding to a matric potential of approximately -10 kPa.

The WDPT test was performed on field-moist samples after equilibration. Three drops of distilled water were placed on the soil surface using a standard dropper, and the time required for complete infiltration of each drop was recorded. The classification of soil water repellency based on WDPT values is presented in Table 2.1.

Table 2.1: Classification of soil water repellency based on WDPT (Dekker and Ritsema, 2009).

Class	WDPT	Classification
0	< 5 s	Wettable (non-water repellent)
1	5 – 60 s	Slightly water repellent
2	60 – 600 s	Strongly water repellent
3	600 – 3600 s	Severely water repellent
4	1 – 3 h	Extremely water repellent
5	3 – 6 h	Extremely water repellent
6	> 6 h	Extremely water repellent

2.2.2 Chemical properties

All soil samples used for chemical analyses were oven-dried at $70-80^{\circ}\text{C}$ and sieved to a particle size of < 2 mm.

2.2.2.1 Soil organic matter

SOM content was determined according to the CMA/2/IV/1 method. A sample was weighed into a pre-weighed porcelain crucible using an analytical balance.

The sample was dried in a ventilated oven at 105°C for a minimum of 16 hours until constant mass was reached. After drying, the crucible was cooled in a desiccator and weighed to determine the dry mass.

For the determination of organic matter content, the dried sample was subsequently combusted in a muffle furnace at 550°C for 4 hours. After ignition, the crucible was again cooled in a desiccator and weighed to obtain the ash mass.

Dry matter content was calculated from the mass difference before and after drying, while organic matter content was determined as loss-on-ignition at 550°C . Results were expressed on a relative mass basis (%).

2.2.2.2 Total C & total N

Total C and total N in soil samples were determined using a PrimacsSNC100 analyser based on high-temperature combustion followed by gas analysis. Both total C and total N include organic and inorganic fractions present in the soil.

Soil samples were combusted in a pure oxygen atmosphere at 1200 °C. During combustion, carbon present in the sample was converted to carbon dioxide (CO₂), while nitrogen compounds were oxidised to nitrogen oxides (NO_x).

The resulting gas mixture was transported by a carrier gas through the system. A portion of the combustion gas was directed to an infrared detector, where the CO₂ concentration was measured to quantify total carbon content.

The remaining gas fraction was carried by helium through a copper reduction oven, where nitrogen oxides were reduced to molecular nitrogen (N₂). Subsequently, the gas stream passed through scrubbers to remove CO₂ and water vapour. The purified gas was then analysed using a thermal conductivity detector to determine the nitrogen content.

2.2.2.3 Cation exchange capacity

The CEC of the soil was determined using an ammonium saturation method as described by Van Ranst et al. (1999). The exchange complex was subsequently saturated with ammonium ions by repeated extraction with a 1 M ammonium acetate (NH₄OAc) solution at pH 7. During this step, all exchangeable base cations (such as Ca²⁺, Mg²⁺, K⁺, and Na⁺) were displaced and replaced by NH₄⁺ ions. After saturation, excess ammonium acetate was removed by washing the soil with alcohol to eliminate unbound NH₄⁺ without affecting the adsorbed fraction. The adsorbed ammonium ions were then displaced by extraction with a neutral salt solution, 1 M KCl, releasing NH₄⁺ into the solution. The amount of displaced ammonium was subsequently quantified by distillation using an automatic Vapodest system. The CEC was calculated based on the amount of ammonium released per unit mass of soil and expressed in meq/100 g. This method provides a measure of the total number of negatively charged exchange sites in the soil under standardized pH conditions.

2.2.2.4 Soil pH

Soil pH was determined in a soil–water suspension according to ISO 10390:1994. A suspension was prepared by mixing soil with deionized water at a fixed ratio. The mixture was stirred thoroughly and allowed to equilibrate for a defined period. The pH of the suspension was then measured using a calibrated glass electrode pH meter. Calibration was performed using standard buffer solutions (pH 7.0) prior to measurement.

2.2.3 Statistical analysis

Normality of the data was assessed using the Shapiro–Wilk test, and logarithmic transformations were applied where appropriate to improve normality. Variables that did not meet the assumption of normality were analysed using non-parametric statistical tests. Soil water repellency were ordinal data and was therefore analysed using non-parametric methods.

To evaluate the effect of fire at each sampling date, burned and unburned areas were compared using independent-samples Welch's t-tests for normally distributed variables and Mann–Whitney U tests for non-normally distributed or ordinal variables.

To assess temporal variation in fire effects among the three sampling dates, the fire effect was first quantified for each sampling date by calculating the difference between burned and unburned plots. This was done by subtracting the mean value of the corresponding unburned plots from each burned plot value.

To assess whether the magnitude of the fire effect changed over time, differences among sampling dates were analysed using one-way analysis of variance (ANOVA) for normally distributed variables and the Kruskal–Wallis test for non-normally distributed or ordinal variables. When significant differences were detected, post hoc comparisons were performed using Duncan's multiple range test for parametric data and Dunn's test with Bonferroni correction for non-parametric or ordinal data.

2.3 Vegetation surveys

Vegetation surveys were conducted repeatedly throughout the study period (A.5) to monitor temporal changes in plant community composition and structure. Sampling was performed at regular intervals, and during each sampling campaign, plant species were identified as accurately as possible together with their corresponding vegetation coverage across all plots. For species that became highly abundant during later stages of the monitoring period, estimating the surface area of individual plants was not longer feasible. In these cases, the percentage coverage of the species within the plot was visually estimated instead. In addition, the recorded species data were regularly compared with an independent vegetation inventory dataset collected by a field ecologist (Lucien Calle) from Het Zeeuwse Landschap, who frequently visited the study area and also surveyed vegetation outside the burned zone. These records provided a reference framework that could be used to validate uncertain identifications and compare observed species occurrences within the burned area.

Species richness was calculated at two levels: (i) per plot per sampling date, and (ii) across all plots combined for each sampling date.

Due to the early developmental stage and limited morphological characteristics of some individuals during the sampling campaigns, species-level identification was not always possible with sufficient certainty. Taxa that could only be identified to genus level were therefore retained as separate entities, since these records could potentially represent multiple species. Consequently, observations recorded as *Senecio* spp. and *Senecio vulgaris*, for example, were treated as distinct taxa in the analyses.

For the plot-level richness, species richness was calculated separately for each plot by counting the number of unique taxa recorded within that individual plot during each sampling campaign. For the date-level richness analysis, species names from all plots sampled on the same date were pooled. Total richness was then calculated as the number of unique species across all plots combined.

To quantify vegetation diversity at the plot level, the Shannon diversity index (H) was calculated as:

$$H = - \sum_{i=1}^S p_i \ln(p_i) \quad (2.1)$$

where p_i is the relative coverage of taxon i , calculated by dividing the coverage of that taxon by the total coverage of all recorded taxa in the same plot.

To quantify the evenness of vegetation coverage among recorded taxa within each plot, Pielou's evenness (J) was calculated as:

$$J = \frac{H}{\ln(S)} \quad (2.2)$$

where S is the number of recorded taxa. When no taxa were present, both H and J were set to zero. When only one taxon was present, evenness was also set to zero, as evenness is not defined for $S = 1$.

Bare ground was not included in the calculations. Therefore, evenness reflects the distribution of coverage among recorded taxa only and does not account for the proportion of unvegetated surface.

Shannon diversity and Pielou's evenness were also calculated across all plots combined for each sampling date. For this analysis, all taxon-coverage records from all plots were pooled per date, and coverage values were summed per taxon before calculating the relative coverage values.

2.4 Wildfire detection

All remote sensing analyses were performed in Python using Jupyter Notebooks on the [Terrascope platform](#), provided by VITO. Terrascope offers cloud-based notebook environments and direct access to Copernicus Earth Observation data, including Sentinel-2 imagery. Satellite data retrieval and processing were carried out through an OpenEO connection to the Copernicus Data Space Ecosystem.

Sentinel-2 Level-2A surface reflectance imagery was used throughout the study. For each study site, wildfire perimeter polygons were loaded as vector data and transformed to WGS84. The fire perimeters were used to spatially constrain the analysis by defining an area of interest (AOI) based on the perimeter bounding box with an additional buffer of 0.001 degrees in all directions, corresponding approximately to 100 m. For Clinge, where multiple perimeter polygons were available, the AOI was based on the largest polygon.

Clouds were removed using the Sentinel-2 Scene Classification Layer (SCL). The cloud masking workflow was adapted from Copernicus Data Space Ecosystem (2025). Pixels classified as cloud shadow (SCL class 3), medium-probability cloud (class 8), high-probability cloud (class 9), and cirrus (class 10) were masked prior to compositing. The cloud masks were additionally smoothed using a Gaussian kernel. Sentinel-2 composites were generated for predefined temporal intervals using OpenEO temporal reducers, which selected either the earliest ('first') or latest ('last') valid observation within each interval.

2.4.1 Burned area detection

Pre-fire and post-fire Sentinel-2 composites were generated for each burned area using predefined temporal intervals. For each study site, a pre-fire interval of one month before the wildfire event and a post-fire interval of one month after the wildfire event were defined. The pre-fire composite was generated using the 'last' temporal reducer, while the post-fire composite was generated using the 'first' temporal reducer. An overview of the evaluated indices is provided in Table 2.2.

Table 2.2: Burned area indices and corresponding Sentinel-2 bands used in this study.

Index	Formula	Sentinel-2 bands used
NDVI	$NDVI = \frac{NIR - R}{NIR + R}$	B08 (NIR, 842 nm) B04 (Red, 665 nm)
NDVI red edge	$NDVI_{red\ edge} = \frac{NIR - RE}{NIR + RE}$	B08 (NIR, 842 nm) B05 (Red edge, 705 nm)
NBR	$NBR = \frac{NIR - SWIR}{NIR + SWIR}$	B08 (NIR, 842 nm) B12 (SWIR2, 2190 nm)
NBR+	$NBR+ = \frac{SWIR - NIR - G - B}{SWIR + NIR + G + B}$	B12 (SWIR2, 2190 nm) B08 (NIR, 842 nm) B03 (Green, 560 nm) B02 (Blue, 490 nm)
BAI	$BAI = \frac{1}{(0.1 - R)^2 + (0.06 - NIR)^2}$	B04 (Red, 665 nm) B08 (NIR, 842 nm)
NBR2	$NBR2 = \frac{SWIR1 - SWIR2}{SWIR1 + SWIR2}$	B11 (SWIR1, 1610 nm) B12 (SWIR2, 2190 nm)
NDSWIR	$NDSWIR = \frac{SWIR_1 - NIR_{narrow}}{SWIR_1 + NIR_{narrow}}$	B11 (SWIR1, 1610 nm) B8A (Narrow NIR, 865 nm)

For each index, pre-fire and post-fire images were generated, after which a difference image was calculated as:

$$\Delta Index = \text{Pre-fire index} - \text{Post-fire index}$$

Burned and unburned pixels were separated using the fire perimeter. Kernel density functions, which provide smoothed estimates of the underlying pixel-value distributions, were fitted to both pixel-value distributions. The threshold was determined from the intersection of the resulting density curves. This threshold was applied to create a binary burned area mask, after which isolated pixels were removed to

reduce classification noise. A ground-truth raster mask was generated from the mapped fire perimeter and compared pixel-by-pixel with the classified burn mask. From the resulting confusion matrix, precision, recall, and the F1-score were calculated. The F1-score was used as the primary performance metric because it combines precision and recall into a single measure:

$$F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (2.3)$$

where precision measures the proportion of predicted burned pixels that are correctly classified as burned, while recall measures the proportion of reference burned pixels that are successfully detected by the classification.

2.4.2 Vegetation recovery

2.4.2.1 Post-fire vegetation recovery dynamics using the PFSI in Clinge

Post-fire vegetation recovery was analysed using the Post-Fire Stability Index (PFSI), calculated from consecutive Sentinel-2 NBR2 composites. To retain sufficient observations across all temporal intervals, SCL class 10 (cirrus clouds) was not masked, and no Gaussian smoothing was applied.

PFSI was calculated as:

$$PFSI = \frac{NBR2_t - NBR2_{t-1}}{\sqrt{\left| \frac{NBR2_{t-1}}{1000} \right|}}$$

where t represents the current interval and $t - 1$ the previous interval.

To link the PFSI values as accurately as possible to the field measurements, the same temporal intervals as the vegetation field campaigns were used. An overview of these intervals is provided in Appendix Table A.6. Within each interval, the 'last' reducer was applied in order to select the most recent valid Sentinel-2 observation and therefore obtain imagery as close as possible to the field measurements. The PFSI value for each vegetation plot was calculated by identifying all raster pixels intersecting the plot polygon and computing the mean value of these intersecting pixels, which consisted of either two or four raster pixels depending on the plot. These average PFSI values could subsequently be compared with the change in vegetation coverage within each plot between consecutive field campaigns.

2.4.2.2 Seasonal post-fire recovery dynamics using the PFSI

The seasonal PFSI analysis was performed for all study sites using meteorological seasons as temporal intervals. The first post-fire spring interval extended from the fire date to 1 June 2025, corresponding to 18 March–1 June for Arlon, 23 March–1 June for Clinge, 12 April–1 June for Houffalize, and 22 May–1 June for Maasmechelen. Subsequent intervals were defined as summer 2025 (1 June–1 September), fall 2025 (1 September–1 December), winter 2025 (1 December–1 March 2026), and spring 2026 (1 March–1 June 2026).

For the Clinge and Maasmechelen study sites, SCL class 7 (unclassified pixels) was additionally included in the cloud mask, as these pixels introduced noise in the resulting imagery.

The first post-fire interval used the 'first' reducer, while all subsequent seasonal intervals used the 'last' reducer to represent end-of-season vegetation conditions. For Maasmechelen, no valid image was available during the short spring 2025 interval. To nevertheless obtain a summer 2025 PFSI image, an additional image representing the beginning of the summer season was selected.

2.4.2.3 One-year post-fire recovery dynamics using the PFSI

A one-year post-fire PFSI analysis was performed for all study sites to quantify net spectral recovery between the earliest and latest valid observations within the first post-fire year.

3. Results and discussion

3.1 Soil analysis

By comparing burned and unburned areas across the three sampling campaigns, we assess both the immediate and temporal effects of fire on soil conditions. As a first step in the analysis, the assumption of normality was evaluated. Results of the Shapiro–Wilk normality test are presented in Table 3.1.

Table 3.1: Results of the Shapiro–Wilk normality tests. Bold p-values indicate variables meeting the assumption of normality.

Variable	Transformation	p-value
Bulk density	None	0.0228
Gravimetric soil moisture	None	0.4055
Soil organic matter	Log-transformed	0.2046
Total C	Log-transformed	0.0552
Total N	None	0.1601
Cation exchange capacity	Log-transformed	0.3234
Soil pH	None	0.0002

3.1.1 Temporal analysis

Temporal variation in fire effects, expressed as differences between burned and unburned plots, is shown for all measured soil properties in Appendix Figures A.1–A.8. Table 3.2 summarizes the significant differences identified by the post-hoc analysis. For most soil properties, the burned–unburned differences differed significantly between April and August. In contrast, differences between August and November were generally no longer significant, except for CEC. This pattern indicates that fire effects were pronounced shortly after the wildfire but diminished over time for most soil properties (see Section 3.1.2 for a more detailed analysis). The difference between April and November remained significant for most variables, with the exception of CEC and pH. Bulk density showed no significant temporal variation, reflecting its relative stability over time. As the overall Kruskal–Wallis test was not significant, no post-hoc analysis was performed for this variable. Complete results of the ANOVA and Kruskal–Wallis tests are provided in Appendix Table A.8.

Table 3.2: Post-hoc analysis of burned–unburned differences. Significant p-values are shown in bold.

Property	Post-hoc test	04-18 vs 08-08	08-08 vs 11-26	04-18 vs 11-26
Bulk density	/	/	/	/
Water repellency	Dunn (Bonferroni)	9.28×10^{-7}	1.0000	4.47×10^{-5}
Soil moisture	Duncan	0.0067	0.4514	0.0336
SOM	Duncan	0.0015	0.7972	0.0023
Total C	Duncan	0.0059	0.4342	0.0322
Total N	Duncan	0.0075	0.6238	0.0197
CEC	Duncan	0.0009	0.0319	0.1581
pH	Dunn (Bonferroni)	0.0072	0.2112	0.2676

3.1.2 Post-fire soil properties in burned and unburned areas

In the figures presented below, p-values indicate significant differences between burned and unburned areas within each sampling date. The absence of a p-value indicates that no significant difference was detected. The letters above the boxplots correspond to the temporal analysis presented in Section 3.1.1.

3.1.2.1 Bulk density

Figure 3.1 shows the temporal evolution of bulk density in burned and unburned areas across the three sampling campaigns. In April, bulk density was significantly lower in the burned area than in the unburned area ($p = 0.031$). The unburned plots showed a slightly higher median and lower variability, while the burned plots exhibited a wider spread and generally lower values. In August and November, no significant differences between burned and unburned areas were observed. Although the visual differences between areas appeared to decrease over time, the overall temporal analysis did not indicate a significant change in the burned–unburned difference across the sampling campaigns. This suggests that bulk density remained relatively stable over the study period.

While our study showed a significant decrease in soil bulk density shortly after the fire, many studies report an increase. Magomani and van Tol (2018), drawing on the work of Certini (2005), attribute this increase to the clogging of soil pores by ash. In the same context, and based on Giovannini et al. (1988), Magomani and van Tol (2018) further explain that burning can destabilize soil aggregates through the loss of organic binding agents, resulting in reduced macroporosity and consequently higher bulk density.

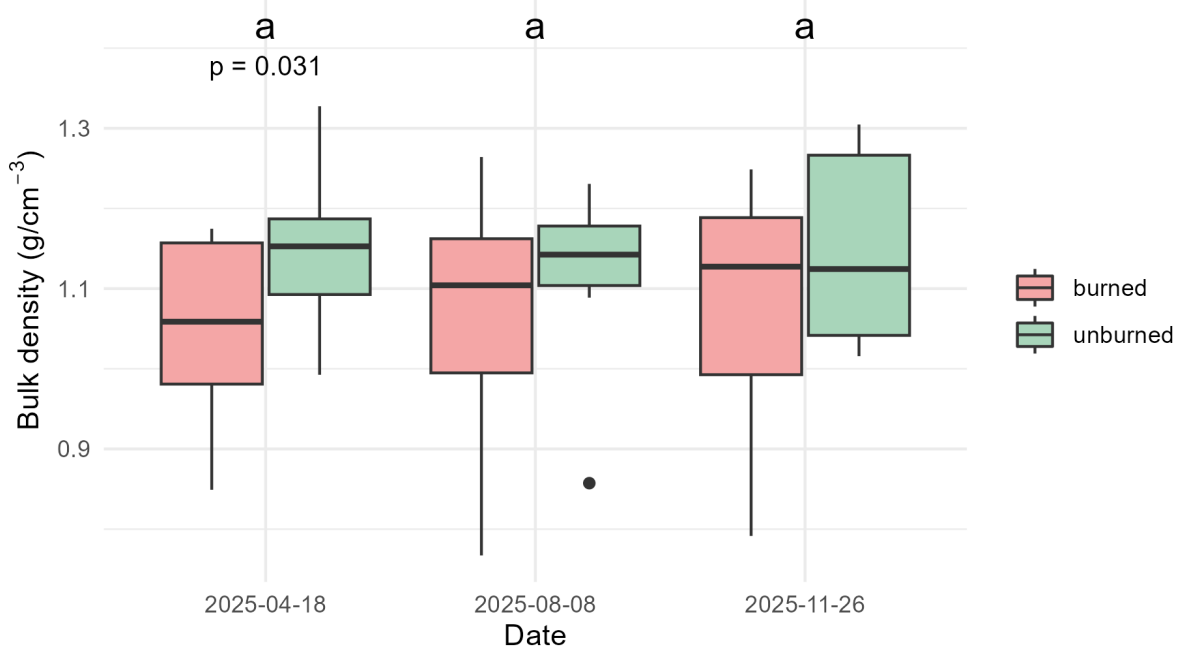


Figure 3.1: Bulk density over time in burned (red) and unburned (green) areas. Different letters indicate significant changes in the burned–unburned difference between sampling dates, whereas p-values indicate whether burned and unburned areas differed significantly within each sampling date.

Our observations are more consistent with Chief et al. (2012), who found no significant changes in SOM after a low-intensity prescribed burn, in agreement with our results (Section 3.1.2.3), and an initial decrease in bulk density. This decrease was attributed to the expansion of vaporized soil water during heating, which disrupts aggregates and temporarily increases pore space. Subsequent compaction and settling gradually restore bulk density to pre-fire levels. Brye (2006) also reported a long-term decrease in bulk density under annual burning, linked to increased root biomass and SOM inputs. As no significant changes in SOM were observed in our study, this last mechanism is unlikely to explain our results.

3.1.2.2 Soil water repellency & gravimetric soil moisture

For the April sampling campaign, one sample from the unburned area was excluded from the water repellency analysis because its water drop penetration time (> 1 h) strongly differed from the two other samples from the same location (≈ 1 min). It was therefore classified as class 4, whereas the other samples belonged to classes 1 and 2. As this discrepancy likely resulted from sample handling (e.g., surface smearing), the value was considered unrepresentative and removed. The class 1 sample was reassigned to class 2, as the difference between both classes was only a few seconds.

Figure 3.2 presents the temporal evolution of soil water repellency in burned and unburned areas.

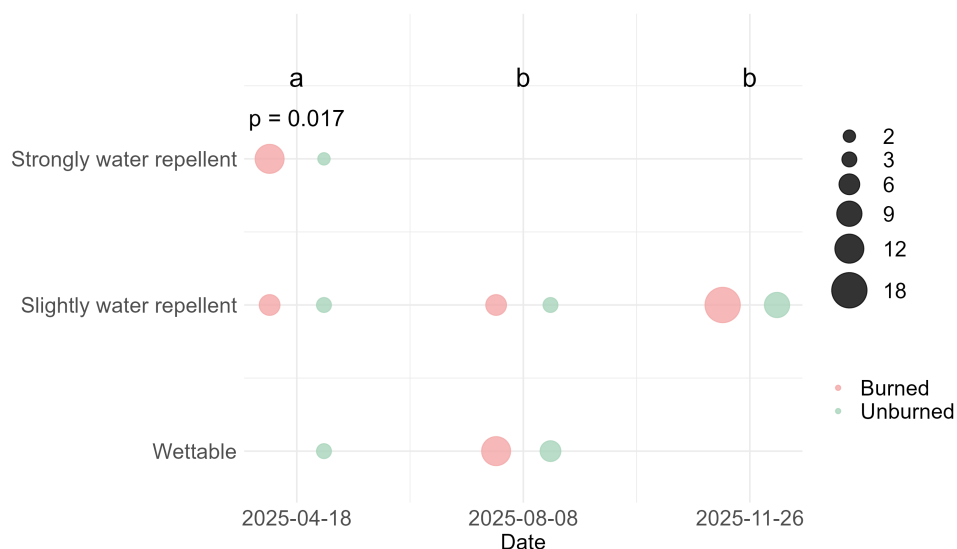


Figure 3.2: Water repellency classes over time in burned (red) and unburned (green) areas. Bubble sizes represent the number of observations. See Figure 3.1 for explanation.

In April, the burned area contained a significantly higher proportion of strongly water repellent samples than the unburned area ($p = 0.017$). This sampling campaign also differed significantly from both August and November, whereas no significant differences were observed between the latter two dates. By August, strongly water repellent samples had disappeared, with most samples classified as wettable or slightly water repellent, and no significant differences remained between burned and unburned areas. In November, slightly water repellent conditions dominated both areas. Overall, these results suggest that fire initially increased soil water repellency, but that this effect diminished over time.

Figure 3.3 presents the temporal evolution of gravimetric soil moisture (%) in burned and unburned areas. In April, gravimetric soil moisture was similar between burned and unburned areas. In August, soil moisture was significantly higher in the burned area ($p = 0.021$), while in November values remained slightly higher but no longer differed significantly. Soil moisture differed significantly between April and both August and November, whereas no significant difference was observed between the latter two sampling periods. Burned areas generally retained higher moisture levels during the later sampling campaigns.

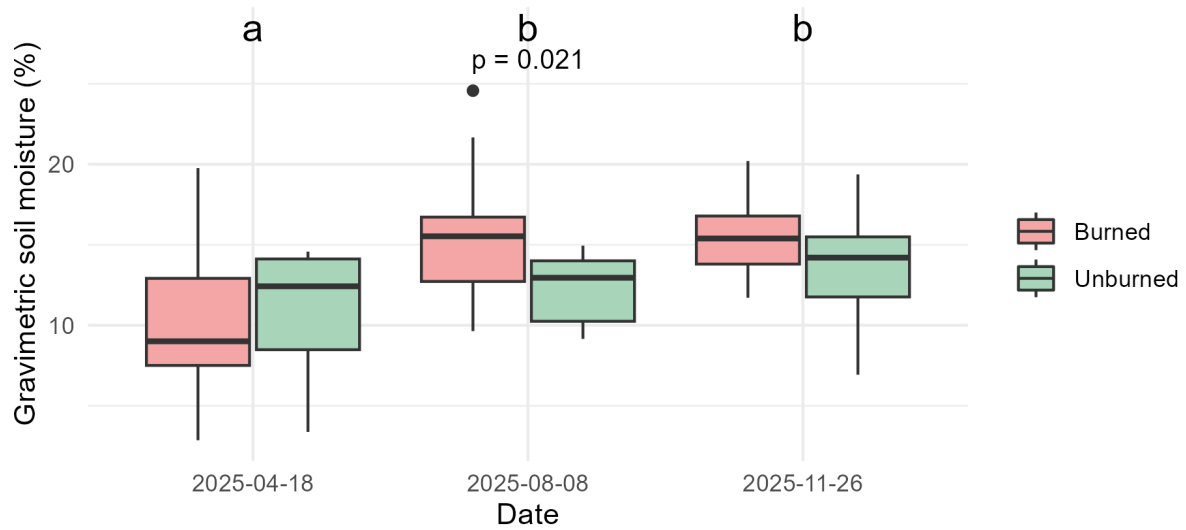


Figure 3.3: Gravimetric soil moisture over time in burned (red) and unburned (green) areas. See Figure 3.1 for explanation.

The results indicate a clear relationship between gravimetric soil moisture and water repellency, with lower soil moisture generally associated with stronger water repellency. During the first sampling campaign, soil moisture was low in both burned and unburned plots, and strongly water repellent conditions were also observed in some unburned plots. This was likely related to the exceptionally dry conditions preceding sampling, with only 40.5 mm of rainfall recorded between February 2025 and 18 April 2025 (Weather Underground, 2026). The resulting topsoil drying likely enhanced water repellency and may explain why no significant differences in soil moisture were observed between treatments despite significant differences in water repellency.

These observations are consistent with Stoof et al. (2011), who showed that water repellency increases as soil moisture decreases, even in unburned soils. The same study suggested that vegetation loss after fire increases soil temperatures and evaporation, resulting in drier surface soils. Stoof et al. (2011) similarly reported significant differences in water repellency following fire, but not in soil moisture.

Besides soil moisture effects, water repellency may also have been enhanced by hydrophobic organic compounds remaining in ash. Rajapaksha et al. (2025) showed that compounds such as C–H, C=O, COO[−], C–O, and C–O–C can persist after low- to moderate-intensity burning and form hydrophobic coatings on ash particles, potentially contributing to the elevated water repellency observed in the burned plots.

3.1.2.3 Soil organic matter

Figure 3.4 presents the temporal evolution of soil organic matter (SOM) (%) in burned and unburned areas.

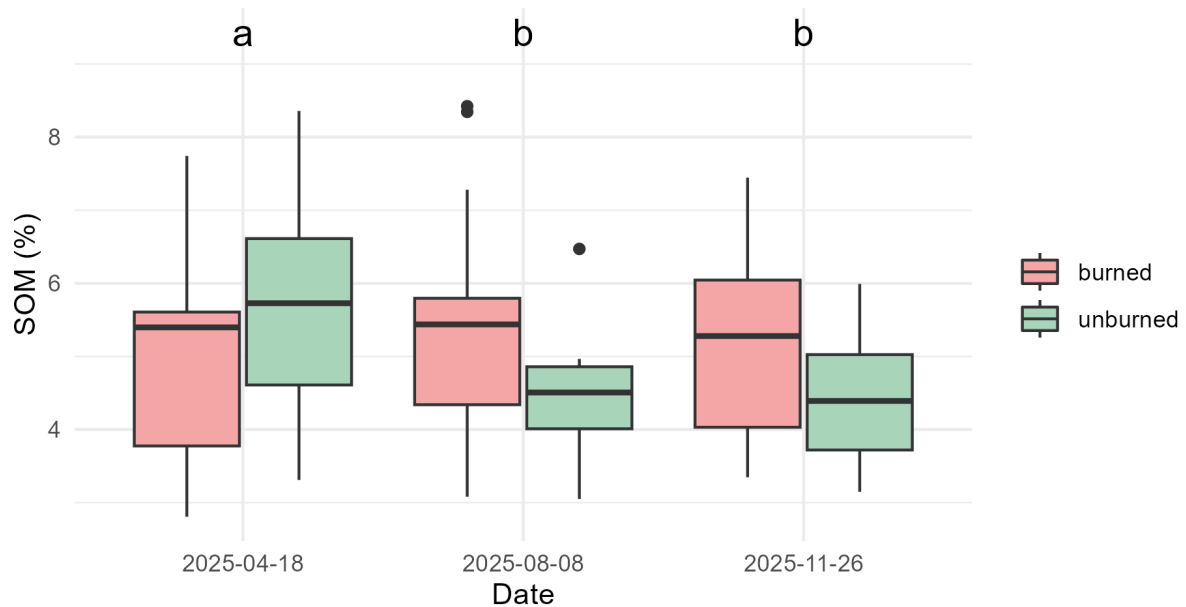


Figure 3.4: SOM over time in burned (red) and unburned (green) areas. See Figure 3.1 for explanation.

In April, SOM values were generally higher in the unburned area, whereas in August and November they were higher in the burned area. Variability was relatively high in both areas in April and November, while August showed a narrower distribution in the unburned area, despite the presence of an outlier. No significant differences between burned and unburned areas were detected within any sampling campaign. However, the temporal analysis showed that the burned–unburned difference in April differed significantly from that in both August and November.

According to Osman (2018), sandy soils generally accumulate and retain less SOM due to their low clay content, high aeration, and enhanced oxidation rates. The effects of fire on SOM are highly variable and depend on factors such as fire type, intensity, and topography (González-Pérez et al., 2004). In a meta-analysis, Johnson and Curtis (2001) found lower soil carbon contents after prescribed fires but higher carbon stocks after wildfires, which they attributed to charcoal formation. Similarly, Inbar et al. (2014) reported higher organic matter contents in burned than in unburned soils. Although no statistically significant differences in SOM were detected between burned and unburned plots in our study, SOM values tended to be slightly higher in burned plots during August and November, which is consistent with these findings.

3. Results and discussion

In contrast, immediately after the fire in April, SOM values were generally higher in the unburned plots, possibly reflecting the combustion of litter and surface organic matter in the burned plots (Dzwonko et al., 2015). However, this interpretation should be treated with caution, as the median SOM of the burned plots changed little over time and the apparent difference in April was mainly associated with the broad distribution of values in the unburned plots.

3.1.2.4 Total C

Figure 3.5 presents the temporal evolution of total C (%) in burned and unburned areas.

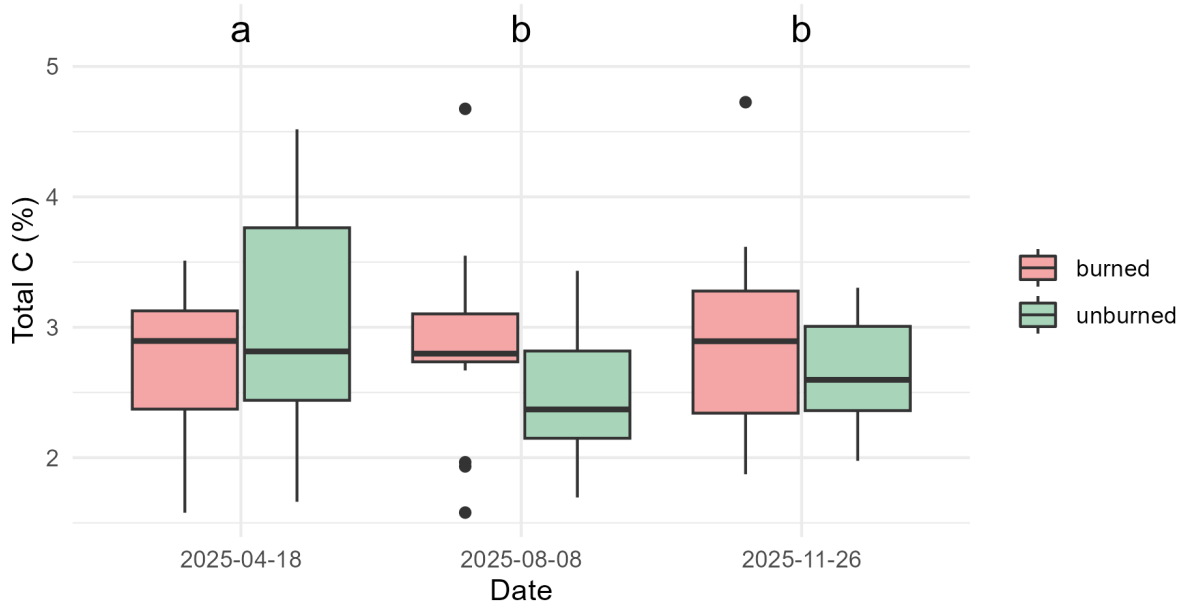


Figure 3.5: Total C over time in burned (red) and unburned (green) areas. See Figure 3.1 for explanation.

Although no significant differences were observed between burned and unburned areas, some patterns were apparent. Total C values were comparable between areas in April, although variability was greater in the unburned area. In August and November, total C values in the unburned area tended to be lower than in April, whereas values in the burned area remained relatively stable throughout the study period. The temporal analysis showed that April differed significantly from both August and November, while no significant difference was detected between the latter two sampling campaigns.

The contribution of inorganic carbon was likely limited. Santín et al. (2012) reported that inorganic C accounts for only about 3% of total ash weight in dark ash, which is typically associated with low-severity fires such as the one in Clinge. This interpretation is supported by the observation that total C values were often approximately half of the measured SOM values, consistent with the general assumption that soil organic carbon constitutes about 50% of SOM (Weil and Brady, 2017).

The effect of fire on total C remains variable in the literature. Muqaddas et al. (2015) reported a decrease in total C following low-intensity burning, attributed to CO₂ emissions from biomass combustion. In contrast, Alcañiz et al. (2016) observed an increase after low-severity fires due to black carbon formation and ash incorporation, which may explain the slightly higher total C values observed in the burned area during August and November. Despite these potential processes, no significant changes in total C were detected in the present study.

3.1.2.5 Total N

Figure 3.6 presents the temporal evolution of total N (%) in burned and unburned areas.

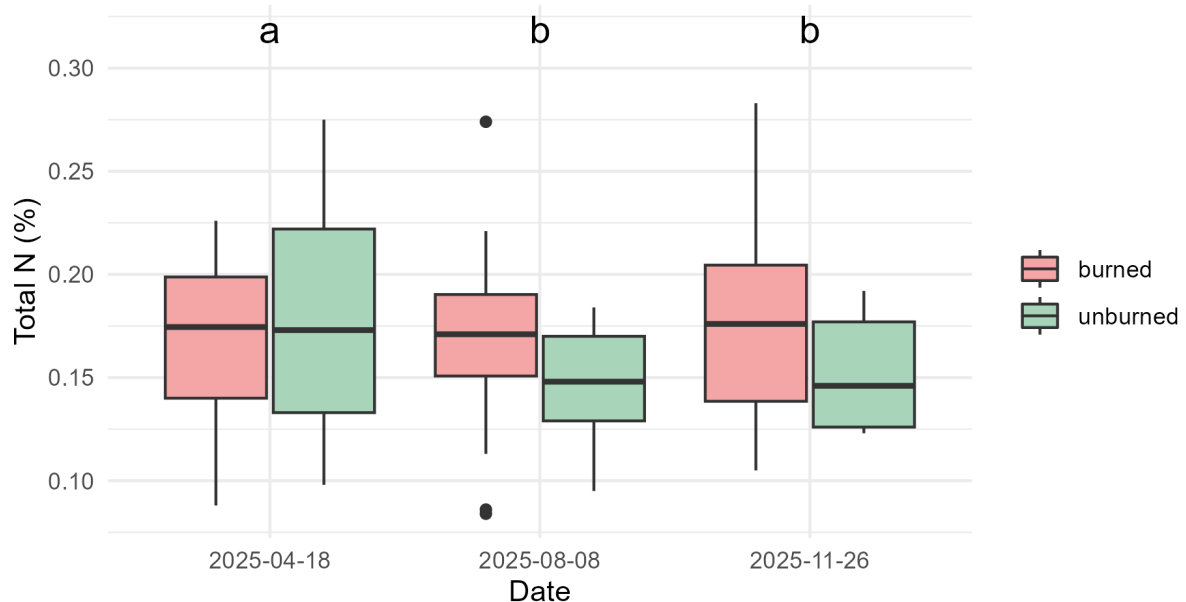


Figure 3.6: Total N over time in burned (red) and unburned (green) areas. See Figure 3.1 for explanation.

Total N values were similar between burned and unburned zones throughout the study period, and no significant differences between zones were detected within any sampling campaign. However, the temporal analysis showed that the burned–unburned difference in April differed significantly from that in August and November. Variability was highest in the unburned zone in April, while the other groups showed a more moderate spread. A few outliers were present in the burned zone in August.

Sandy soils are generally characterized by low fertility and limited nitrogen availability, because nutrients are rapidly lost through leaching processes (Osman, 2018). Liu et al. (2018) explained that partially burned vegetation, litter, and organic-rich surface soil can remain in the ash after a fire. These residual organic materials may subsequently be incorporated into the soil through rainfall, thereby increasing total nitrogen content. This mechanism could potentially explain why total N values in the burned plots were generally higher than those in the unburned plots during the later sampling periods. In April, however, no clear difference was observed, likely because of the large variability within the unburned zone.

Although fire can reduce soil nitrogen through volatilization at temperatures above 200 °C (Dzwonko et al., 2015), total N in the burned zone was never lower than in the unburned zone, suggesting that substantial nitrogen volatilization did not occur. Similar findings have been reported following low-intensity fires (Akburak et al., 2017).

3.1.2.6 Cation exchange capacity

Figure 3.7 presents the temporal evolution of cation exchange capacity (CEC) (meq/100 g) in burned and unburned areas. A significant difference was only detected in August ($p = 0.009$), with a decline in CEC in the unburned plots, whereas CEC values in the burned plots remained relatively stable throughout the study period. Temporal analysis further showed that the burned–unburned difference in CEC in August differed significantly from that in April and November. However, this result should be interpreted with caution, as the number of samples in the unburned plots was relatively limited ($n = 9$).

In general, sandy soils are expected to have a relatively low CEC (Osman, 2018). Previous studies have often reported increased CEC values after fire. Inbar et al. (2014), for example, attributed this increase mainly to higher SOM contents in burned soils. Since no significant differences in SOM were observed between burned and unburned plots in the present study, the absence of a consistent fire effect on CEC may partly be explained by the lack of post-fire SOM accumulation.

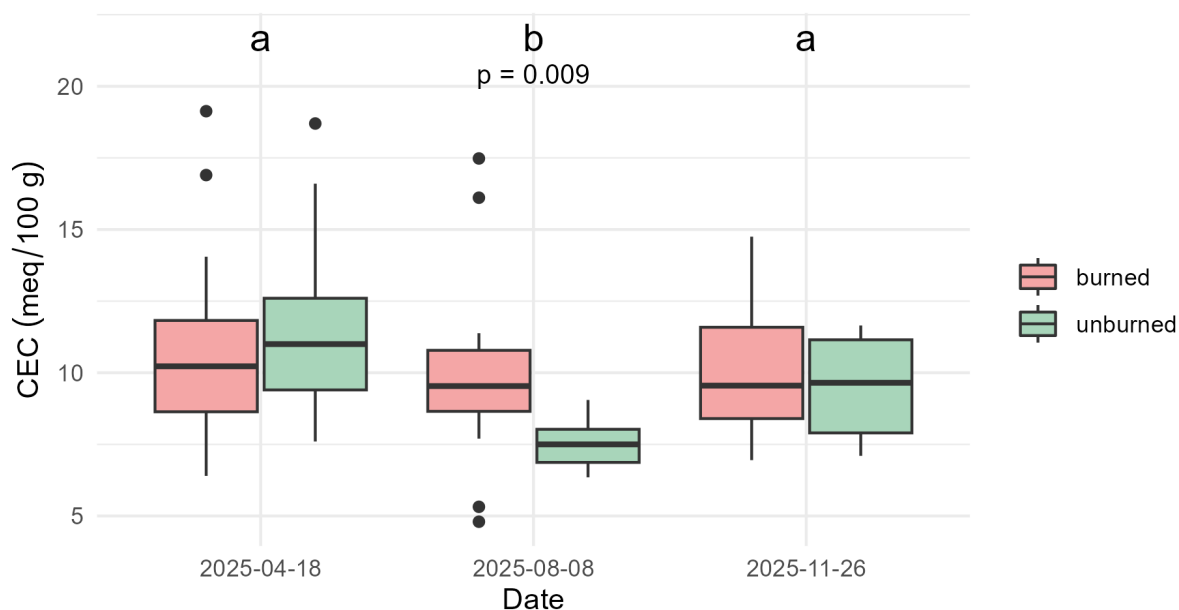


Figure 3.7: CEC over time in burned (red) and unburned (green) areas. See Figure 3.1 for explanation.

However, Downing et al. (2017) reported increased CEC values despite stable SOM contents, suggesting that fire-induced changes in SOM quality, such as the formation of black carbon or biochar, can also enhance CEC. The absence of a clear increase in CEC in the present study therefore suggests that such effects were limited.

3.1.2.7 Soil pH

Figure 3.8 presents the temporal evolution of soil pH in burned and unburned areas. pH was significantly higher in the unburned than in the burned zone in August ($p = 0.003$) and November ($p = 0.045$), while no significant zone difference was observed in April. Temporal analysis showed that the burned–unburned difference was significantly between April and August, whereas November did not differ significantly from either April or August. The delayed emergence of pH differences suggests that fire effects on soil acidity were influenced not only by direct thermal effects, but also by subsequent environmental processes such as rainfall and leaching.

Previous studies often report increased soil pH after fire due to ash inputs and the addition of base cations. For example, Akburak et al. (2017) observed a slight increase in pH following a low-intensity fire, while Dzwonko et al. (2015) found that pH increases after a high-intensity fire may develop gradually over time.

3. Results and discussion

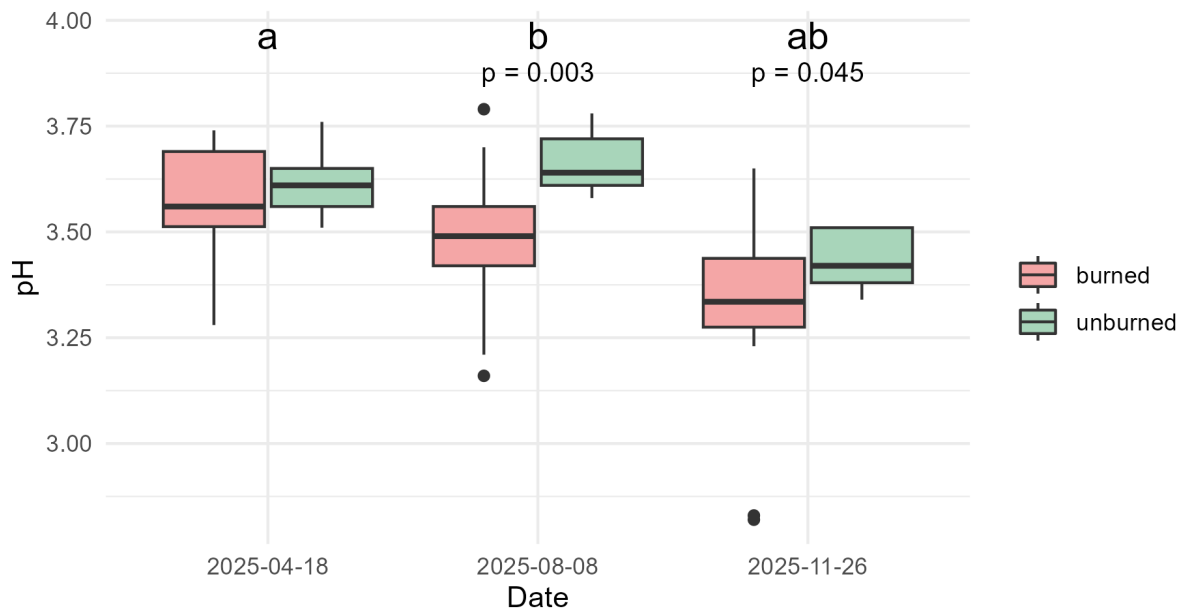


Figure 3.8: pH over time in burned (red) and unburned (green) areas. See Figure 3.1 for explanation.

In contrast, pH values in the burned plots of our study were lower than those in the unburned plots during the later sampling periods. This may indicate that any initial ash-induced alkalinization diminished over time through ash removal by wind or the leaching of base cations following the return of rainfall after July (Weather Underground, 2026). The soil characteristics of the study area may have amplified these post-fire acidification processes. According to Osman (2018), sandy soils generally contain low amounts of organic matter and clay, resulting in a limited buffering capacity. Because nutrients and base cations are easily leached from sandy soils, these soils are particularly prone to gradual acidification. This might further explain our observations.

Vegetation type may also have influenced soil pH dynamics. Coniferous species promote soil acidification through the slow decomposition of needle litter and the release of organic acids (Berger and Berger, 2012; Perković et al., 2019). Following the return of rainfall after July, the downward transport of these dissolved organic acids may have further contributed to the lower pH values observed in the burned plots during the later sampling periods. Atmospheric nitrogen deposition may have partly contributed to the low initial pH values and the observed acidification, although it is unlikely to explain the entire decline. A global meta-analysis by Tian and Niu (2015) showed that nitrogen deposition reduces soil pH through nitrate leaching and the depletion of base cations.

Overall, the results suggest that soil pH dynamics after fire are governed by a combination of ash inputs, vegetation characteristics, soil texture and post-fire rainfall.

3.2 Vegetation analysis

This section examines how vegetation recovered during the first year following the Clinge wildfire, with a particular focus on temporal and spatial variation in vegetation structure and composition. Several aspects of vegetation recovery were investigated, including changes in total vegetation coverage, species richness, species evenness, and vegetation composition within the burned and unburned area.

It should be noted that vegetation identification was sometimes complicated by the very early developmental stages of many plants, large amounts of leaf litter, sand deposition caused by animal burrowing activity (most likely rabbits), and fallen trees that partly covered some plots.

3.2.1 Vegetation coverage

Figure 3.9 illustrates the visual evolution of the burned area throughout the monitoring period.



Figure 3.9: Visual overview of the vegetation recovery.

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Figure 3.10 shows the temporal variation in relative vegetation coverage across all plots during the monitoring period. Monthly precipitation totals were obtained from the Weather Underground station ISINTJ5 (Weather Underground, 2026), while the 1991–2020 monthly precipitation averages for Sint-Gillis-Waas were obtained from the Royal Meteorological Institute of Belgium (Koninklijk Meteorologisch Instituut van België, 2025). An overview of monthly precipitation totals and missing observation days in the Weather Underground dataset is provided in Appendix Table A.9.

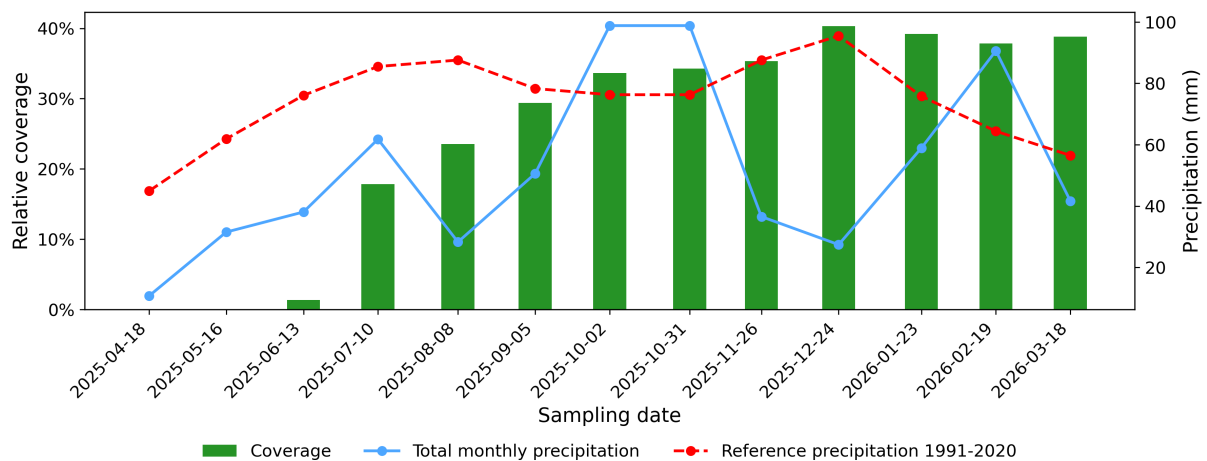


Figure 3.10: Temporal variation in relative vegetation coverage across all plots. Green bars represent the percentage of the total plot area covered by vegetation, while the blue and red lines indicate observed monthly precipitation and long-term reference precipitation, respectively.

Overall, vegetation coverage increased strongly over time, especially between June and July, when the largest increase occurred. This coincided with higher monthly precipitation than in previous months, suggesting a link between precipitation and vegetation recovery. Soil analyses also showed low soil moisture in April, indicating that limited water availability may have constrained recovery. Nevertheless, this relationship was not always straightforward, as vegetation coverage continued to increase during periods of decreasing precipitation, such as in August, November, December, and March, although the increases were less pronounced. This may indicate that the vegetation had become sufficiently established and had developed a root system. From December onwards, vegetation coverage also stabilized, with winter conditions likely reducing the rate of further growth.

Figure 3.11 shows the temporal variation in vegetation coverage per plot after standardization by plot area, allowing direct comparison among plots of different sizes. During the first months of the study, vegetation coverage per unit area remained very low across all plots, whose locations and labels are shown in Figure 2.1. From July onward, clear spatial differences emerged. Plots C and CD showed the strongest vegetation development, while plot DE became increasingly dominant later in the season. All three plots were located in the central part of the burned

area and had the highest vegetation coverage by the end of the monitoring period. In contrast, plot A, located at the forest edge and ignition site, maintained extremely low vegetation coverage throughout the study. Plot AB, also near the forest edge and characterized by abundant dead wood, remained relatively sparsely vegetated. Similarly, plot E, situated near the forest edge, showed only limited vegetation development compared to the more central plots.

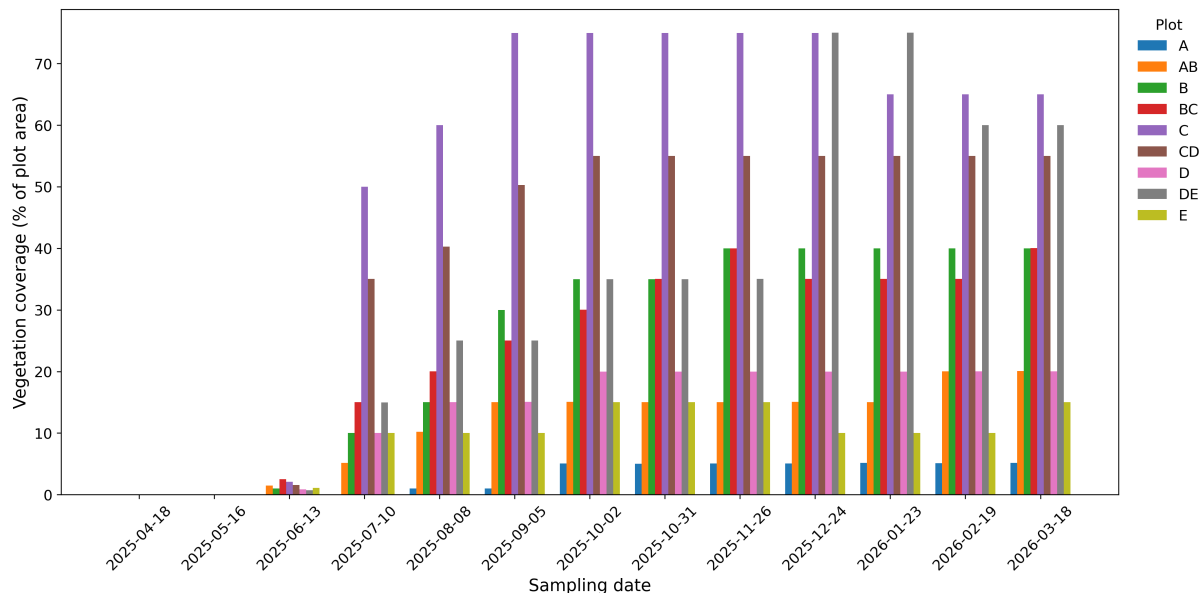


Figure 3.11: Area-normalized vegetation coverage per plot across sampling dates. Vegetation cover is expressed as coverage per unit area (m^2/m^2).

At first sight, these patterns may suggest that plots C, CD, and DE showed the strongest vegetation recovery. However, vegetation coverage alone does not necessarily indicate successful ecosystem recovery, as additional analyses of species richness and evenness are needed before ecological recovery can be assessed.

3.2.2 Species richness

Before examining temporal and spatial patterns in species richness within the plots, an additional comparison was made with the broader burned area surrounding the plots using the vegetation inventory by field ecologist Lucien Calle from Het Zeeuwse Landschap. Within the plots, 34 unique taxa identified to species level and 38 including genus-level identifications were recorded across approximately 1415 m^2 , corresponding to 0.024 and 0.027 taxa per m^2 , respectively. In contrast, the surrounding burned area outside the plots contained 53 unique taxa identified to species level across approximately 18971 m^2 , corresponding to only 0.003 taxa per m^2 . However, these values should be interpreted with caution, as vegetation surveys within the plots were conducted in greater detail.

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In addition, the burned area as a whole contained proportionally larger, highly sun-exposed open areas without surrounding vegetation providing shade, where fewer species were able to establish, as discussed in the following sections. Nevertheless, the results suggest that most species present in the burned area were captured within the monitoring plots.

Figure 3.12 illustrates the temporal variation in total species richness across all plots during the monitoring period. Overall, total species richness generally increased throughout the monitoring period, although occasional decreases occurred. Species richness rose rapidly from 7 species in April to 16 species in July, followed by moderate fluctuations during late summer and fall. Towards the end of the monitoring period (spring 2026), species richness increased again, reaching the highest observed value of 18 species in March 2026. An overview of all recorded plant species in the burned plots is provided in Appendix Table A.10. Individual species composition is not discussed in detail here, as a more extensive descriptive analysis of vegetation composition is presented in Section 3.2.4.

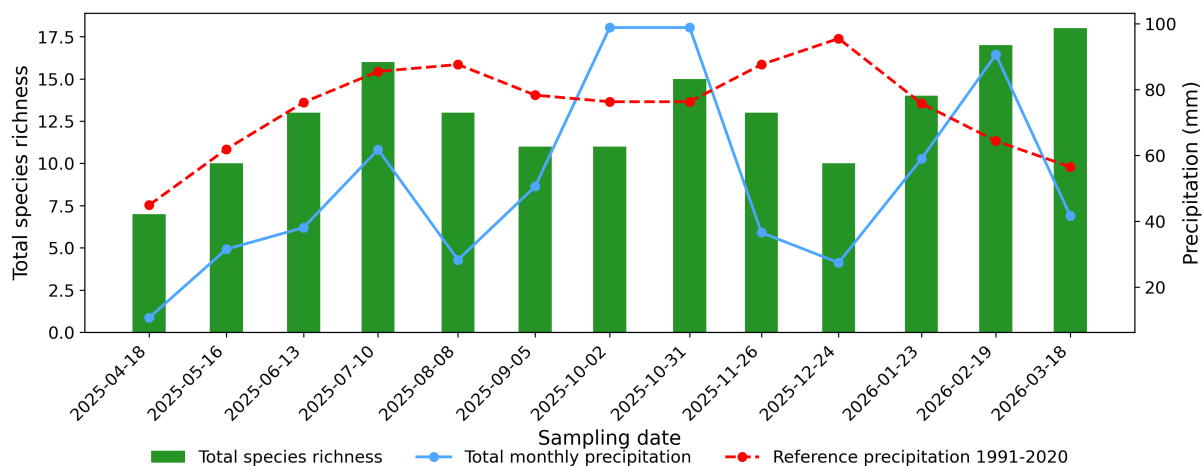


Figure 3.12: Temporal variation in total species richness across all plots. Green bars represent total species richness, while the blue and red lines indicate observed monthly precipitation and long-term reference precipitation, respectively.

Species richness largely followed precipitation patterns throughout the monitoring period. Wetter periods, such as July, October, and February, generally coincided with an increase in richness, whereas drier periods were associated with a stagnation or declines in richness. This relationship appeared stronger than for total vegetation coverage, suggesting that rainfall availability played an important role in species establishment and persistence during recovery. October should, however, be interpreted with caution because two sampling campaigns were conducted that month. March 2026 formed the main exception, with species richness increasing despite lower precipitation compared to February.

Figure 3.13 illustrates the temporal variation in species richness per plot after standardization by plot area. During the first months of the study, species richness per unit area remained relatively low across all plots. In the early stages of the monitoring period, plot E at the forest edge generally exhibited the highest species richness, often followed by plots AB or D. In July and August, plot AB showed the highest richness values. From October onward, plot A, located at the forest edge and fire ignition point, consistently showed the highest richness values, while plot E remained among the richest plots. In contrast, plots C, CD, and DE, located in the central part of the burned area, generally maintained the lowest richness values throughout most of the monitoring period despite their high vegetation coverage observed in the previous analyses. Overall, the results indicate that plots with the highest vegetation coverage did not necessarily correspond to the plots with the highest species richness.

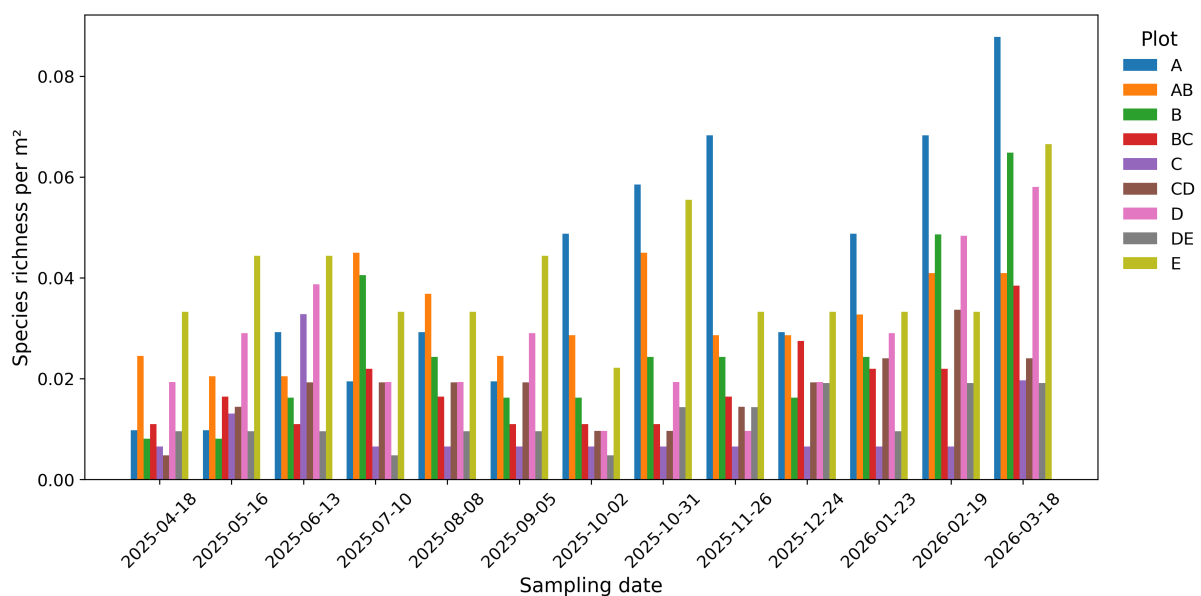


Figure 3.13: Area-normalized species richness per plot across sampling dates.

A major factor contributing to these spatial differences was likely the contrasting environmental conditions among the plots. Plots A, AB and E were located at or closer to the forest edge, where shading and forest-like conditions were more pronounced (for location plots, see Figure 2.1). In plots A and AB, large amounts of dead wood were also present, creating additional shade and structural shelter. Similar patterns have been reported in previous post-fire studies (Owen et al., 2017; Teste et al., 2009; Turner et al., 1998; Haire and McGarigal, 2010). However, the ecological mechanisms underlying these patterns will be discussed in more detail in Section 3.2.5. In contrast, plot C represented a far more exposed environment with much greater exposure to direct sunlight. The pronounced differences between these environments are illustrated in Appendix Figure A.9.

3.2.3 Pielou's evenness

Figure 3.14 illustrates the temporal variation in Pielou's evenness across all plots during the monitoring period. Pielou's evenness describes how equally vegetation coverage was distributed among the recorded species, with higher values indicating a more even distribution of species abundances. Overall, Pielou's evenness strongly decreased throughout the monitoring period. The highest values were observed during the first sampling campaigns, after which evenness rapidly declined and remained extremely low for the rest of the study period. However, these initially high values should be interpreted with caution. During the early post-fire stages, vegetation coverage was still extremely limited and consisted mainly of bare ground with only a few small plant individuals occupying similarly small surface areas. Due to the way Pielou's evenness is calculated (Equation 2.2), this resulted in high evenness values despite the limited vegetation development. The strong decline in evenness over time therefore likely reflects the increasing dominance of a limited number of species, particularly sheep sorrel (*Rumex acetosella*), during vegetation recovery rather than a true reduction in ecological quality. This species is discussed in more detail later in this section.

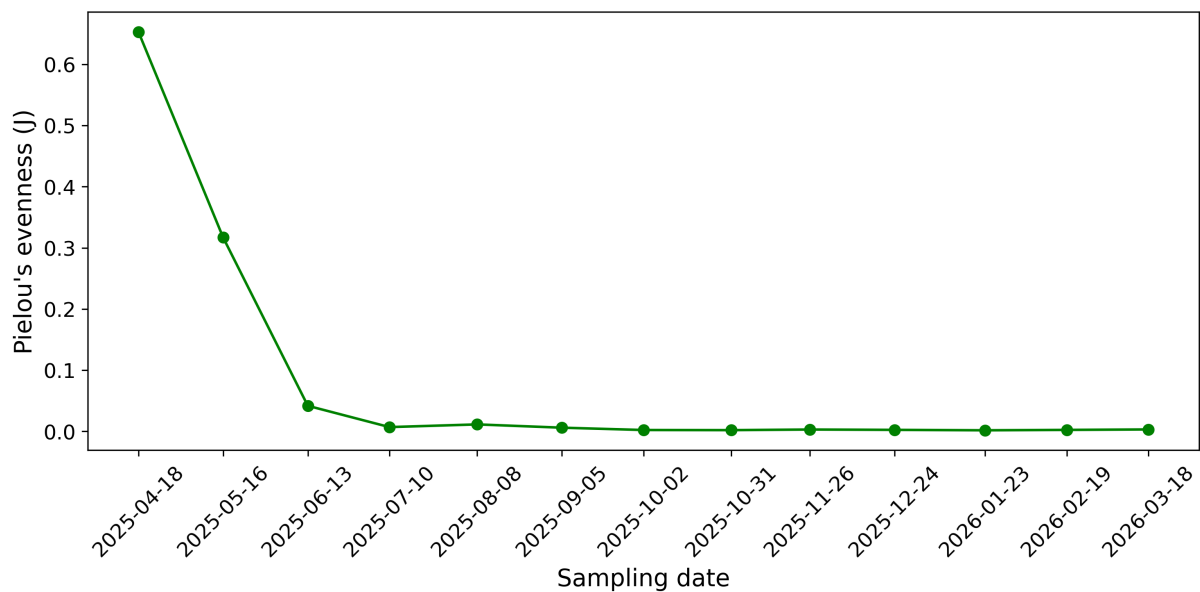


Figure 3.14: Pielou's evenness across all plots over time.

Figure 3.15 illustrates the temporal variation in Pielou's evenness per plot. Similar to the overall pattern, evenness values were highest during the first sampling dates and rapidly decreased afterwards. From July onward, most plots exhibited extremely low evenness values. During this period, plot A at the forest edge consistently showed the highest evenness values, while plot AB, also near the forest edge, frequently ranked second highest. These patterns support the observation that plots closer to the forest edge maintained more balanced species distributions than the more exposed central plots, although overall evenness remained low across the study area.

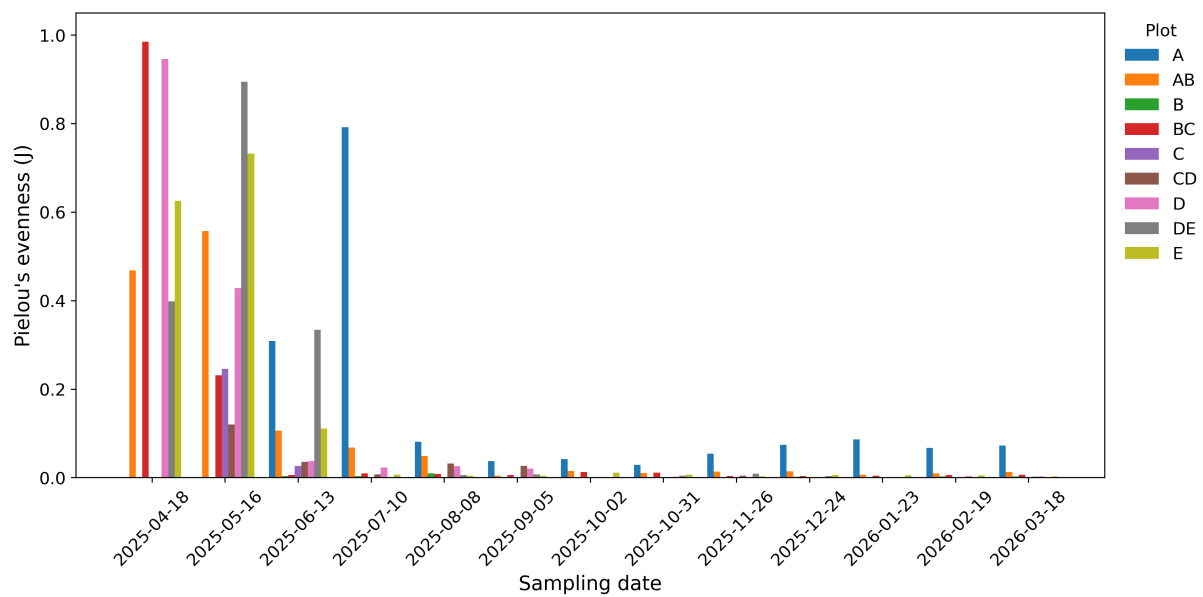


Figure 3.15: Pielou's evenness per plot across sampling dates.

The low evenness values observed throughout much of the monitoring period were largely driven by the dominance of Sheep's sorrel (*Rumex acetosella*), a species that thrives in dry, nutrient-poor, acidic soils and is commonly found in open and disturbed environments (Ecopedia, 2026b; Flora van Nederland, 2021). These conditions closely match those observed in the study area, including acidic soils (Section 3.1.2.7), recurring dry conditions (Section 3.1.2.2), and low fertility (Section 3.1.2.6).

As shown in Figures 3.3, 3.10, and 3.12, the monitoring period was characterised by recurring dry conditions and low soil moisture, favouring drought-tolerant pioneer species such as *R. acetosella*. This was particularly evident in plot C, which consistently exhibited among the highest vegetation coverage values throughout most of the monitoring period (Section 3.2.1). Compared to plots near the forest edge, plot C received more direct sunlight and less structural shelter (Appendix Figure A.9).

3.2.4 Vegetation composition

The species comparison in Tables 3.3 and 3.4 is based exclusively on plant species occurring only within the burned plots or only in the unburned zone surrounding the burned perimeter. Species present in both zones were excluded, and only plants identified to species level were included. This should be considered when interpreting the results, as considerably more species were identified in the unburned zone due to its more advanced vegetation development, which made species easier to identify.

Table 3.3: Plant species retrieved in the unburned zone only (Ecopedia, 2026a; Flora van Nederland, 2026).

Unburned	Description
<i>Acer campestre</i> (Field maple)	Clay, loam, or sand; moist; moderately to highly nutrient-rich; neutral to calcareous soils; nitrogen-rich shrublands.
<i>Agrostis capillaris</i> (Common bentgrass)	Nutrient-poor to moderately rich; dry to moist acidic humus-rich soils; rough humus indicator; low to moderate nitrogen; pioneer species.
<i>Aronia x prunifolia</i> (Purple chokeberry)	Moderately nutrient-rich and moist habitats.
<i>Calamagrostis epigejos</i> (Wood small-reed)	Nutrient-poor; dry to moist soils with fluctuating water levels; host plant for specialized insects; moderate to high nitrogen.
<i>Chamaenerion angustifolium</i> (Rosebay willowherb)	Nutrient-poor to moderately rich; dry to moist; colonizes disturbed sites; moderate acid indicator; strongly nitrogen-rich soils.
<i>Cirsium vulgare</i> (Spear thistle)	Highly nutrient-rich; moist, little-disturbed soils; weak acid to base indicator; strongly nitrogen-rich soils.
<i>Digitalis purpurea</i> (Foxglove)	Moderately to highly nutrient-rich; dry to moist forest soils; acidic, lime-poor soils; moderate to high nitrogen.
<i>Frangula alnus</i> (Alder buckthorn)	Nutrient-poor; moist to wet acidic habitats.
<i>Hypericum perforatum</i> (St. John's wort)	Moderately nutrient-rich; dry; moderate acid indicator; nitrogen-poor soils.
<i>Juglans regia</i> (Walnut)	Clay, loam, or sand; moist soils.
<i>Lolium perenne</i> (Perennial ryegrass)	Highly nutrient-rich; dry to moist habitats.
<i>Lonicera periclymenum</i> (Honeysuckle)	Nutrient-poor to moderately poor; dry to moist nutrient-poor forest soils.
<i>Luzula campestris</i> (Field wood-rush)	Nutrient-poor to moderately rich; dry to slightly moist acidic unfertilized soils.
<i>Phytolacca americana</i> (American pokeweed)	Invasive exotic species.

Unburned	Description
<i>Poa trivialis</i> (Rough meadow-grass)	Moderately to highly nutrient-rich; moist to wet meadows, forests, and roadsides.
<i>Populus tremula</i> (European aspen)	All soil types; dry to moist; nutrient-poor to rich; pioneer on aerated sandy to loamy soils.
<i>Quercus rubra</i> (Northern red oak)	Tolerates poor dry soils; weaker on heavy clay; nutrient-poor to moderately rich soils.
<i>Sambucus nigra</i> (Black elder)	Moderately nutrient-rich; moist; nitrogen indicator species.
<i>Sorbus aucuparia</i> (Rowan)	Small tree of nutrient-poor acidic soils; dry to moderately moist habitats.
<i>Teucrium scorodonia</i> (Wood sage)	Nutrient-poor; dry; indicator of lime-poor soils; nitrogen-poor soils.
<i>Veronica officinalis</i> (Heath speedwell)	Nutrient-poor; dry acidic soils; low to moderate nitrogen levels.

Table 3.4: Plant species retrieved in the burned zone only (Ecopedia, 2026a; Flora van Nederland, 2026).

Burned	Description
<i>Cirsium arvense</i> (Creeping thistle)	Moderately to highly nutrient-rich; light shade to full sun; dry to moist; ruderal and pioneer habitats; nitrogen-rich soils.
<i>Conyza sumatrensis</i> (Tall fleabane)	Dry, warm, disturbed habitats; pioneer species from South America; non-invasive exotic.
<i>Cytisus scoparius</i> (Scotch broom)	Moderately nutrient-rich; dry acidic soils; low to moderate nitrogen; sandy and heathland soils.
<i>Erigeron canadensis</i> (Canadian fleabane)	Moderately to highly nutrient-rich; dry; non-invasive exotic; thrives on dry, moderately nitrogen-rich sandy soils; pioneer after disturbance.
<i>Fallopia convolvulus</i> (Black bindweed)	Nutrient-poor to highly nutrient-rich; dry to moist sandy disturbed soils; pioneer species; nitrogen-rich soil indicator.
<i>Galium aparine</i> (Cleavers)	Moderately to highly nutrient-rich; dry to moist; strongly nitrogen-rich soils.
<i>Juncus effusus</i> (Soft rush)	Moderately nutrient-rich; wet acidic lime-poor habitats; disturbed ecosystem indicator; low to moderate nitrogen.
<i>Persicaria maculosa</i> (Redshank)	Highly nutrient-rich; moist disturbed habitats; annual pioneer species; nitrogen-rich soils.
<i>Picea abies</i> (Norway spruce)	Clay, loam, and sand; moist; prefers acidic soils.
<i>Salix caprea</i> (Goat willow)	Moderately nutrient-rich; moist to wet; pioneer species; weak acid to base indicator; nitrogen-rich soils.

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Burned	Description
<i>Senecio inaequidens</i> (Narrow-leaved ragwort)	Moderately nutrient-rich; moist; invasive exotic; pioneer habitats on moist to dry soils.
<i>Senecio vulgaris</i> (Groundsel)	Highly nutrient-rich; dry to moist disturbed soils; strongly nitrogen-rich habitats.
<i>Solanum nigrum</i> (Black nightshade)	Highly nutrient-rich; moist; all soil types; weak acid to base indicator; strongly nitrogen-rich soils.
<i>Sonchus asper</i> (Prickly sow-thistle)	Highly nutrient-rich; moist; weak acid to base indicator; nitrogen-rich soils.
<i>Stellaria media</i> (Common chickweed)	Moderately to highly nutrient-rich; moist disturbed and fertilized soils.
<i>Taraxacum officinale</i> (Dandelion)	Moderately to highly nutrient-rich; dry to moist; benefits from open disturbed patches.

Based on Table 3.4, species found exclusively in the burned plots were mainly associated with open, disturbed, pioneer conditions. Several species, including *Cirsium arvense*, *Conyza sumatrensis*, *Erigeron canadensis*, *Fallopia convolvulus*, *Persicaria maculosa*, *Salix caprea*, and *Senecio inaequidens*, are described as pioneer species. Together with species associated with disturbed soils, such as *Senecio vulgaris*, *Stellaria media*, and *Taraxacum officinale*, these observations indicate that the burned plots represented a recently disturbed environment with bare and exposed soil surfaces.

In contrast, the unburned zone contained more woody and perennial species associated with established vegetation structures. Table 3.3 includes several shrubs and trees, such as *Acer campestre*, *Frangula alnus*, *Juglans regia*, *Populus tremula*, *Quercus rubra*, *Sambucus nigra*, and *Sorbus aucuparia*, as well as species linked to forest conditions, including *Lonicera periclymenum* and *Poa trivialis*. Nevertheless, several pioneer or disturbance-associated species were also present, including *Agrostis capillaris* and *Chamaenerion angustifolium*.

The burned plots contained several species associated with nutrient-rich or nitrogen-rich soils. Indeed, *Cirsium arvense*, *Galium aparine*, *Persicaria maculosa*, *Senecio vulgaris*, *Solanum nigrum*, and *Sonchus asper* occur on nitrogen-rich or strongly nitrogen-rich soils. *Erigeron canadensis* is described as growing best on moderately nitrogen-rich sandy soils, while *Fallopia convolvulus* is indicated as a species of disturbed, nitrogen-rich sandy soils. This corresponds with the soil analysis (Section 3.1.2.5, Figure 3.6), where total N tended to be higher in the burned plots during August and November compared to the unburned plots, although not statistically significant. However, most vegetation coverage was still dominated by *R. acetosella*, a species typically associated with nutrient-poor and very nitrogen-poor soils.

At the same time, the presence of nitrogen-associated species was not limited to the burned plots (Table 3.3). Several species occurring exclusively in the unburned perimeter zone are also linked to nitrogen-rich or moderately nitrogen-rich conditions, including *Acer campestre*, *Calamagrostis epigejos*, *Chamaenerion angustifolium*, *Cirsium vulgare*, and *Digitalis purpurea*. *Sambucus nigra* is explicitly described as a nitrogen indicator. This indicates that elevated nitrogen availability was not restricted to the burned plots alone, but may also have characterized parts of the surrounding unburned area. This supports the discussion from Section 3.1.2.7 that broader nitrogen enrichment, including atmospheric nitrogen deposition, may already have been present in the study area independent of the fire event.

The soil analysis further helps to interpret the vegetation composition. The pH measurements showed acidic conditions in the burned plots, particularly during the later sampling campaigns (Section 3.1.2.7, Figure 3.8). Several species found exclusively in the burned plots are consistent with acidic conditions according to Table 3.4. For instance *Cytisus scoparius* is described as an acid indicator, *Juncus effusus* is associated with moderately to strongly acidic habitats, and *Picea abies* is described as preferring acidic soils. These species therefore support the lower pH values measured in the burned plots during the sampling campaigns.

3.2.5 Post-fire tree regeneration

Calle et al. (2023) explained that the conifer stands in the Clingse Bossen affected by the bark beetle *Ips typographus* fall under the *Wet natuurbescherming*, specifically the regulations concerning forest stands (“Houtopstanden”). As the burned area is located within these protected forest parcels, the affected stands are legally required to remain forested through either replanting or natural regeneration. It is therefore particularly relevant to examine tree seedling establishment during the first year after the wildfire.

Table 3.5 shows that tree regeneration mainly occurred in plots A and AB near the forest edge, while the more central plots showed little to no regeneration. This pattern suggests that proximity to surviving forest edges facilitated early post-fire recolonization. Similar results were reported by Owen et al. (2017), who found lower pine regeneration in the interior of high-severity burn patches than near forest edges, likely due to shorter dispersal distances and more favourable microclimatic and soil conditions near the edges.

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Table 3.5: Tree species recorded in the study plots and their coverage.

Date	Plot	Tree species	Coverage (cm ²)
2025-05-16	AB	<i>Prunus serotina</i> (Black cherry)	30
2025-06-13	AB	<i>Prunus serotina</i> (Black cherry)	1250
2025-07-10	AB	<i>Acer pseudoplatanus</i> (Sycamore maple)	50
2025-07-10	AB	<i>Betula</i> spp. (Birch)	50
2025-07-10	AB	<i>Prunus serotina</i> (Black cherry)	3500
2025-07-10	AB	<i>Salix caprea</i> (Goat willow)	25
2025-08-08	AB	<i>Prunus serotina</i> (Black cherry)	4000
2025-08-08	AB	<i>Salix caprea</i> (Goat willow)	23
2025-09-05	AB	<i>Acer pseudoplatanus</i> (Sycamore maple)	50
2025-09-05	AB	<i>Salix caprea</i> (Goat willow)	10
2025-10-02	A	<i>Quercus robur</i> (Pedunculate oak)	75
2025-10-02	AB	<i>Acer pseudoplatanus</i> (Sycamore maple)	50
2025-10-02	AB	<i>Prunus serotina</i> (Black cherry)	100
2025-10-31	AB	<i>Acer pseudoplatanus</i> (Sycamore maple)	100
2025-10-31	AB	<i>Picea abies</i> (Norway spruce)	6.25
2025-10-31	AB	<i>Prunus serotina</i> (Black cherry)	100
2025-11-26	AB	<i>Acer pseudoplatanus</i> (Sycamore maple)	125
2026-03-18	A	<i>Acer pseudoplatanus</i> (Sycamore maple)	4
2026-03-18	AB	<i>Betula</i> spp. (Birch)	1
2026-03-18	B	<i>Betula</i> spp. (Birch)	4
2026-03-18	BC	<i>Betula</i> spp. (Birch)	1
2026-03-18	D	<i>Betula</i> spp. (Birch)	1

The observed edge effect may also be linked to underground ecological interactions near surviving trees. Teste et al. (2009) showed that mycorrhizal networks connected to mature trees improved seedling survival and regeneration under stressful conditions.

The importance of nearby seed sources for post-fire recovery was also emphasized by Turner et al. (1998), who compared multiple large disturbances to identify general succession patterns. They concluded that recovery slows down with increasing distance from surviving seed sources, particularly after severe disturbances. In large open burned areas, recolonization may therefore take decades because seeds must disperse from vegetation along the disturbed edges. Haire and McGarrigal (2010) found similar results.

An important observation in the present study was the occurrence of *Prunus serotina* in plot AB. Its coverage increased strongly during the first months after the fire, suggesting rapid post-fire regrowth. During later observations, however, the plant appeared to have been cut or grazed, making it impossible to determine whether its later decline resulted from natural mortality. Nevertheless, the rapid establishment of this invasive exotic species underlines a potential invasion risk during post-fire succession. Turner et al. (1998) noted that large disturbances can create favourable conditions for invasive species establishment and spread, potentially altering ecosystem dynamics. Similar concerns were raised by Jacquemyn et al. (2005), who showed that fire strongly promoted the spread of *Molinia caerulea* in the heathlands of the Kalmthoutse Heide through increased seed production, germination, and seedling establishment.

In the more open plots B, BC, and D, tree regeneration was mainly limited to small *Betula* spp. seedlings with very low coverage values approximately one year after the fire. Dzwonko et al. (2015) similarly observed birch seedling emergence during the first year after fire and suggested that the seeds likely did not survive in the soil, meaning the seedlings probably originated from seeds dispersed by surviving trees in less severely burned areas.

It will be important to monitor whether the observed *Betula* seedlings survive in the coming years, as this may indicate whether spontaneous forest regeneration is possible. If birch establishment remains unsuccessful, this could suggest that the current dominance of *Rumex acetosella* suppresses further tree establishment and delays forest succession. Dzwonko et al. (2015) found that strong competition from herbaceous vegetation could substantially limit tree seedling establishment after fire.

3.3 Wildfire detection

This section evaluates the use of Sentinel-2 spectral indices for wildfire detection and post-fire vegetation recovery monitoring across four recent wildfire events in Clinge, Arlon, Houffalize, and Maasmechelen. First, the performance of several spectral indices for burned area detection is compared using threshold-based classification approaches. Next, post-fire vegetation recovery dynamics are analysed using the Post-Fire Stability Index, including field-based validation in Clinge, seasonal recovery patterns and one-year post-fire recovery responses across the four study areas.

3.3.1 Burned area detection

Figure 3.16 shows an example of the burned area detection workflow using the NBR index for the Arlon study site. The figure illustrates how pre-fire and post-fire images are used to create a difference image, after which burned and unburned pixels are separated. Kernel density estimation (KDE) is then applied to their pixel-value distributions, and the intersection of the resulting density curves is used to determine an optimal threshold value. This threshold is then applied to generate a burn mask, followed by the removal of isolated pixels to reduce classification noise. The final burn mask (bottom right panel) is subsequently compared with the reference fire perimeter to calculate the F1-score. Although only the NBR workflow for Arlon is shown here, the same procedure was applied to all spectral indices and study sites. Complete workflows, intermediate results, and the RGB composites of the pre-fire and post-fire images used in the analyses are provided in Appendix A.5.

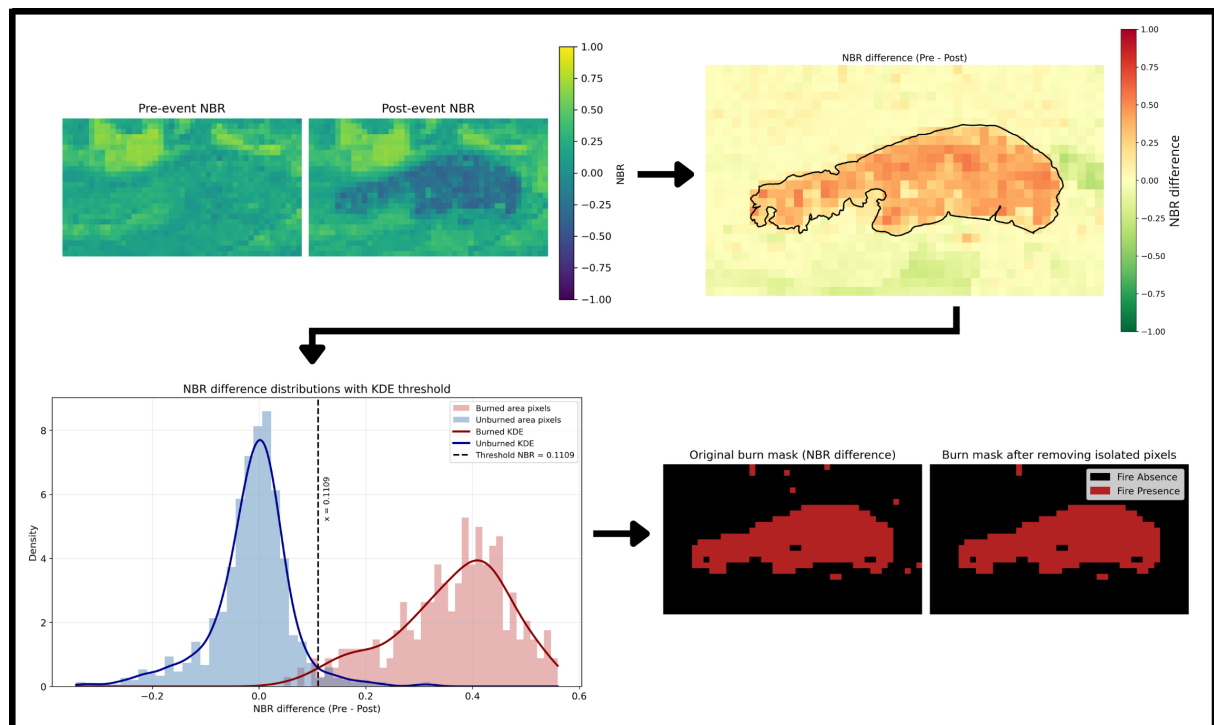


Figure 3.16: Burned area detection workflow using NBR index in Arlon

Figure 3.17 shows the burn masks obtained with the best-performing index for each study area. In all cases, the detected burned pixels closely match the reference fire perimeter, resulting in high F1-scores and only limited false positives and false negatives. The best results were obtained with BAI for Clinge ($F1 = 0.9076$) and Houffalize ($F1 = 0.8367$), NBR for Maasmechelen ($F1 = 0.9480$), and NBR2 for Arlon ($F1 = 0.9493$).

Notably, BAI was the best-performing index in two of the four study areas. These findings agree with Mpakairi et al. (2020), who reported good BAI performance across different land-cover types, particularly in shrublands and evergreen forests.

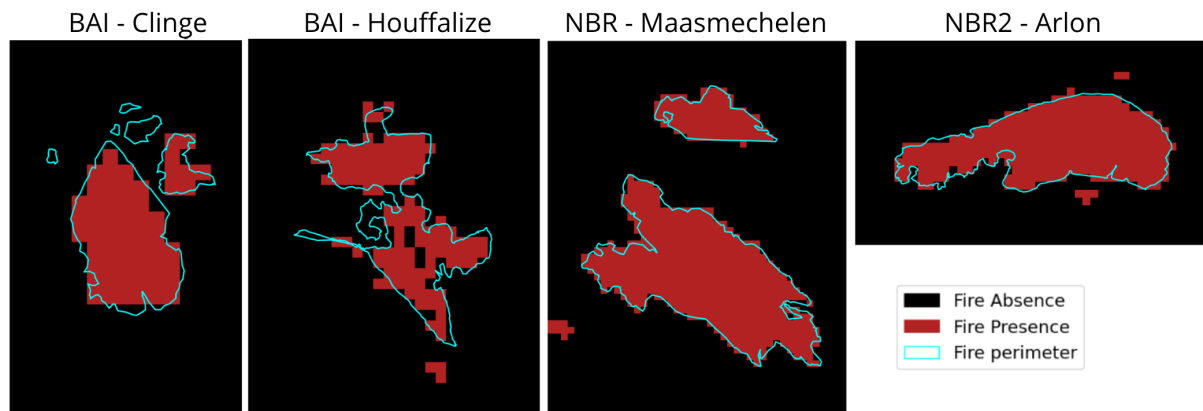


Figure 3.17: Burn masks generated by the best-performing spectral index for each study area.

Although BAI produced the highest F1-scores in two of the four study areas, Figure 3.18 shows that NBR and NBR2 generally yielded high classification accuracies across the study sites, with median F1-scores approaching 0.9. However, both indices also exhibited greater variability than BAI. This was especially pronounced for NBR2, indicating less consistent performance between locations. Silvestre (2021) also reported that NBR provided the highest separability for detecting small burned areas. Similarly, Pérez et al. (2022) identified NBR2 as one of the most effective indices.

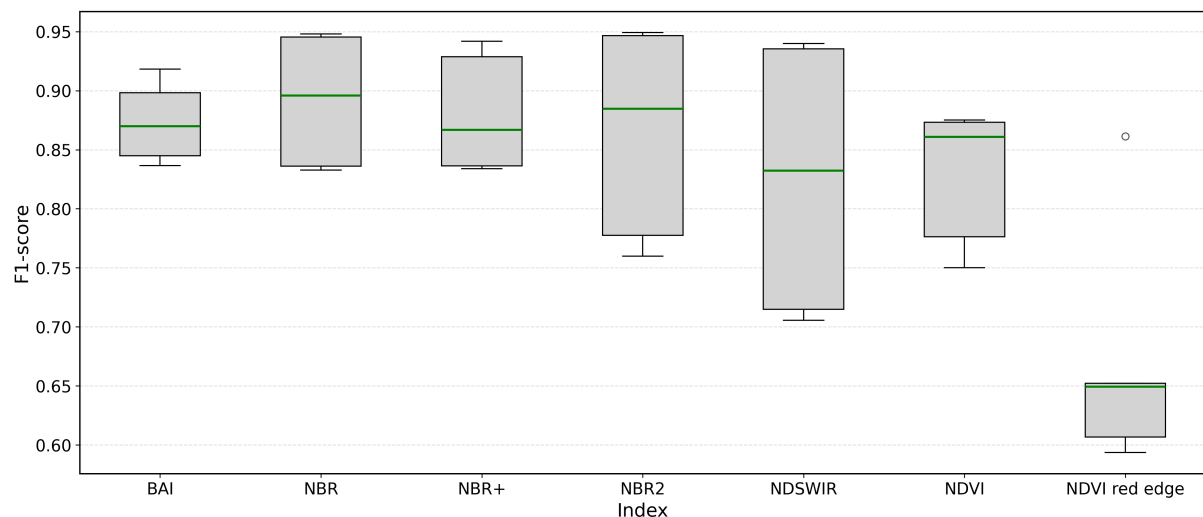


Figure 3.18: Distribution of F1-scores for each spectral index across the four study areas: Clinge, Arlon, Maasmechelen, and Houffalize.

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BAI achieved relatively strong and stable classification results, with median F1-scores around 0.87. NDVI and NBR+ also produced satisfactory results, although their variability between sites was somewhat larger. The good performance of NBR+ agrees with the findings of Alcaras et al. (2022), who reported that NBR+ consistently achieved the highest overall accuracy. NDSWIR showed the largest variation in F1-scores, ranging from approximately 0.7 to 0.94. The NDVI red edge index underperformed relative to the other indices, with median F1-scores around 0.65. This contrasts with the observations of Fernández-Manso et al. (2016), who demonstrated that Sentinel-2 red edge indices outperformed conventional spectral indices for burn severity discrimination.

Figure 3.19 shows the distribution of threshold values obtained for each spectral index across the study sites. NDVI and NDSWIR exhibited the smallest spread in threshold values, indicating relatively consistent threshold behaviour between locations, although NDVI contained a single outlier. In contrast, NBR, NBR+, NBR2, and NDVI red edge showed greater variability between study sites. However, as these distributions are based on only four observations per index, differences in variability should be interpreted with caution. BAI showed a distinct threshold behaviour compared to the other indices. Threshold values were extremely small, requiring a separate scale for visualization. This is because BAI is a spectral distance measure, whereas the other indices are normalized. The threshold outlier observed in Clinge (-1.92×10^{-7}) demonstrates the sensitivity of this index to local conditions, indicating lower threshold stability than the other indices.

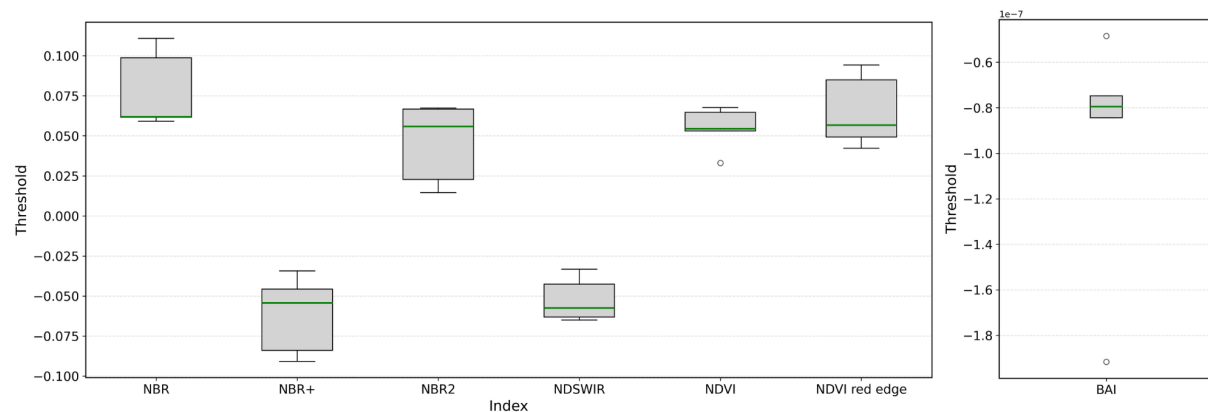


Figure 3.19: Distribution of the optimal threshold values selected for each spectral index across the four study areas: Clinge, Arlon, Maasmechelen, and Houffalize.

Taken together, the results indicate that NBR provides the most reliable and transferable performance for burned area mapping, combining high classification accuracy with comparatively stable threshold behaviour. However, this conclusion should be interpreted with caution, as only four study areas are analysed.

3.3.2 Vegetation recovery

Many remote-sensing studies assess post-fire vegetation recovery by comparing post-fire spectral values with pre-disturbance conditions (Storey et al., 2016; Torres et al., 2018; Hislop et al., 2018). However, defining a reliable pre-fire baseline is often difficult, especially in landscapes already affected by other disturbances (Gibson et al., 2022). This was particularly relevant in Clinge, where bark beetle (*Ips typographus*) outbreaks had already caused widespread mortality in Norway spruce (*Picea abies*) stands before the fire.

To overcome these limitations, this study used the Post-Fire Stability Index (PFSI) proposed by Gibson et al. (2022). Instead of comparing post-fire conditions to a historical baseline, the PFSI measures rates of spectral change relative to surrounding unburned vegetation. Near-zero values indicate stable or recovered systems, positive values indicate active vegetation recovery and increasing canopy development, and negative values indicate vegetation decline or ongoing degradation (Gibson et al., 2022). The NBR2-based implementation was selected because both Gibson et al. (2022) and Storey et al. (2016) demonstrated its strong performance for post-fire recovery monitoring.

3.3.2.1 Post-fire vegetation recovery dynamics using the PFSI in Clinge

The temporal evolution of the PFSI values for the Clinge vegetation plots is shown in Figure 3.20. The corresponding NBR2 and RGB figures are included in the Appendix Figures A.19 and A.20. Cloud-free imagery was not available for all pixels and dates. Therefore, pixels affected by remaining cloud contamination were removed, resulting in the purple NaN regions shown in Figure 3.20.

Overall, the burned area shows a different temporal pattern than the surrounding vegetation. The highest PFSI values occur between June and July 2025, when the burned plots show a strong positive response. This pattern coincides with the marked increase in vegetation coverage observed in Section 3.2.1. In contrast, the surrounding vegetation becomes slightly negative, likely due to the dry conditions in the preceding months. Between September and October 2025, the burned area remains slightly positive, whereas the surrounding vegetation becomes more negative, possibly due to seasonal leaf fall in the unburned forest, an effect absent in the treeless burned area. By February–March 2026, both burned and unburned areas show more similar responses.

3. Results and discussion

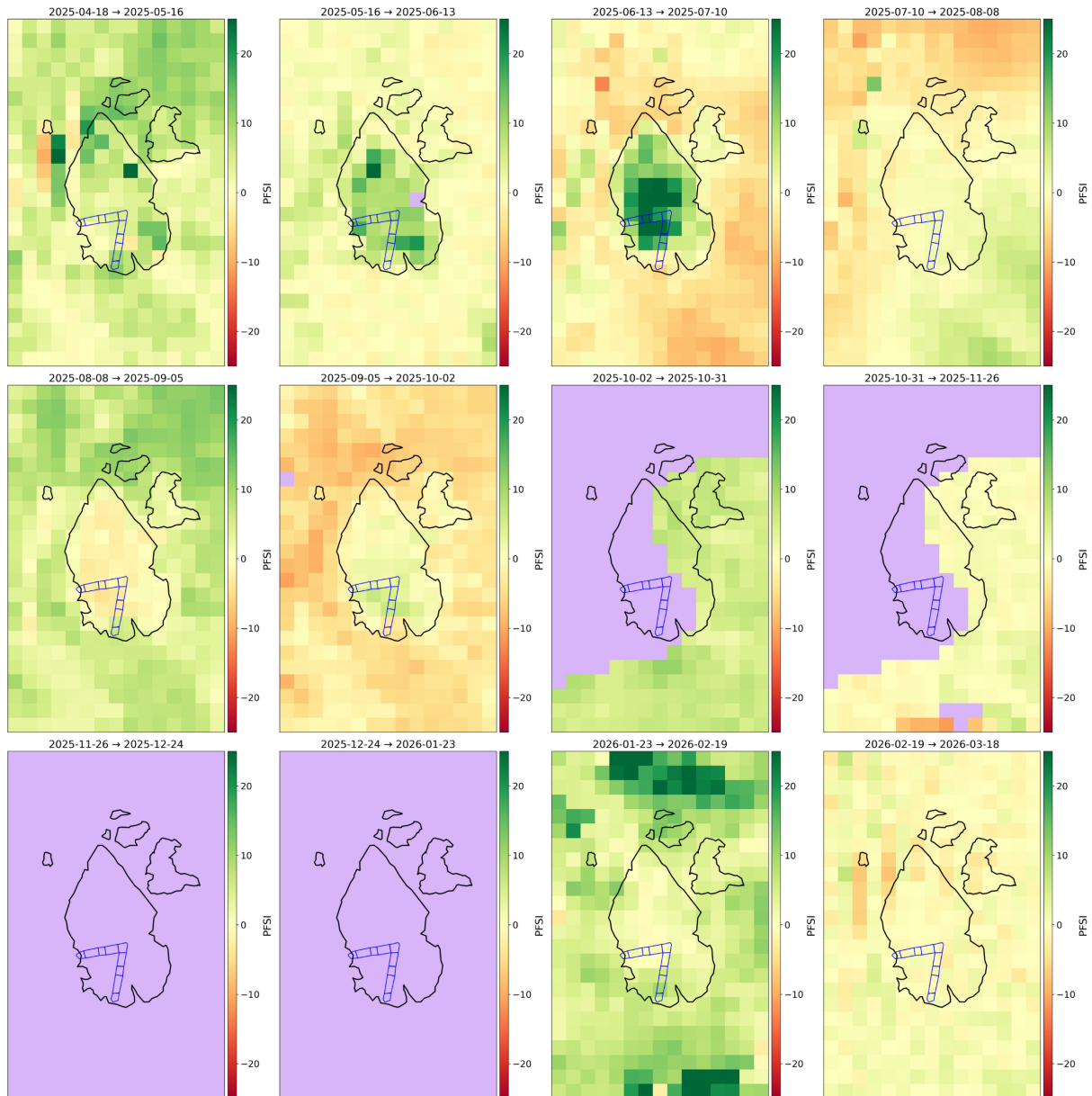


Figure 3.20: Monthly PFSI maps for the Clinge vegetation plots from April 2025 to March 2026. The black outline represents the fire perimeter and purple areas represent missing data.

To evaluate whether these satellite-based patterns were reflected in the field measurements, vegetation coverage change was compared with the mean PFSI value of the overlapping pixels. Figures 3.21, 3.22 and 3.23 compare field-measured vegetation coverage change with the mean PFSI values of the corresponding pixels over time. Plots A, AB and B show a weak relationship between vegetation coverage change and PFSI, likely because large amounts of dead wood cover the small germinating plants, making them difficult to detect. In addition, plots A and AB are located at the edge of the forest, where overhanging tree canopies likely obscured the detection of germinating plants.

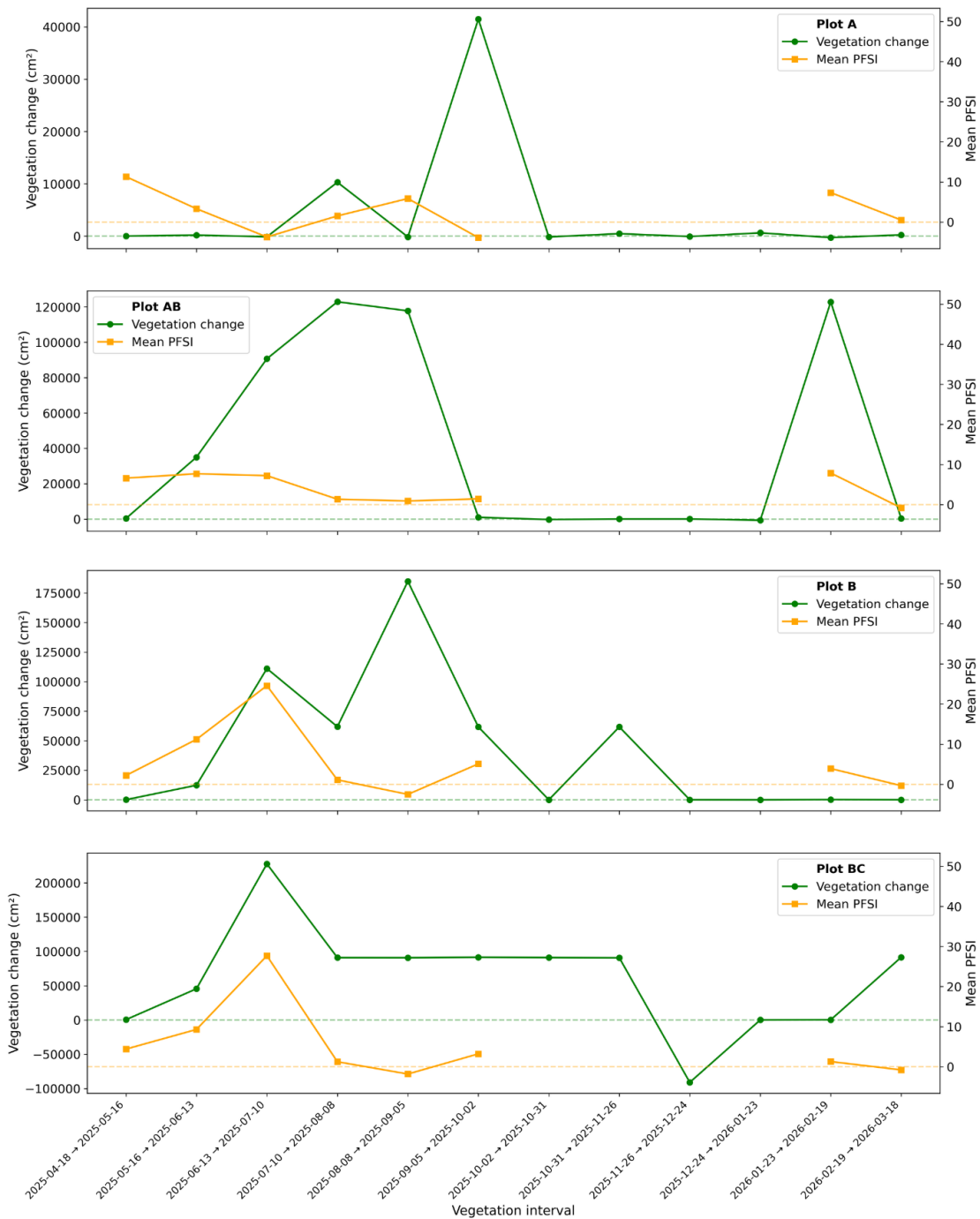


Figure 3.21: Change in vegetation coverage (green; cm²) and mean PFSI values (orange) for plots A, AB, B, and BC.

In contrast, the more central plots BC, C, CD, D and DE show a clearer agreement between field observations and PFSI values. These plots show a strong vegetation increase around June–July, corresponding to the highest positive PFSI values. Afterwards, vegetation growth becomes more stable, reflected by lower but still positive PFSI values.

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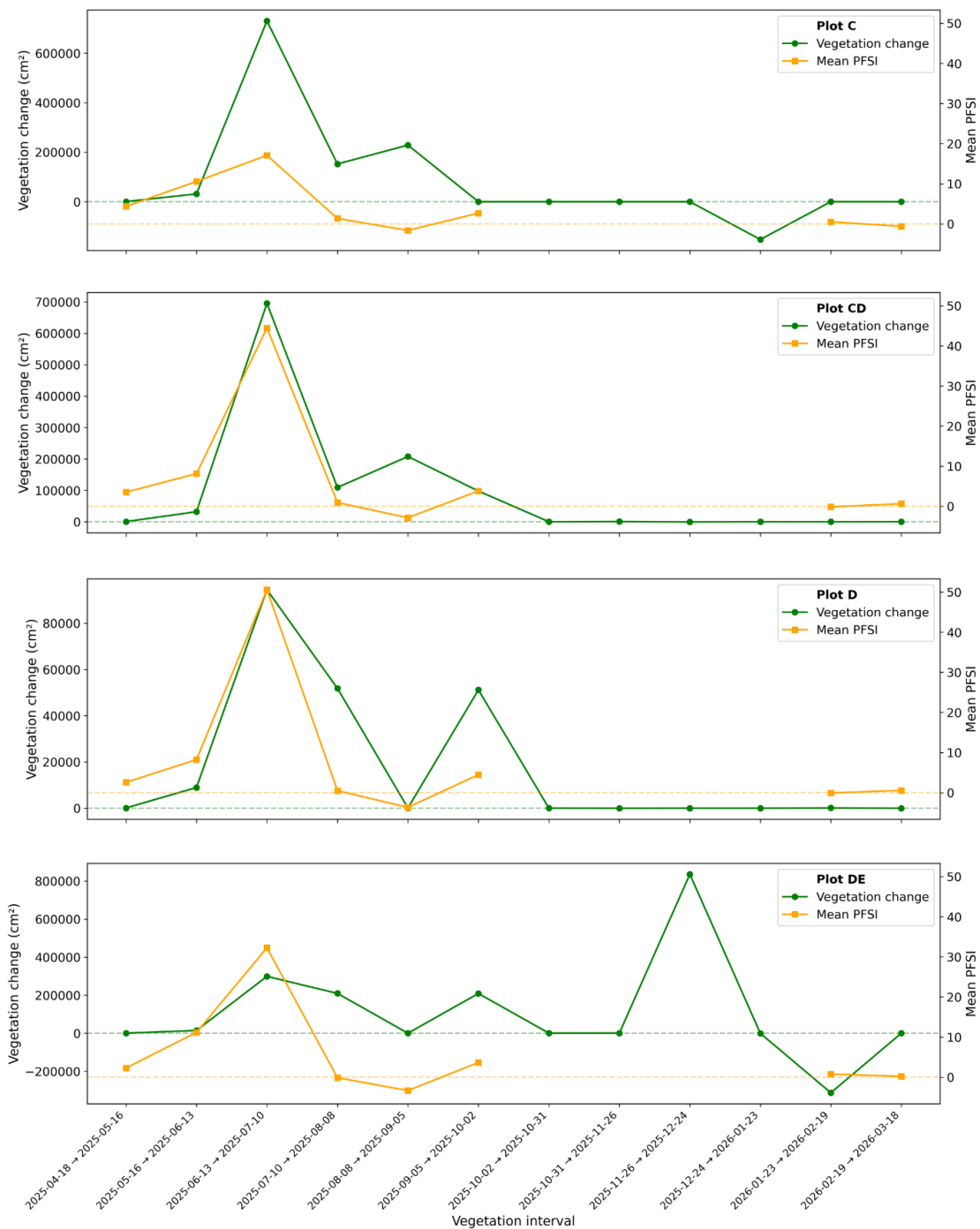


Figure 3.22: Change in vegetation coverage (green; cm²) and mean PFSI values (orange) for plots C, CD, D, and DE.

Plot E also exhibits relatively small PFSI variation compared to the measured vegetation change and the other plots, likely because the plot was located near the forest edge, where overhanging tree canopies may have interfered with the detection of understory vegetation.

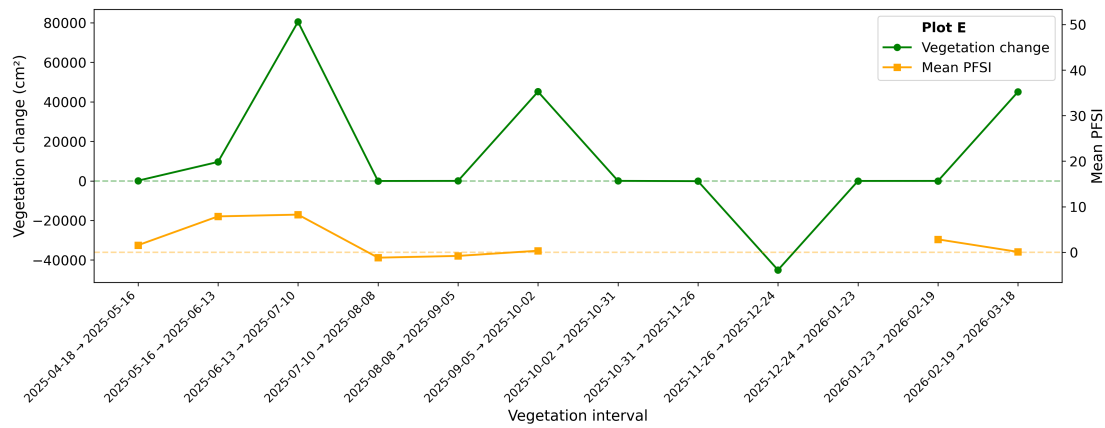


Figure 3.23: Change in vegetation coverage (green; cm²) and mean PFSI values (orange) for plot E.

Overall, the figures show that the PFSI captures the main post-fire vegetation dynamics in the Clinge study area, despite the relatively cloudy imagery. However, comparison with field measurements demonstrates that the index does not always accurately represent plot-level vegetation change. Factors such as dead wood, small seedlings, and the small size of the plots relative to the satellite spatial resolution influence the relationship between field observations and satellite-derived PFSI values.

Additionally, the vegetation analysis in Section 3.2 showed that the area was mainly dominated by sheep sorrel (*R. acetosella*), indicating relatively low ecological diversity. This demonstrates that although the PFSI effectively captures vegetation recovery dynamics and increased vegetation activity after fire, it does not provide information about the ecological quality or diversity of the recovering vegetation. In this case, the strong recovery signal mainly reflects the expansion of a single dominant species. Nevertheless, the analysis confirms that the PFSI is a useful index for monitoring post-fire vegetation recovery dynamics and was therefore also applied to the other study areas.

3.3.2.2 Seasonal post-fire recovery dynamics using the PFSI

To further evaluate post-fire recovery dynamics, the PFSI was analysed at a seasonal scale across the four study areas. The corresponding RGB and NBR2 figures are included in the Appendix Figures A.21 and A.22.

Figure 3.24 shows the seasonal evolution of the PFSI, revealing clear spatial and temporal differences between the four study areas. The distributions of PFSI values and their mean values are shown in Appendix Figure A.24 and Table A.13. In general, the burned areas show the strongest positive PFSI values during summer 2025, indicating rapid post-fire vegetation recovery shortly after the fire event.

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For Clinge, an extreme outlier within the fire perimeter (PFSI = 156613.75) was excluded because it strongly skewed the mean values. The strongest summer response is visible in Maasmechelen and Clinge. Houffalize and Arlon also show positive summer responses, although these are spatially more heterogeneous.

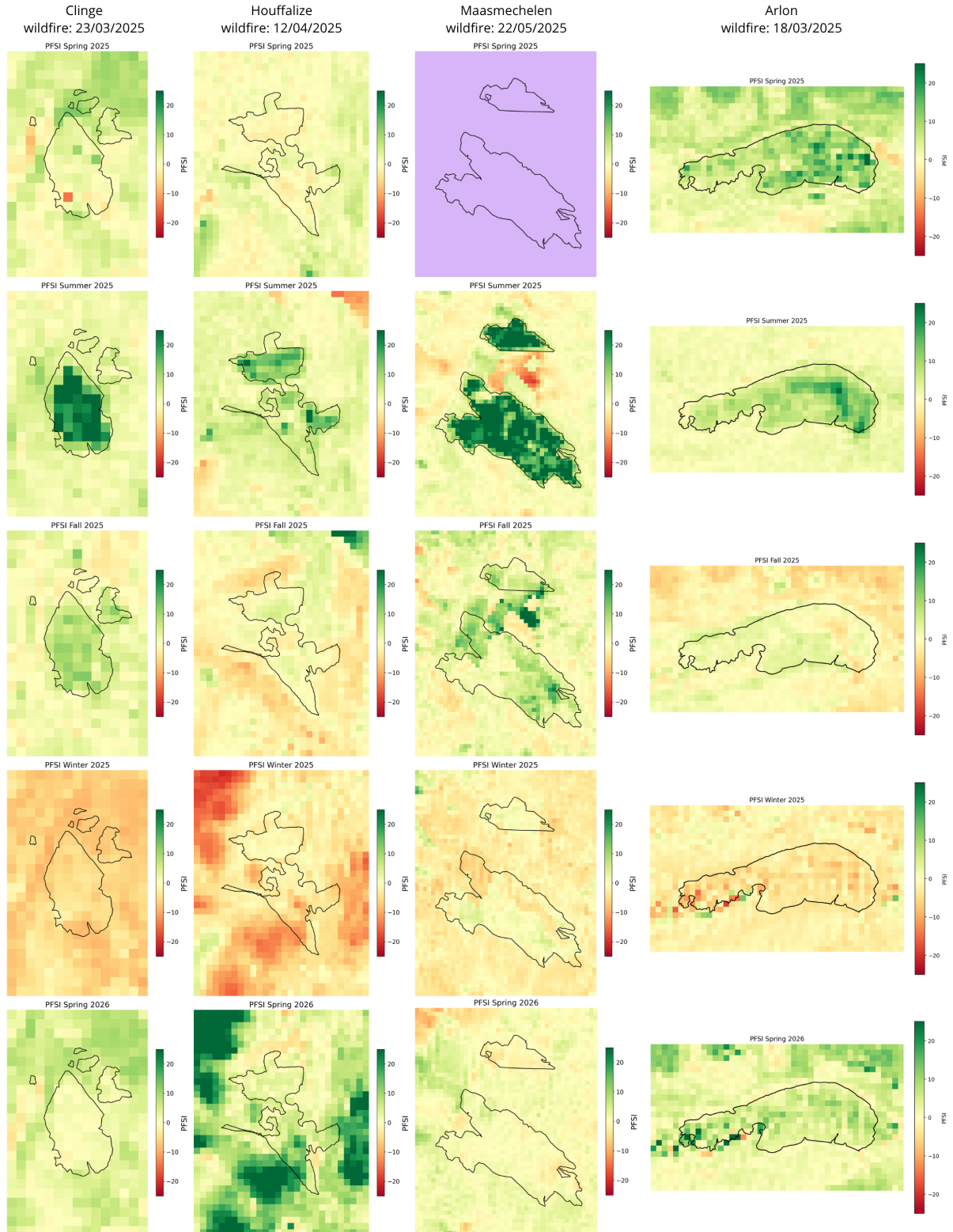


Figure 3.24: Seasonal evolution of PFSI values across the four study areas. The black outlines represent the fire perimeters and purple areas missing data.

During fall 2025, PFSI values generally decrease across all sites, reflecting reduced vegetation growth after the peak growing season. However, the burned areas still maintain generally higher and greener PFSI values than the surrounding unburned vegetation. By winter 2025, all regions are dominated by near-neutral to negative PFSI values. Strong negative values are especially visible in Houffalize. However, the pronounced orange-red patterns in Houffalize were likely influenced by remaining cloud contamination that could not be fully removed, meaning this winter image should be interpreted with caution. In spring 2026, PFSI values within the burned areas became more similar to those of the surrounding unburned vegetation, although the relatively high PFSI values observed in Houffalize were also likely affected by residual cloud contamination.

The boxplots of mean seasonal PFSI values shown in Figure 3.25 confirm the patterns observed in the spatial maps. Burned areas generally show higher PFSI values than unburned areas during summer and fall 2025, with the largest spread occurring in summer 2025, indicating strong spatial variability in post-fire recovery intensity. In contrast, unburned areas show a much smaller spread and remain closer to stable conditions. During winter 2025, both burned and unburned areas shift toward negative values due to reduced vegetation activity. By spring 2026, positive values reappear in both groups, while the spread within burned areas becomes considerably smaller, suggesting that post-fire recovery dynamics become less distinct between the locations.

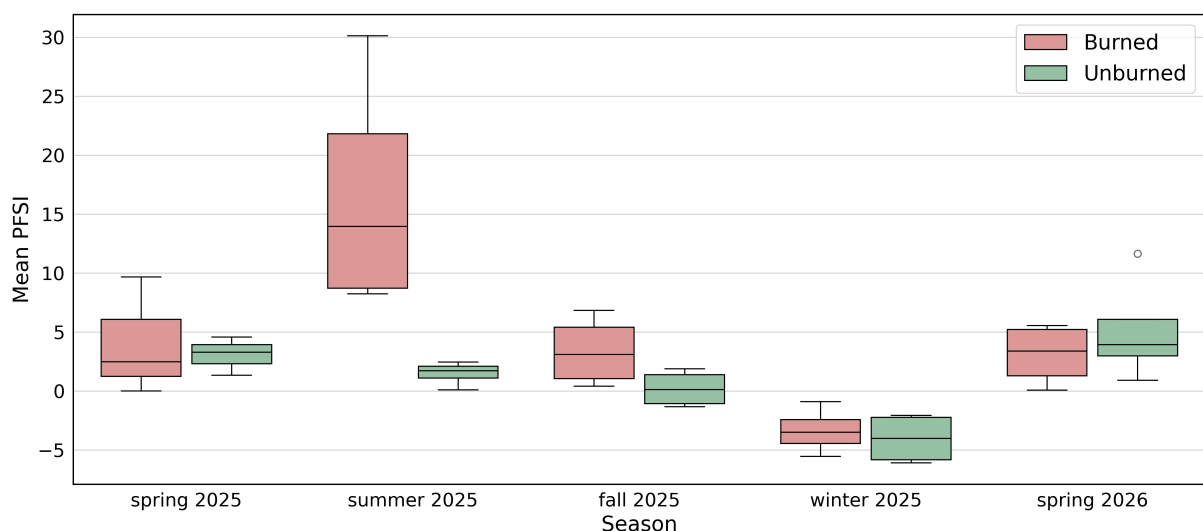


Figure 3.25: Seasonal distribution of mean PFSI values in burned and unburned areas across the four study sites: Clinge, Arlon, Maasmechelen, and Houffalize.

3.3.2.3 One-year post-fire recovery dynamics using the PFSI

Because the PFSI was originally developed to analyse post-fire recovery trajectories over multiple years (Gibson et al., 2022), the index was also evaluated over the maximum available period in this study: the first full year following each fire event.

The resulting spatial patterns are shown in Figure 3.26. The exact distributions of the PFSI values can be found in Appendix Figure A.25. The results show clear differences in post-fire recovery dynamics between the study sites. Maasmechelen exhibits by far the highest positive PFSI values, with very strong recovery signals visible across almost the entire burned area.

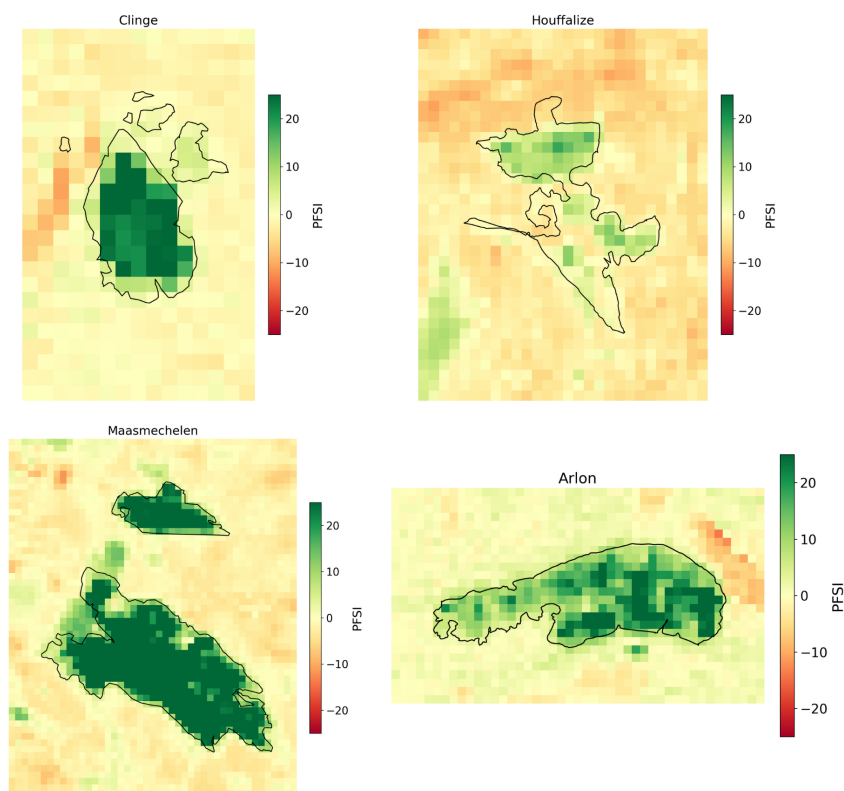


Figure 3.26: Spatial distribution of one-year post-fire PFSI values across the four study areas: Clinge, Arlon, Maasmechelen, and Houffalize.

A likely explanation for this strong response in Maasmechelen is the rapid post-fire expansion of *Molinia caerulea* (purple moor grass), which quickly colonises disturbed heathland environments after wildfires (Jacquemyn et al., 2005). This was also confirmed by the local forest ranger, Corina Cools (personal communication, May 21, 2026), who reported that large parts of the burned area were already covered again by purple moor grass within eight days after the fire. In addition, sheep sorrel (*Rumex acetosella*) was also observed in the area.

In contrast, Houffalize shows considerably lower recovery values than the other study areas. Although positive PFSI values occur within the burned area, the overall recovery signal remains weak. Moreover, Houffalize is the only site where PFSI values outside the fire perimeter are lower than those observed in the unburned areas of the other study sites, suggesting reduced vegetation condition in the surrounding vegetation, possibly related to drought stress during that year. The unburned reference areas of the other study sites generally show mean PFSI values close to zero, consistent with the conceptual framework of Gibson et al. (2022), where near-zero values represent relatively stable vegetation conditions.

Figure 3.27 summarizes the mean PFSI values inside and outside the fire perimeter. Maasmechelen exhibits by far the highest mean PFSI value within the burned area, whereas Houffalize shows the weakest recovery response. Furthermore, Houffalize is the only study site where the mean PFSI value outside the fire perimeter is negative, while the unburned areas of the other sites remain closer to zero.

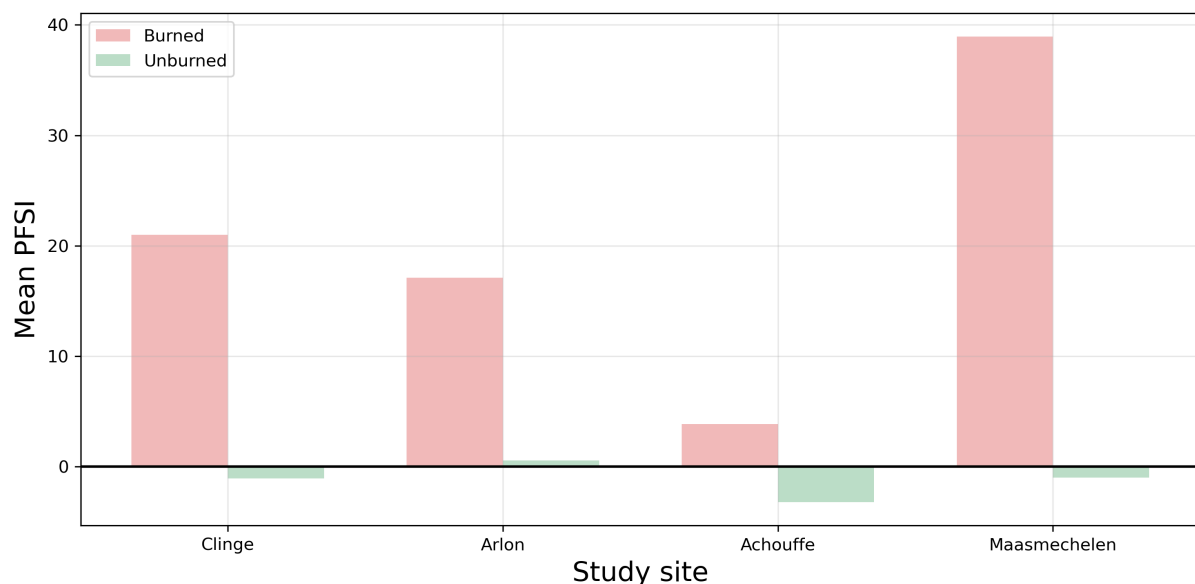


Figure 3.27: Mean one-year post-fire PFSI values for each study site: Clinge, Arlon, Maasmechelen, and Houffalize.

The observed patterns are consistent with Gibson et al. (2022), who found that high PFSI values mainly occur during early post-fire recovery and reflect rapid vegetation regrowth. However, while Gibson et al. (2022) analysed recovery over periods of up to ten years, the present study only covers the first seasonal cycle after fire. Therefore, these results should be interpreted as short-term recovery dynamics rather than indicators of long-term ecosystem stabilization. Similarly, Zegrar et al. (2025) confirmed the usefulness of the PFSI for monitoring post-fire recovery in Mediterranean forests in northwestern Algeria, although they reported generally lower PFSI values and slower recovery during the first post-fire years. Apart from these two studies, no further applications of the PFSI were found in the literature.

Conclusion

This thesis investigates the ecological impacts of the 23 March 2025 wildfire in the Clingse Bossen and evaluates the potential of Sentinel-2 remote sensing for burned area detection and post-fire vegetation recovery monitoring in Clinge, Arlon, Maasmechelen and Houffalize.

Wildfire effects on soil properties

The results from the Clingse Bossen wildfire study demonstrate that the 2025 wildfire affected soil properties, even though the fire was likely of low intensity. Shortly after the fire, burned plots showed higher soil water repellency than unburned plots. The exceptionally dry conditions prior to sampling likely intensified this response by reducing soil moisture. Bulk density was also significantly lower in burned plots shortly after the fire. However, both the increase in soil water repellency and the decrease in bulk density weakened over time, suggesting that these post-fire effects were largely temporary. The wildfire furthermore affected soil pH. Although wildfire is often associated with increased pH due to ash deposition, burned plots showed lower pH values during the later sampling periods. This was likely caused by the leaching of base cations following rainfall, combined with the limited buffering capacity of the sandy soils and the influence of conifer needles.

Wildfire effects on vegetation recovery

The strongest increase in vegetation coverage in the burned area in the Clingse Bossen occurred between June and July. By the end of the monitoring period, vegetation covered approximately 40% of the burned area, and species richness had increased from 7 species in April 2025 to a maximum of 18 species in March 2026. However, recovery was highly uneven, as species evenness remained close to zero throughout the monitoring period. This pattern was largely driven by the dominance of *Rumex acetosella* (sheep sorrel), a species well adapted to dry, acidic, nutrient-poor, and disturbed sandy soils. Although this rapid colonization demonstrates that vegetation can quickly re-establish after fire, the dominance of *R. acetosella* may suppress tree seedling establishment through competition for light, water, and space, thereby slowing forest succession. In addition, the invasive species *Prunus serotina* (American black cherry) was observed in the burned area and may benefit from the open conditions created by the wildfire, potentially hindering native tree regeneration and altering forest succession.

The original *Picea abies* stand is unlikely to recover naturally, as it had already been severely affected by the bark beetle *Ips typographus* before the wildfire occurred. Rather than affecting an intact forest, the wildfire impacted an ecosystem that was already under considerable ecological stress. The combination of both disturbances may lead to long-term shifts in forest composition and ecosystem functioning. Whether the area will develop into a forest again and retain its key ecosystem services remains uncertain and requires further monitoring, as vegetation recovery in forest ecosystems typically occurs over years to decades, whereas this study only monitored the first post-fire year.

Methods for wildfire detection in Belgium

The remote sensing analysis confirmed that Sentinel-2 is suitable for burned area detection in small and fragmented Belgian landscapes. Among the tested indices, the Normalized Burn Ratio (NBR) proved robust across a range of Belgian vegetation types, consistently achieving strong classification results across the four study sites and being associated with relatively consistent threshold values. Although the best-performing index varied between sites, NBR appears suitable for operational burned area mapping.

The Post-Fire Stability Index (PFSI) proved useful for monitoring post-fire vegetation recovery dynamics over time. Across all four study sites, the strongest positive PFSI values were generally observed during the first post-fire summer. However, recovery trajectories differed considerably among sites. Maasmechelen showed the strongest recovery response, whereas Houffalize exhibited weaker recovery patterns. The results further demonstrate that strong spectral recovery signals do not necessarily reflect high ecological recovery, as increased vegetation activity may also result from the expansion of a limited number of dominant species. Nevertheless, the PFSI successfully captured the main temporal and spatial patterns of post-fire vegetation recovery across the four different study areas.

This study relied exclusively on optical imagery and did not include radar data. Future research could therefore investigate the added value of radar-based approaches, which are not affected by cloud cover.

Challenges and opportunities for forest management

As relatively few studies have examined post-fire ecological responses in Belgium, additional long-term research is needed to better understand recovery trajectories, identify when ecosystems require active restoration, and determine which ecosystems are most vulnerable. Such knowledge will become increasingly important when multiple wildfires occur simultaneously and management agencies must prioritize interventions.

The increasing risk of wildfires in Belgium provides an opportunity to better integrate wildfire management into forest and nature management. Future management approaches will need to balance biodiversity conservation, ecosystem resilience, and wildfire risk reduction. For example, while dead wood provides important ecological benefits, it can also increase fuel loads under certain conditions. Greater attention to wildfire ecology and fire risk could therefore also be integrated into education programmes such as Bioscience Engineering: Forest and Nature Management, helping to better prepare future managers.

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A. Appendices

A.1 Literature review

Table A.1: Overview of optical satellites and their main characteristics (European Space Agency, 2025b).

Satellite	Spectral bands (nm)	Resolutions
Pléiades Neo	Panchromatic: 450–800 Deep Blue: 400–450 Blue: 450–520 Green: 530–590 Red: 620–690 Red Edge: 700–750 Near-infrared: 770–880	Spatial resolution: 30 cm – 1.2 m Revisit time: Twice a day, anywhere
Vision-1	Panchromatic: 450–650 Blue: 440–510 Green: 510–590 Red: 600–670 Red: 760–910	Spatial resolution: 0.87 – 3.48 m Revisit capacity: 1–8 days depending on latitude
WorldView Legion	Pan: 450–800 Coastal: 400–450 Blue: 450–510 Green: 510–580 Yellow: 585–625 Red: 630–690 Red Edge 1: 695–715 Red Edge 2: 730–750 Near IR: 770–895	Spatial resolution: 0.34 – 1.36 m at nadir Revisit time: Up to 15 times per day Spatial coverage: 90 N – 90 S, 180 W – 180 E
GEOSAT-2	Pan: 560–900 Blue: 466–525 Green: 532–599 Red: 640–697 NIR: 770–892	Spatial resolution: 0.75 – 4 m Revisit time: 2 days worldwide Spatial coverage: 90 N – 90 S, 180 W – 180 E

Satellite	Spectral bands (nm)	Resolutions
SPOT-7	PAN: 450–750 Blue: 450–520 Green: 530–590 Red: 620–690 NIR: 760–890	Spatial resolution: 1.5 – 6 m Revisit time: 1 – 3 days Spatial coverage: 90 N – 90 S, 180 W – 180 E
Landsat-9	Deep Blue: 430–450 Blue: 450–510 Green: 523–590 Red: 640–670 NIR: 850–880 SWIR 1: 1570–1650 SWIR 2: 2110–2290 PAN: 500–680 PAN: 1360–1380	Spatial resolution: 100 m Revisit time: 16 days Spatial coverage: 90 N – 90 S, 180 W – 180 E
Sentinel-3	OLCI: 21 bands covering visible, red-edge and NIR (400–1020 nm) SLSTR: visible, NIR, SWIR and thermal IR bands	Spatial resolution: 300 m (OLCI) 500 m (SLSTR VIS/NIR/SWIR) 1 km (SLSTR thermal) Revisit time: ~2 days Global coverage

Table A.2: Overview of radar satellites and their main characteristics

Satellite	Carrier Frequency	Polarization	Spatial Resolution (m)	Revisit Time
ICEYE	9.65 GHz (X-band)	VV	1 – 3 – < 15	20 h
COSMO-SkyMed	9.6 GHz (X-band)	HH, VV, HV, VH	1 – 3 – 15 – 100	5 days
TerraSAR-X TanDEM-X	9.65 GHz (X-band)	HH, VV, HV, VH	0.25 – 1 – 2 – 3 – 18 – 40	11 days
PAZ	9.65 GHz (X-band)	HH, VV, HV, VH	0.25 – 1 – 2 – 3 – 18 – 40	24 h

Table A.3: Sentinel-2 MSI spectral bands and applications (Copernicus Sentinel Wiki, nd).

Band	Centre (nm)	Width (nm)	Resolution (m)	Purpose
B1	443	20	60	Coastal aerosol; Atmospheric correction (aerosol scattering)
B2	490	65	10	Blue; Sensitive to vegetation senescing, carotenoid, browning and soil background; atmospheric correction (aerosol scattering)
B3	560	35	10	Green; Green peak, sensitive to total chlorophyll in vegetation
B4	665	30	10	Red; Maximum chlorophyll absorption
B5	705	15	20	Red edge; Position of red edge; consolidation of atmospheric corrections / fluorescence baseline
B6	740	15	20	Red edge; Position of red edge, atmospheric correction, retrieval of aerosol load
B7	783	20	20	Red edge; Leaf Area Index (LAI), edge of the Near-Infrared (NIR) plateau
B8	842	105	10	NIR; LAI
B8A	865	20	20	NIR; NIR plateau, sensitive to total chlorophyll, biomass, LAI and protein; water vapour absorption reference; retrieval of aerosol load and type
B9	945	20	60	Water vapour; Water vapour absorption, atmospheric correction
B10	1375	30	60	Cirrus (SWIR); Detection of thin cirrus for atmospheric correction
B11	1610	90	20	SWIR; Sensitive to lignin, starch and forest above-ground biomass. Snow/ice/cloud separation
B12	2190	180	20	SWIR; Assessment of Mediterranean vegetation conditions. Distinction of clay soils for the monitoring of soil erosion. Distinction between live biomass, dead biomass and soil, e.g. for burn scar mapping

Table A.4: Scene classification values for Sentinel-2 (Copernicus Sentinel Wiki, nd).

Label	Classification
0	NO_DATA
1	SATURATED_OR_DEFECTIVE
2	CAST_SHADOWS
3	CLOUD_SHADOWS
4	VEGETATION
5	NOT_VEGETATED
6	WATER
7	UNCLASSIFIED
8	CLOUD_MEDIUM_PROBABILITY
9	CLOUD_HIGH_PROBABILITY
10	THIN_CIRRUS
11	SNOW or ICE

A.2 Materials and methods

Table A.5: Dates of vegetation surveys conducted during the study period.

Sampling date
2025-04-18
2025-05-16
2025-06-13
2025-07-10
2025-08-08
2025-09-05
2025-10-02
2025-10-31
2025-11-26
2025-12-24
2026-01-23
2026-02-19
2026-03-18

Table A.6: Intervals used for PFSI calculation.

PFSI step	$t - 1$	t
1	18/03/2025 – 18/04/2025	18/04/2025 – 16/05/2025
2	18/04/2025 – 16/05/2025	16/05/2025 – 13/06/2025
3	16/05/2025 – 13/06/2025	13/06/2025 – 10/07/2025
4	13/06/2025 – 10/07/2025	10/07/2025 – 08/08/2025
5	10/07/2025 – 08/08/2025	08/08/2025 – 05/09/2025
6	08/08/2025 – 05/09/2025	05/09/2025 – 02/10/2025
7	05/09/2025 – 02/10/2025	02/10/2025 – 31/10/2025
8	02/10/2025 – 31/10/2025	31/10/2025 – 26/11/2025
9	31/10/2025 – 26/11/2025	26/11/2025 – 24/12/2025
10	26/11/2025 – 24/12/2025	24/12/2025 – 23/01/2026
11	24/12/2025 – 23/01/2026	23/01/2026 – 19/02/2026
12	23/01/2026 – 19/02/2026	19/02/2026 – 18/03/2026

A.3 Soil analysis

Table A.7: P-values for burned vs. unburned comparisons per sampling date. Significant p-values are shown in bold.

Property	Test used	2025-04-18	2025-08-08	2025-11-26
Bulk density	Wilcoxon	0.0308	0.2317	0.2120
Water repellency	Wilcoxon	0.0169	1.0000	n.a.
Soil moisture	Welch t-test	0.6410	0.0205	0.1670
SOM	Welch t-test on log-data	0.2164	0.0934	0.1485
Total C	Welch t-test on log-data	0.3659	0.1945	0.4119
Total N	Welch t-test	0.4450	0.1135	0.2147
CEC	Welch t-test on log-data	0.4384	0.0090	0.6336
pH	Wilcoxon	0.4248	0.0034	0.0446

Table A.8: Overall temporal analyses of burned–unburned differences. Significant p-values are shown in bold.

Property	Test used	Overall p-value
Bulk density	Kruskal-Wallis	0.3473
Water repellency	Kruskal-Wallis	2.54×10^{-7}
Soil moisture	ANOVA	0.0137
SOM	ANOVA	0.0014
Total C	ANOVA	0.0122
Total N	ANOVA	0.0121
CEC	ANOVA	0.0026
pH	Kruskal-Wallis	0.0188

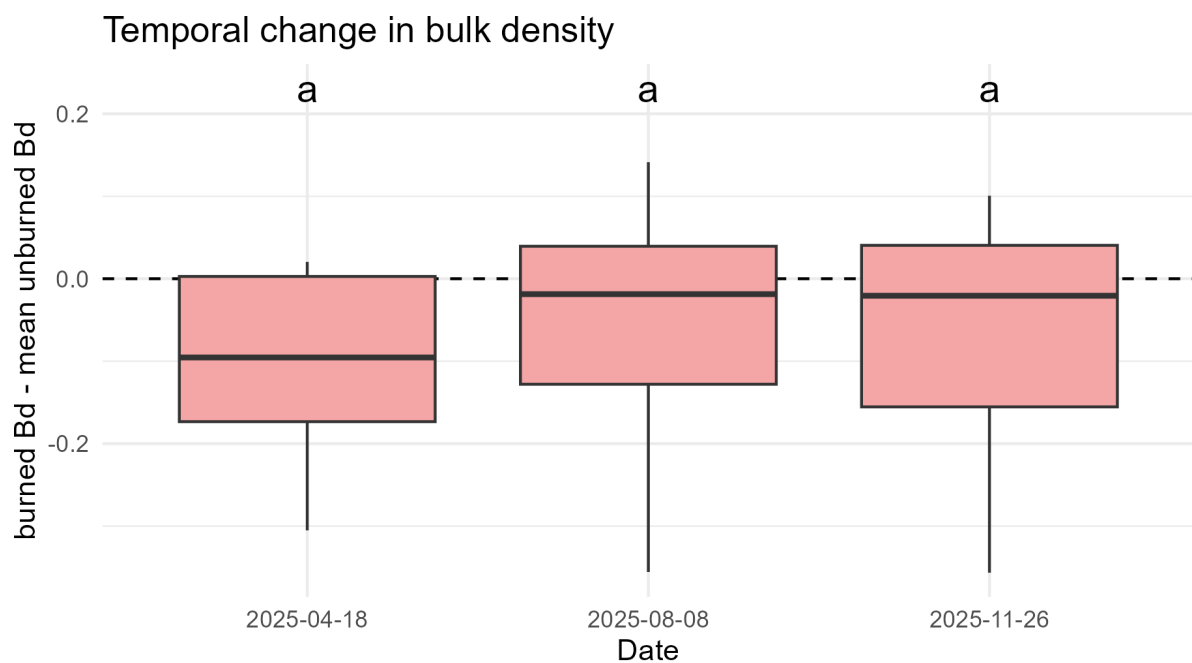


Figure A.1: Temporal variation in the difference in bulk density between burned samples and the mean bulk density of unburned samples collected on the same date. Different letters indicate significant differences between dates based on Dunn's test with Bonferroni correction ($p < 0.05$).

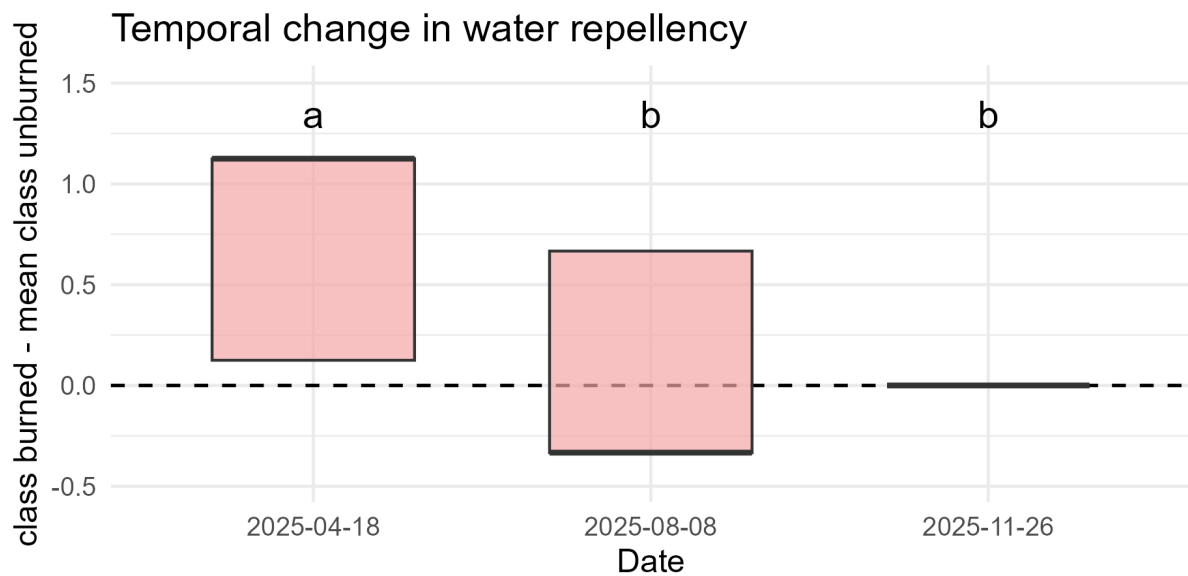


Figure A.2: Temporal variation in the difference in water repellency class between burned samples and the mean water repellency class of unburned samples collected on the same date. Different letters indicate significant differences between dates based on Dunn's test with Bonferroni correction ($p < 0.05$).

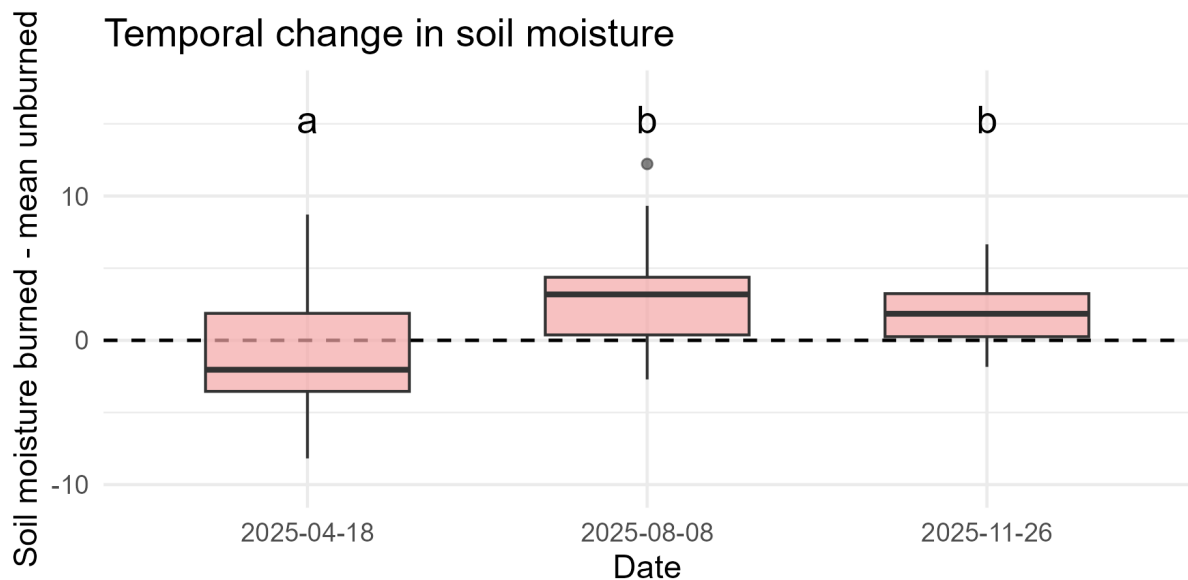


Figure A.3: Temporal variation in the difference in soil moisture between burned samples and the mean soil moisture of unburned samples collected on the same date. Different letters indicate significant differences between dates based on Duncan's test ($p < 0.05$).

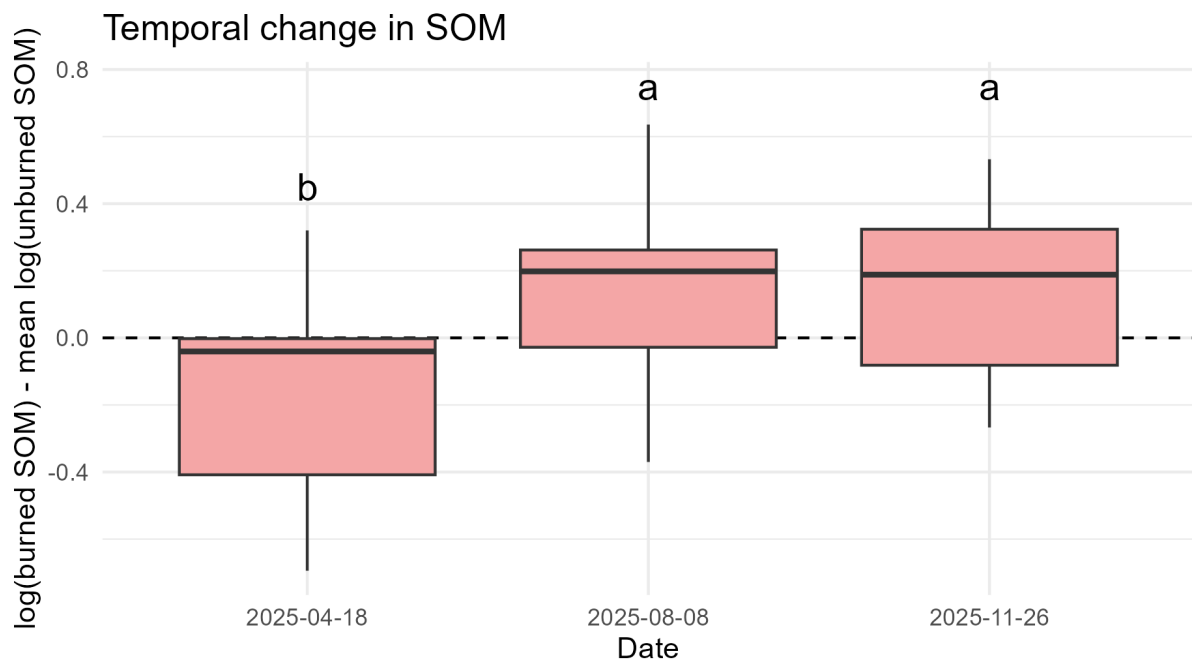


Figure A.4: Temporal variation in the difference in log-transformed SOM between burned samples and the mean log-transformed SOM of unburned samples collected on the same date. Different letters indicate significant differences between dates based on Duncan's test ($p < 0.05$).

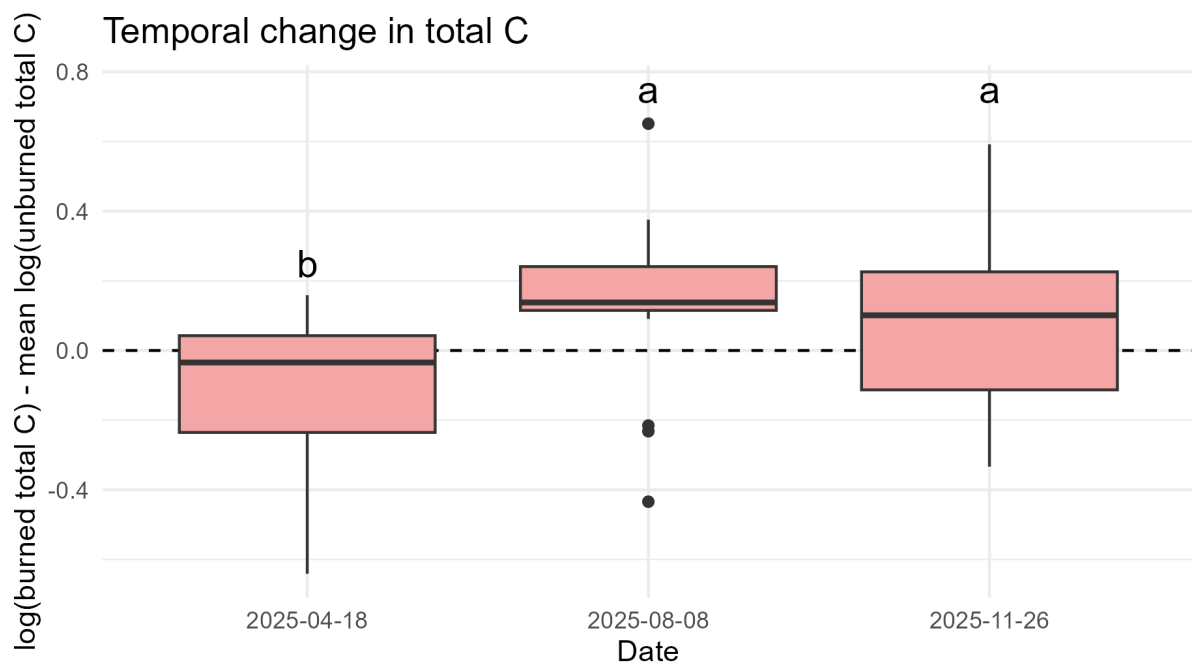


Figure A.5: Temporal variation in the difference in log-transformed total C between burned samples and the mean log-transformed total C of unburned samples collected on the same date. Different letters indicate significant differences between dates based on Duncan's test ($p < 0.05$).

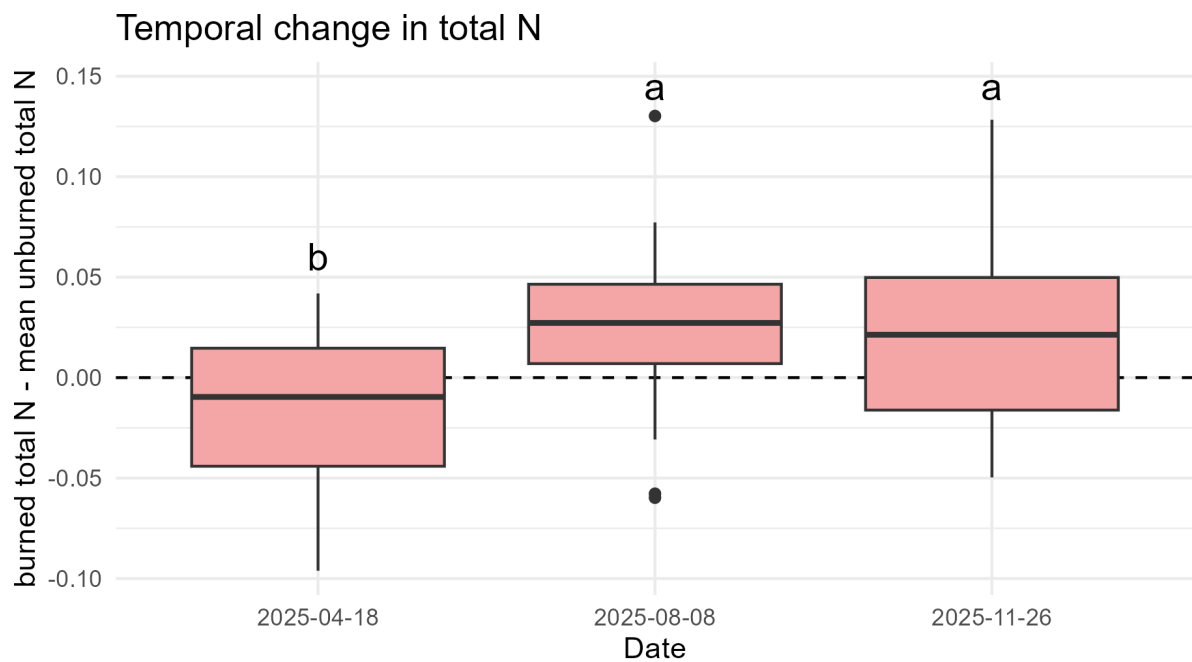


Figure A.6: Temporal variation in the difference in total N between burned samples and the mean total N of unburned samples collected on the same date. Different letters indicate significant differences between dates based on Duncan's test ($p < 0.05$).

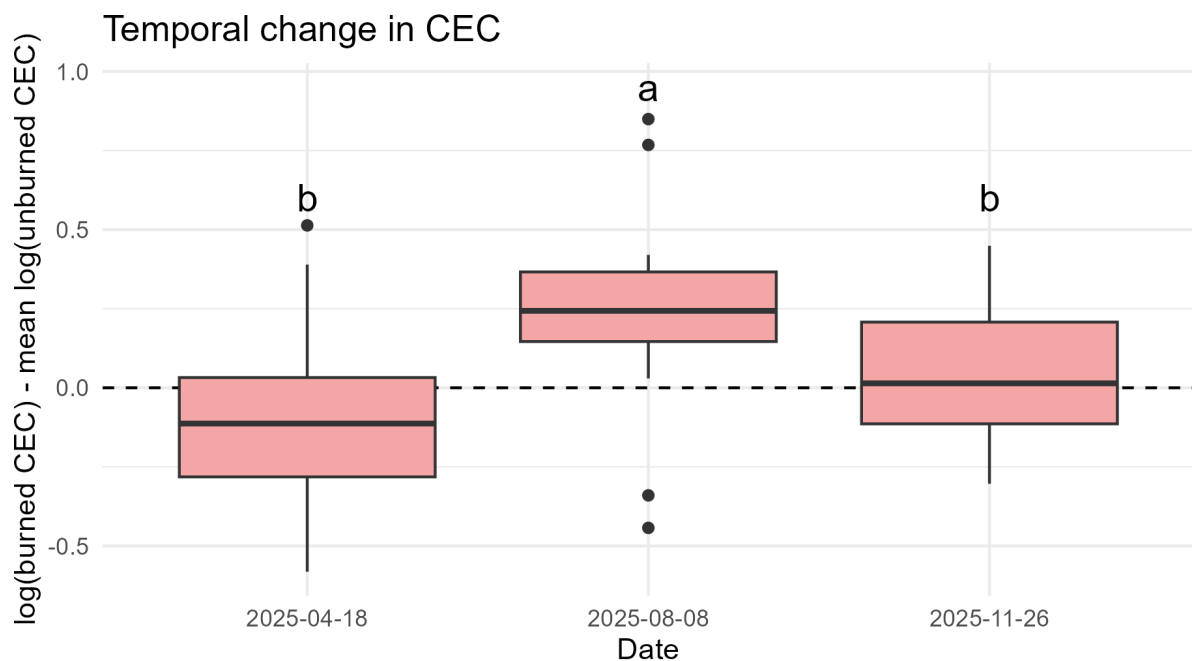


Figure A.7: Temporal variation in the difference in log-transformed CEC between burned samples and the mean log-transformed CEC of unburned samples collected on the same date. Different letters indicate significant differences between dates based on Duncan's test ($p < 0.05$).

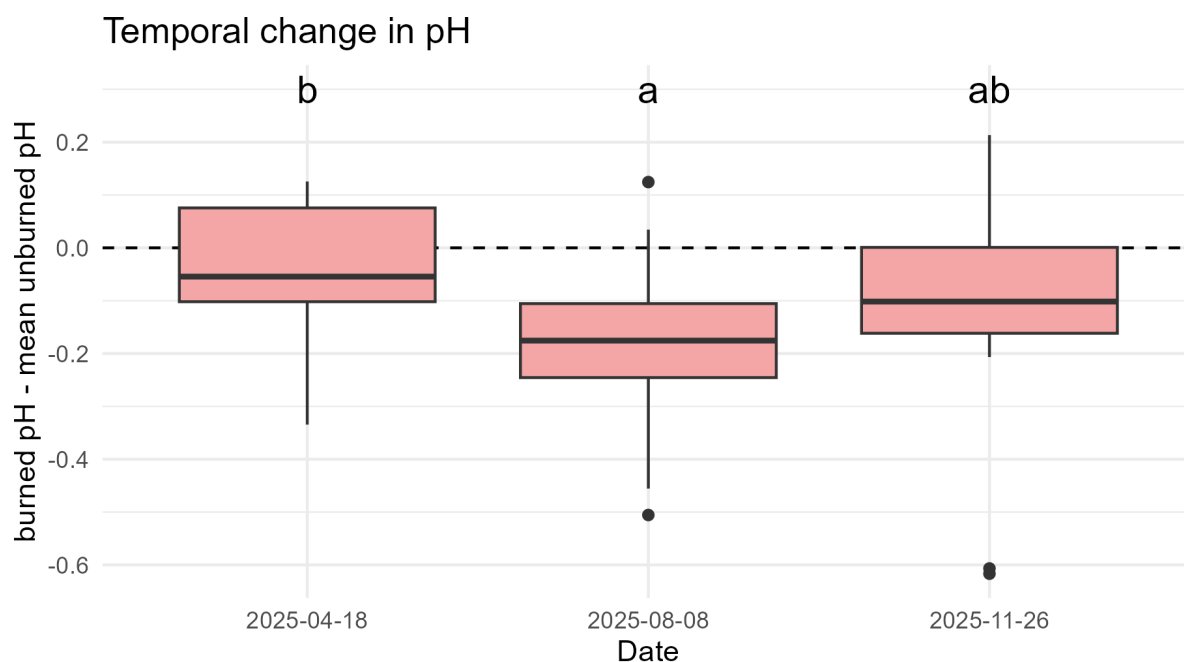


Figure A.8: Temporal variation in the difference in pH between burned samples and the mean pH of unburned samples collected on the same date. Different letters indicate significant differences between dates based on Dunn's test with Bonferroni correction ($p < 0.05$).

A.4 Vegetation analysis

Table A.9: Monthly precipitation measurements recorded at the Sint Jansteen weather station (Latitude/Longitude: 51.26° N, 4.049° E; elevation: 3 m).

Month	Total precipitation (mm)	Days with no data
2025-03	4.21	0
2025-04	10.69	0
2025-05	31.52	0
2025-06	38.07	0
2025-07	61.80	0
2025-08	28.29	0
2025-09	50.60	4
2025-10	98.83	7
2025-11	36.55	5
2025-12	24.89	0
2026-01	53.17	0
2026-02	85.72	0
2026-03	47.11	0

Table A.10: Plant species recorded in the burned plots (Ecopedia, 2026a; Flora van Nederland, 2026).

Species	Description
<i>Acer pseudoplatanus</i>	Nutrient-poor to highly nutrient-rich; slightly moist to dry soils; acidic to calcareous substrates; sensitive to soil acidification, but able to partly counteract or restore humus degradation.
Asteraceae	–
<i>Betula</i> spp.	–
Bryophyta spp.	–
<i>Carduus</i> spp.	–
<i>Cirsium arvense</i>	Moderately to highly nutrient-rich; light shade to full sun; dry to moist; ruderal and pioneer habitats; nitrogen-rich soils; legally controlled species.
<i>Conyza sumatrensis</i>	Dry, warm, disturbed habitats; pioneer species from South America; non-invasive exotic.
<i>Cytisus scoparius</i>	Moderately nutrient-rich; dry acidic soils; low to moderate nitrogen; sandy and heathland soils.
<i>Dryopteris dilatata</i>	Nutrient-poor; shaded habitats, often in conifer plantations; acidic to weakly acidic soils; nitrogen-rich soils.
<i>Epilobium</i> spp.	–
<i>Erigeron canadensis</i>	Moderately to highly nutrient-rich; dry; non-invasive exotic; thrives on dry, moderately nitrogen-rich sandy soils; pioneer after disturbance.
<i>Erigeron</i> spp.	–
<i>Fallopia convolvulus</i>	Nutrient-poor to highly nutrient-rich; dry to moist sandy disturbed soils; native pioneer species; nitrogen-rich soil indicator.
<i>Galeopsis tetrahit</i>	Moderately to highly nutrient-rich; sandy to peaty soils; often found where humus decomposition is accelerated, such as forest edges, roadsides, and arable fields; moderately nitrogen-rich to nitrogen-rich soils.
<i>Galium aparine</i>	Moderately to highly nutrient-rich; dry to moist; strongly nitrogen-rich soils.
<i>Holcus lanatus</i>	Nitrogen-poor to moderately nitrogen-rich soils; occurs on all soil types, provided the soil is sufficiently humus-rich and moisture-retentive.
<i>Hypochaeris radicata</i>	Moderately nutrient-rich; dry to slightly moist grasslands; occurs on sand, sandy loam, loam, and clay; acidic to basic soils.
<i>Hypochaeris</i> spp.	–
<i>Jacobaea vulgaris</i> subsp. <i>vulgaris</i>	Nutrient-poor to moderately nutrient-rich; moist to dry pioneer and grassy habitats; neutral to basic soils.

Species	Description
<i>Juncus effusus</i>	Moderately nutrient-rich; wet acidic lime-poor habitats; disturbed ecosystem indicator; low to moderate nitrogen.
<i>Ornithopus perpusillus</i>	Nutrient-poor; lime-poor sandy soils.
<i>Persicaria maculosa</i>	Highly nutrient-rich; moist disturbed habitats; annual pioneer species; nitrogen-rich soils.
<i>Picea abies</i>	Clay, loam, and sand; moist; prefers acidic soils.
Poaceae spp.	–
<i>Prunus serotina</i>	Nutrient-poor; moist to dry soils; relatively dry habitats with high light availability; pH-indifferent; invasive exotic.
<i>Quercus robur</i>	Nutrient-poor to highly nutrient-rich; dry to wet soils; acidic to neutral or calcareous soils.
<i>Rubus</i> spp.	–
<i>Rumex acetosella</i>	Nutrient-poor; dry acidic habitats; indicator of rather acidic, dry, nutrient-poor conditions; indicator of natuurstreefbeeld: soortenrijk struisgrasland en brem-en gaspeldoornstruweel.
<i>Salix caprea</i>	Moderately nutrient-rich; moist to wet; pioneer species; weak acid to base indicator; nitrogen-rich soils.
<i>Senecio inaequidens</i>	Moderately nutrient-rich; moist; invasive exotic; pioneer habitats on moist to dry soils.
<i>Senecio</i> spp.	–
<i>Senecio sylvaticus</i>	Nutrient-poor to moderately nutrient-rich; open to lightly shaded habitats; dry, lime-poor, sandy, humus-rich soils; mainly slightly acidic to acidic conditions; typical of clear-cuts and other open disturbed sites.
<i>Senecio vulgaris</i>	Highly nutrient-rich; dry to moist disturbed soils; strongly nitrogen-rich habitats.
<i>Solanum nigrum</i>	Highly nutrient-rich; moist; all soil types; weak acid to base indicator; strongly nitrogen-rich soils.
<i>Sonchus asper</i>	Highly nutrient-rich; moist; weak acid to base indicator; nitrogen-rich soils.
<i>Sonchus</i> spp.	–
<i>Stellaria media</i>	Moderately to highly nutrient-rich; moist disturbed and fertilized soils.
<i>Taraxacum officinale</i>	Moderately to highly nutrient-rich; dry to moist; benefits from open disturbed patches.
Unknown seedling	–



A,AB



C

Figure A.9: Contrasting environmental conditions between plots A/AB and plot C.

A.5 Wildfire detection

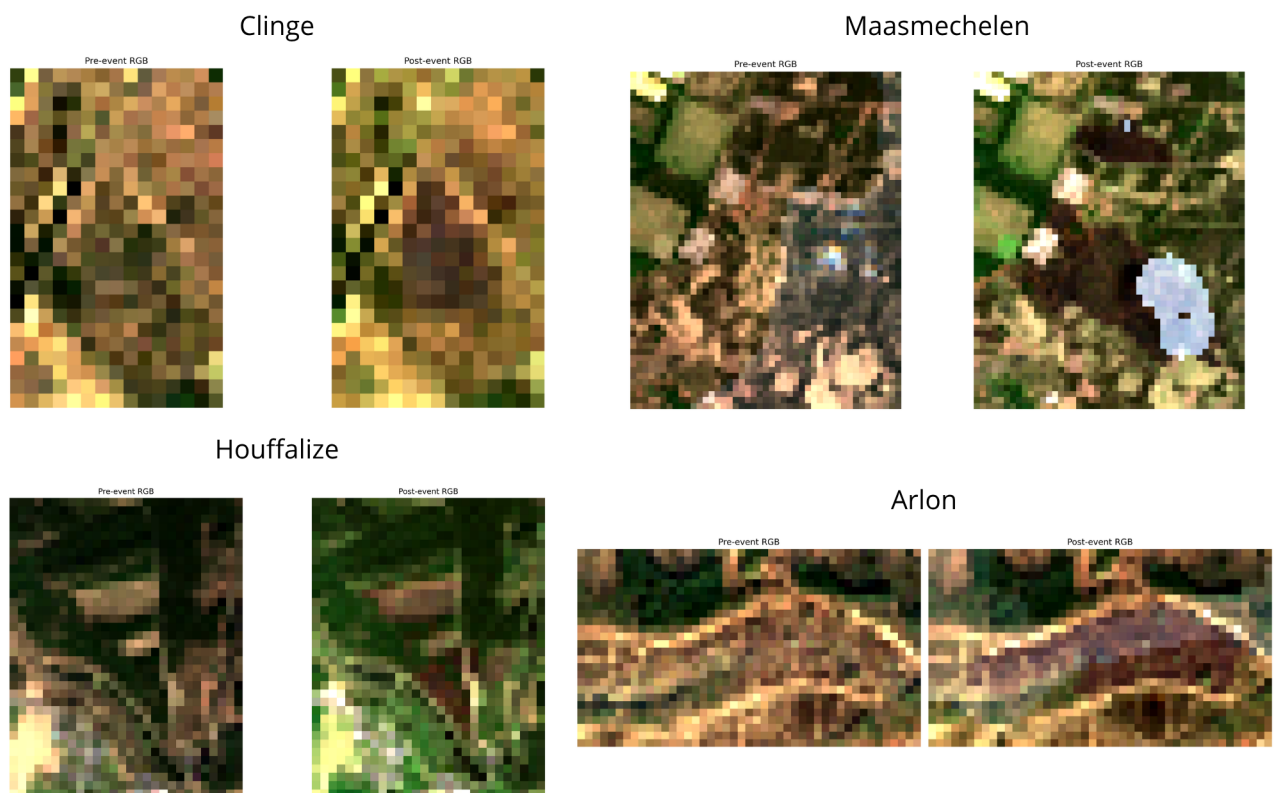


Figure A.10: Pre-fire and post-fire RGB composites for the four study sites (Clinge, Maasmechelen, Houffalize, and Arlon).

Table A.11: F1-scores obtained for each spectral index across the study areas. The highest F1-score per study area is highlighted in bold.

Study area	NBR	NDVI	BAI	NBR+	NBR2	NDSWIR	NDVI RE
Clinge	0.8462	0.8547	0.9076	0.8438	0.8308	0.7429	0.6466
Houffalize	0.8327	0.7500	0.8367	0.8339	0.7597	0.7055	0.5935
Maasmechelen	0.9480	0.8668	0.9182	0.8899	0.9388	0.9218	0.8613
Arlon	0.9455	0.8752	0.8699	0.9418	0.9493	0.9399	0.6521

Table A.12: Optimal threshold values obtained for each spectral index across the study areas.

Study area	NBR	NDVI	BAI	NBR+
Clinge	0.0591	0.0559	-1.92×10^{-7}	-0.0629
Houffalize	0.0615	0.0530	-8.44×10^{-8}	-0.0458
Maasmechelen	0.0621	0.0331	-4.85×10^{-8}	-0.0343
Arlon	0.1109	0.0677	-7.47×10^{-8}	-0.0909

Study area	NBR2	NDSWIR	NDVI RE
Clinge	0.0473	-0.0376	0.0422
Houffalize	0.0145	-0.0575	0.0943
Maasmechelen	0.0646	-0.0333	0.0467
Arlon	0.0673	-0.0650	0.0567

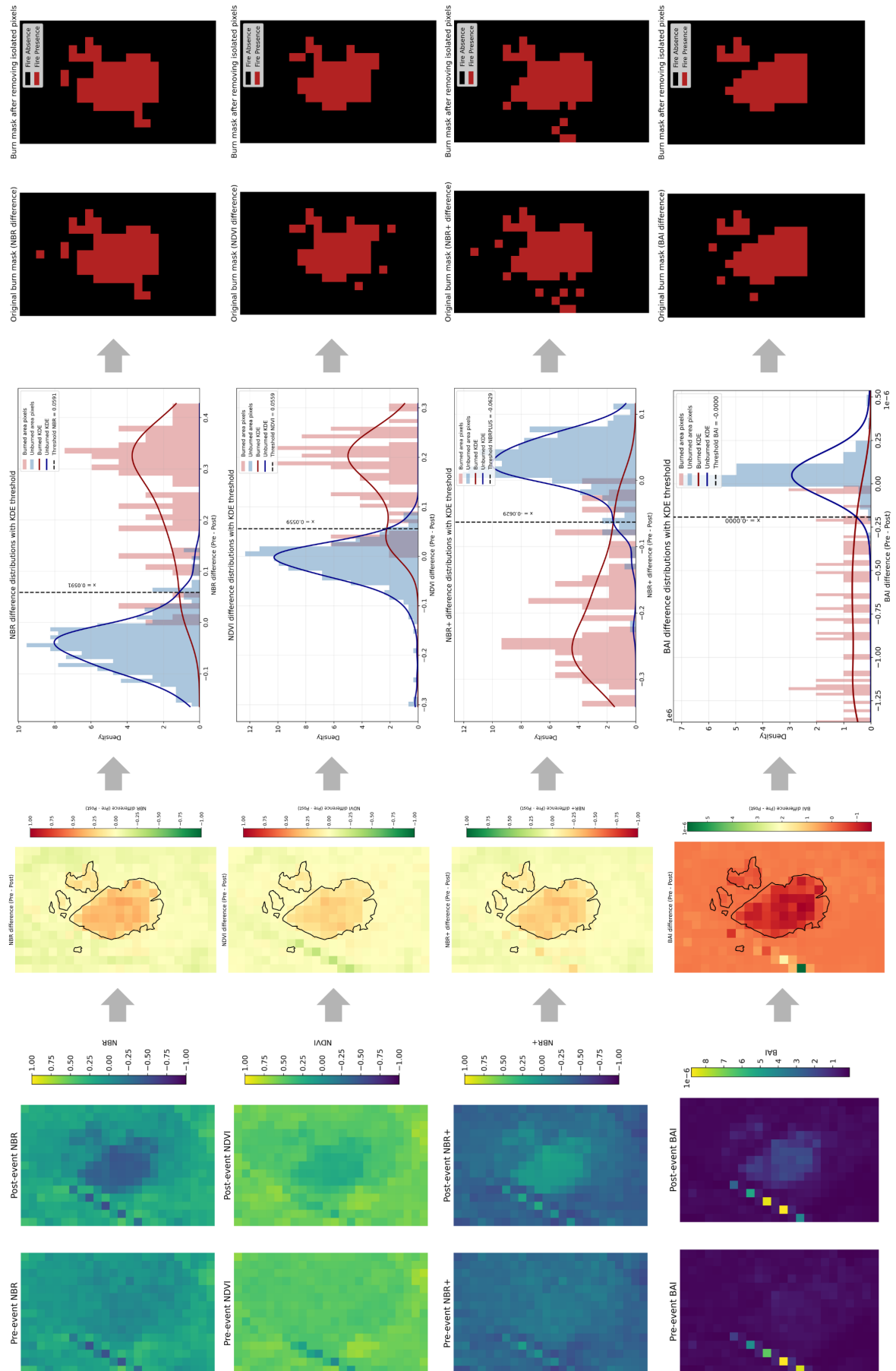


Figure A.11: Burned-area detection workflow for Clinge using NBR, NDVI, NBR+, and BAI.

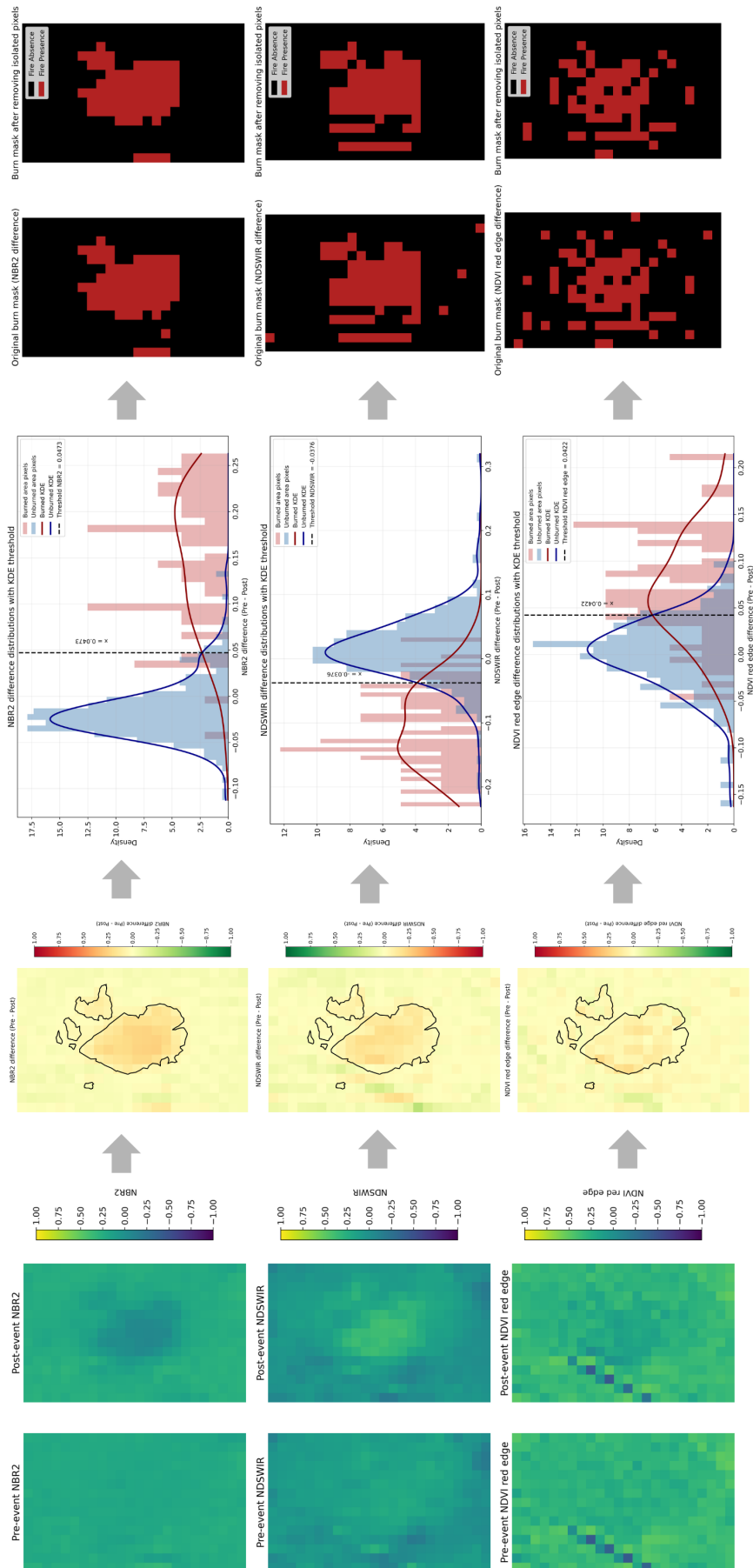


Figure A.12: Burned-area detection workflow for Clinge using NBR2, NDSWIR, and NDVI red-edge.

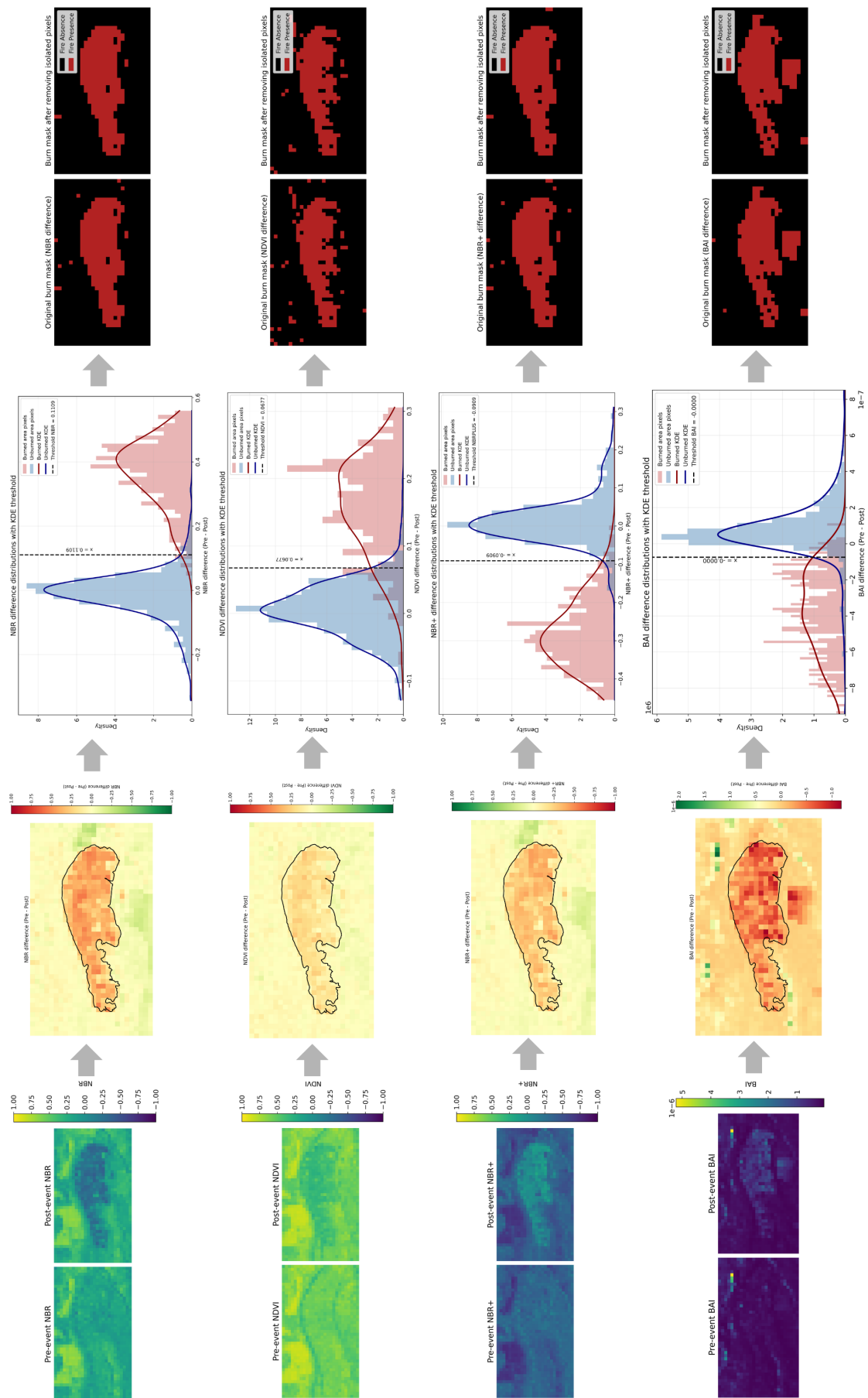


Figure A.13: Burned-area detection workflow for Arlon using NBR, NDVI, NBR+, and BAI.

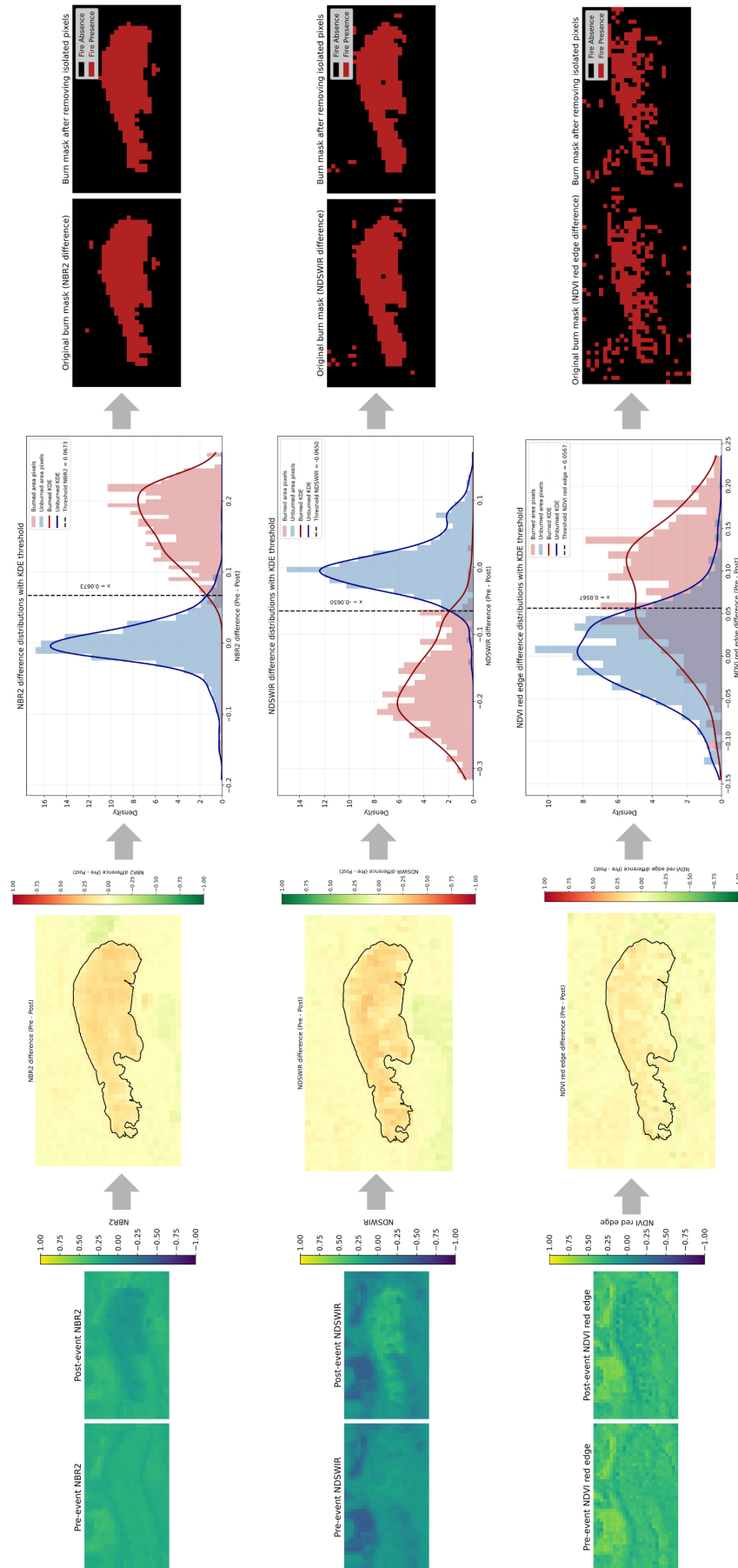


Figure A.14: Burned-area detection workflow for Arlon using NBR2, NDSWIR, and NDVI red-edge.

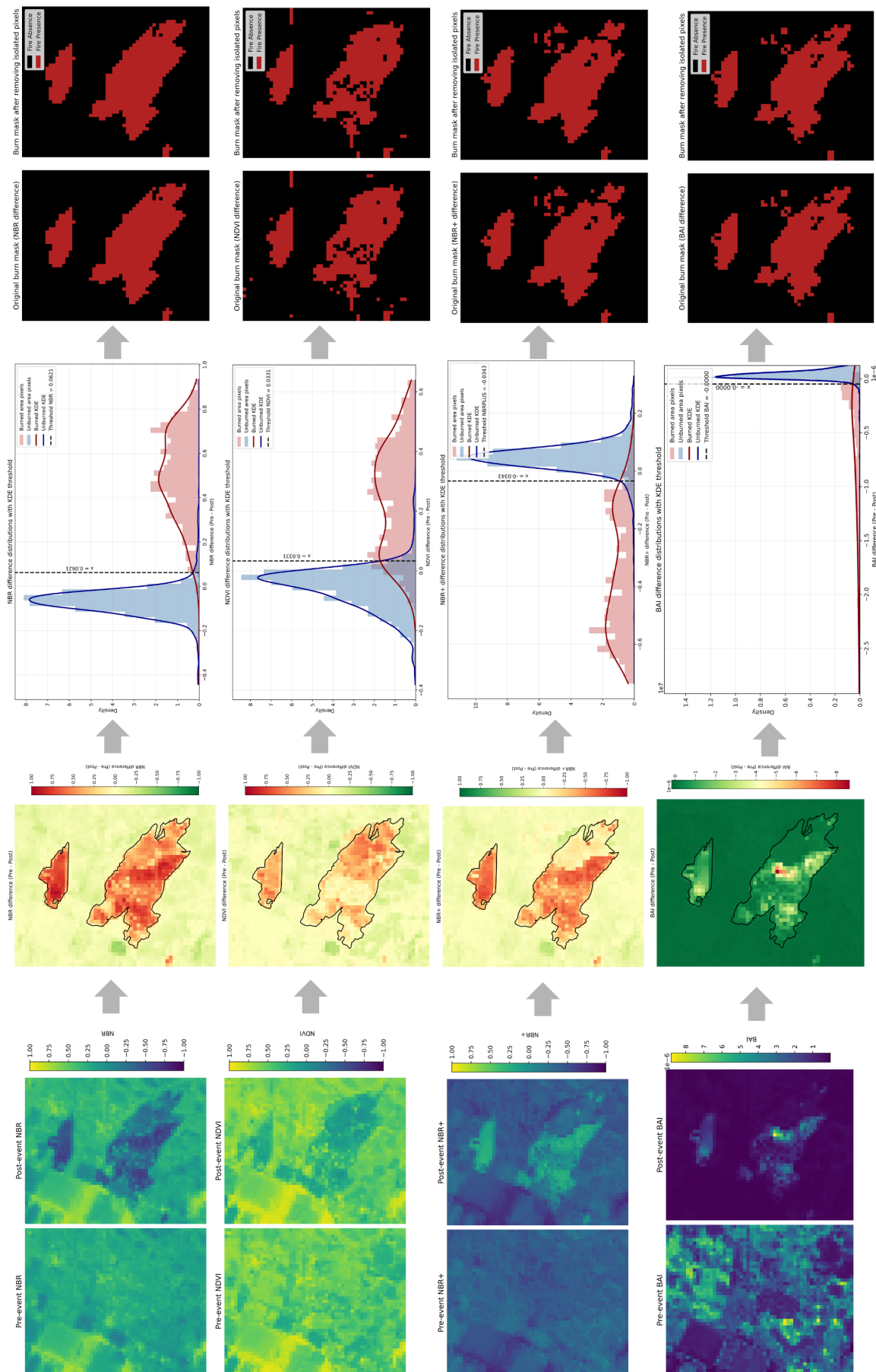


Figure A.15: Burned-area detection workflow for Maasmechelen using NBR, NDVI, NBR+, and BAI.

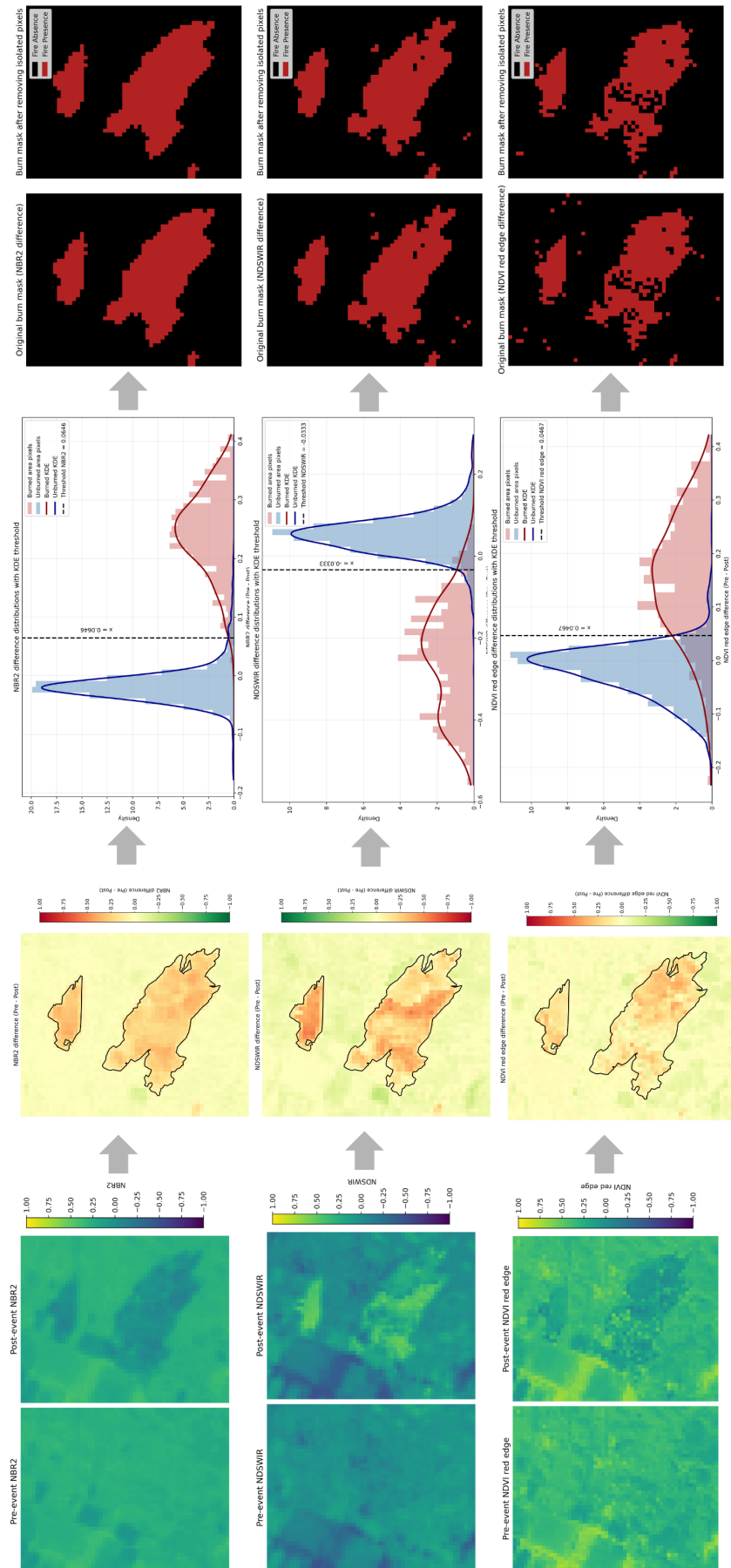


Figure A.16: Burned-area detection workflow for Maasmeechelen using NBR2, NDSWIR, and NDVI red edge.

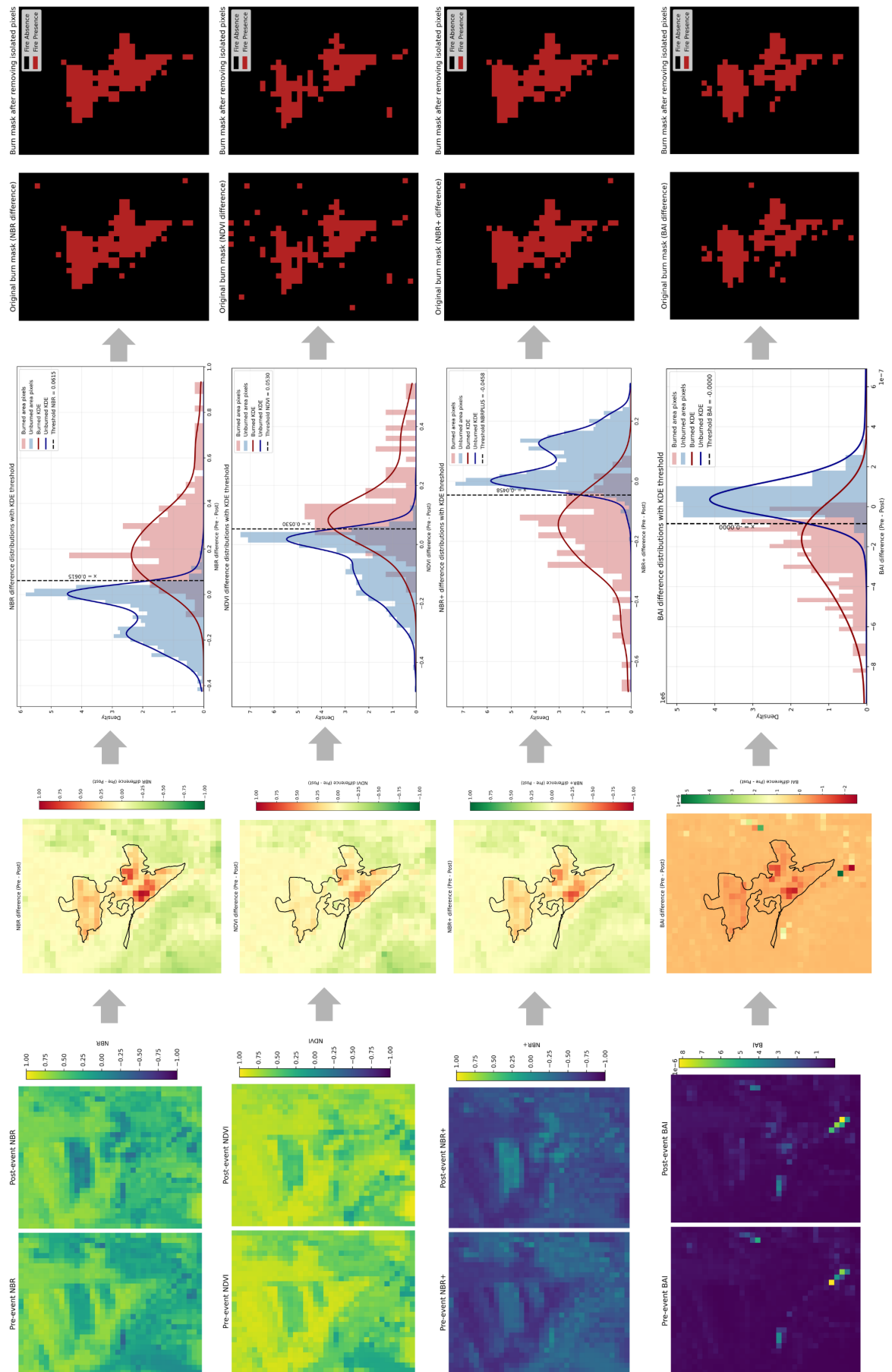


Figure A.17: Burned-area detection workflow for Houffalize using NBR, NDVI, NBR+, and BAI.

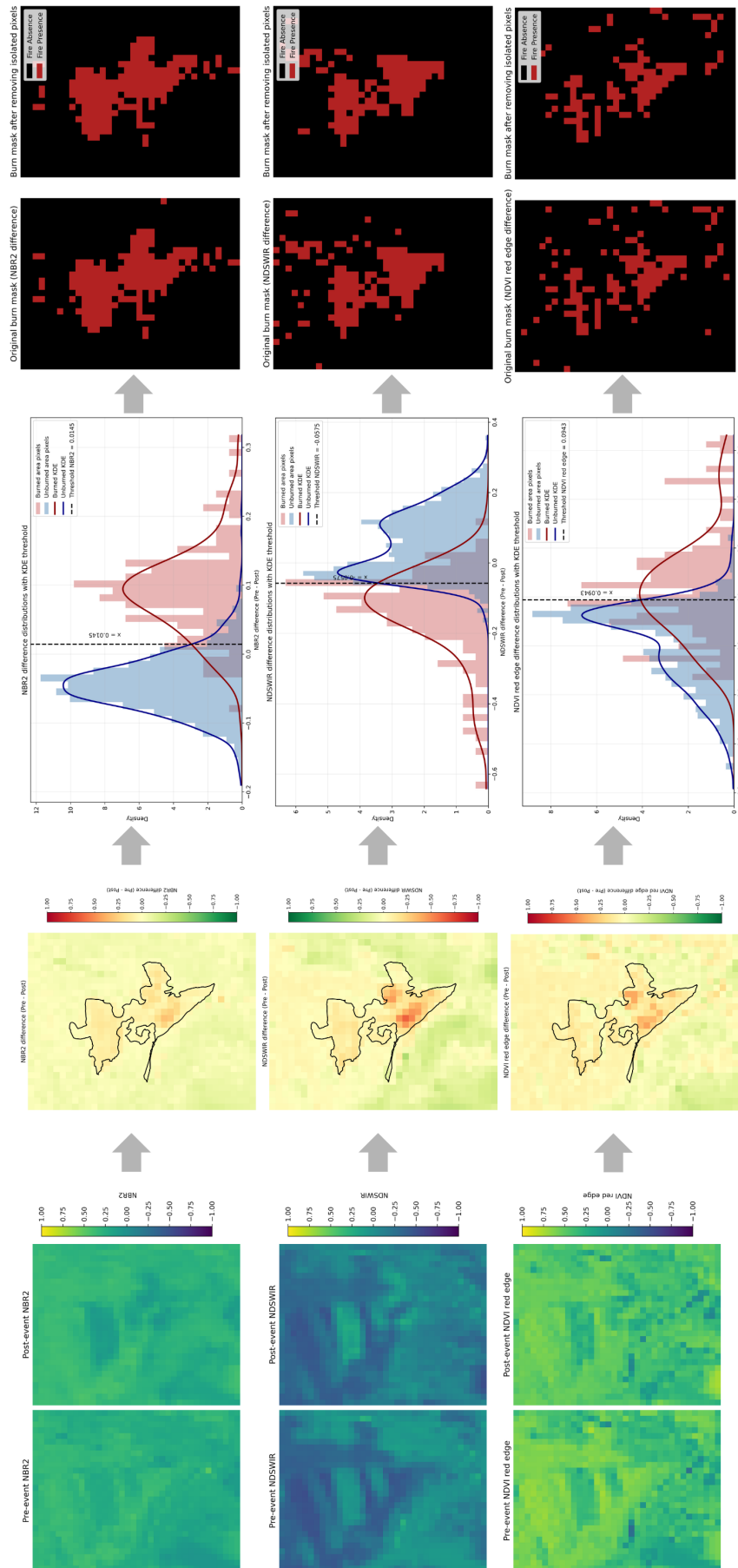


Figure A.18: Burned-area detection workflow for Houffalize using NBR2, NDSWIR, and NDVI red edge.

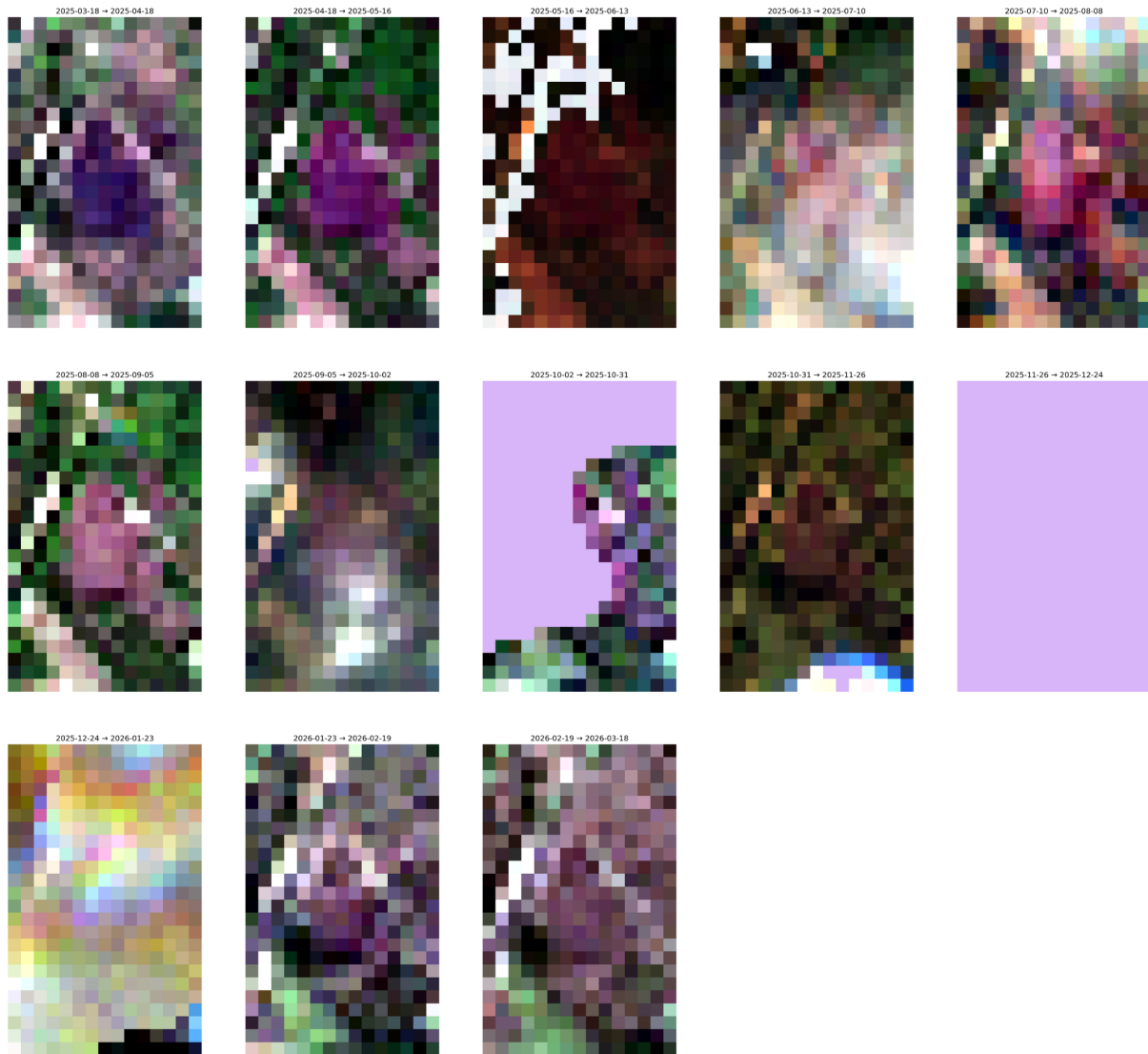


Figure A.19: RGB composites of the Clinge vegetation plots for each monitoring interval. Purple areas represent missing data.

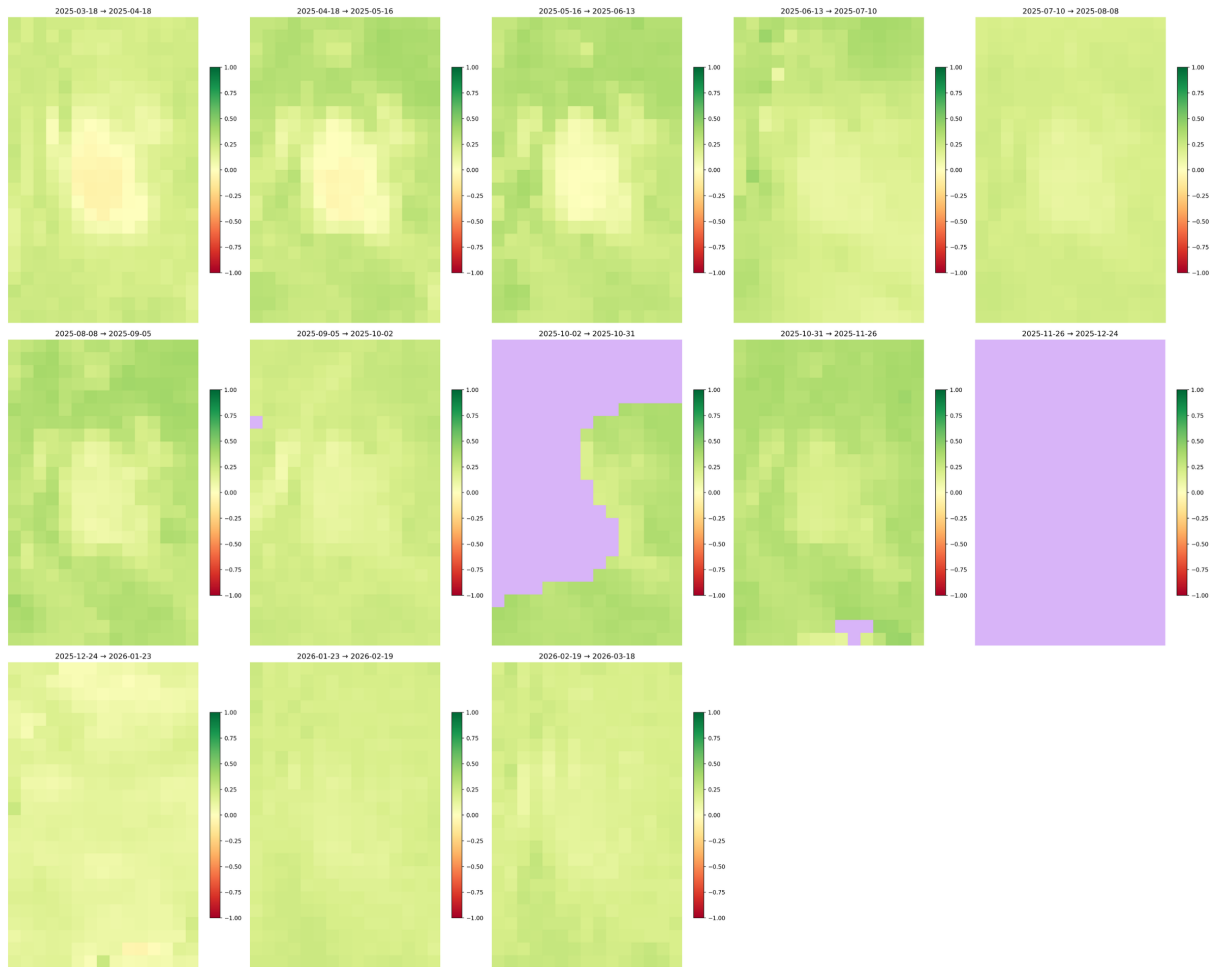


Figure A.20: Monthly NBR2 maps for the Clinge vegetation plots between April 2025 and March 2026. Purple areas represent missing data.

Table A.13: Mean PFSI values for burned and unburned areas across seasons and study areas.

Study area	Area type	Spring 2025	Summer 2025	Fall 2025
Clinge	Burned	2.475	19.021	6.833
	Unburned	3.275	2.436	1.202
Houffalize	Burned	-0.016	8.880	0.394
	Unburned	1.317	1.980	-0.998
Maasmechelen	Burned	–	30.113	4.913
	Unburned	–	0.076	1.869
Arlon	Burned	9.648	8.222	1.265
	Unburned	4.556	1.434	-1.336

Study area	Area type	Winter 2025	Spring 2026
Clinge	Burned	-5.562	1.453
	Unburned	-6.108	4.241
Houffalize	Burned	-2.948	0.716
	Unburned	-5.770	7.114
Maasmechelen	Burned	-0.907	0.800
	Unburned	-2.315	0.128
Arlon	Burned	-4.094	2.991
	Unburned	-2.076	1.743

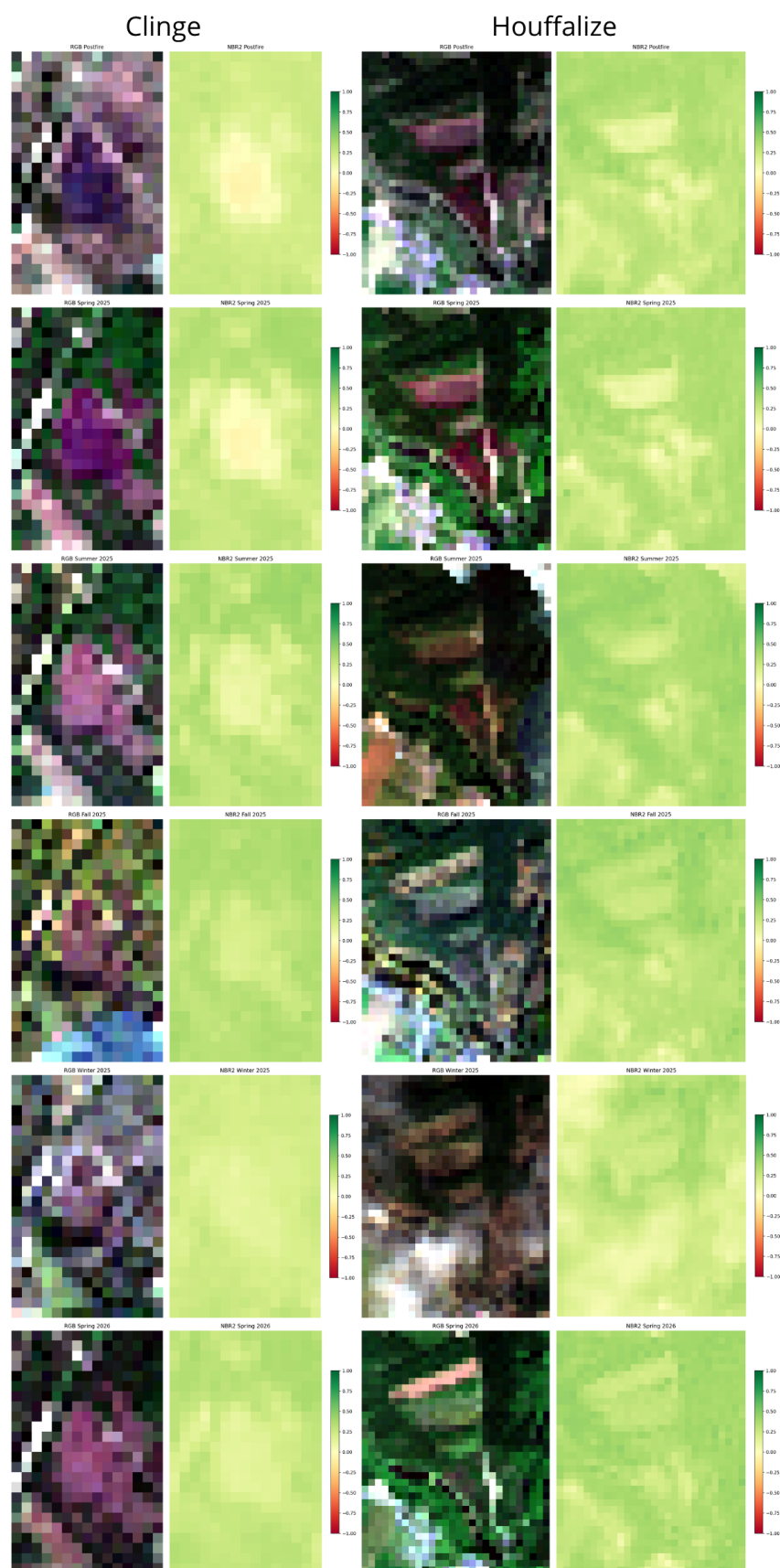


Figure A.21: Seasonal RGB composites and NBR2 maps for the Clinge and Houffalize fire sites.

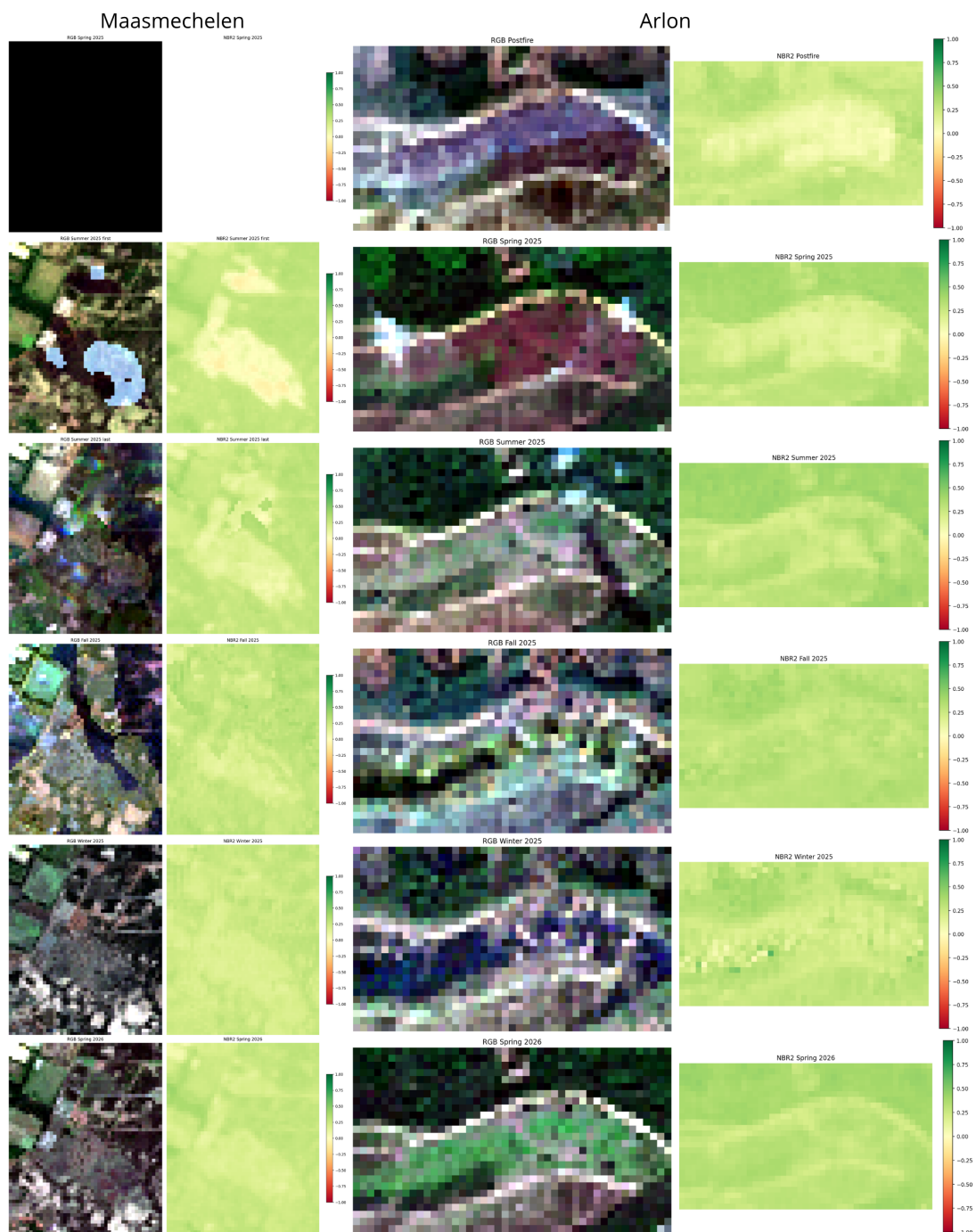


Figure A.22: Seasonal RGB composites and NBR2 maps for the Maasmeechelen and Arlon fire sites.

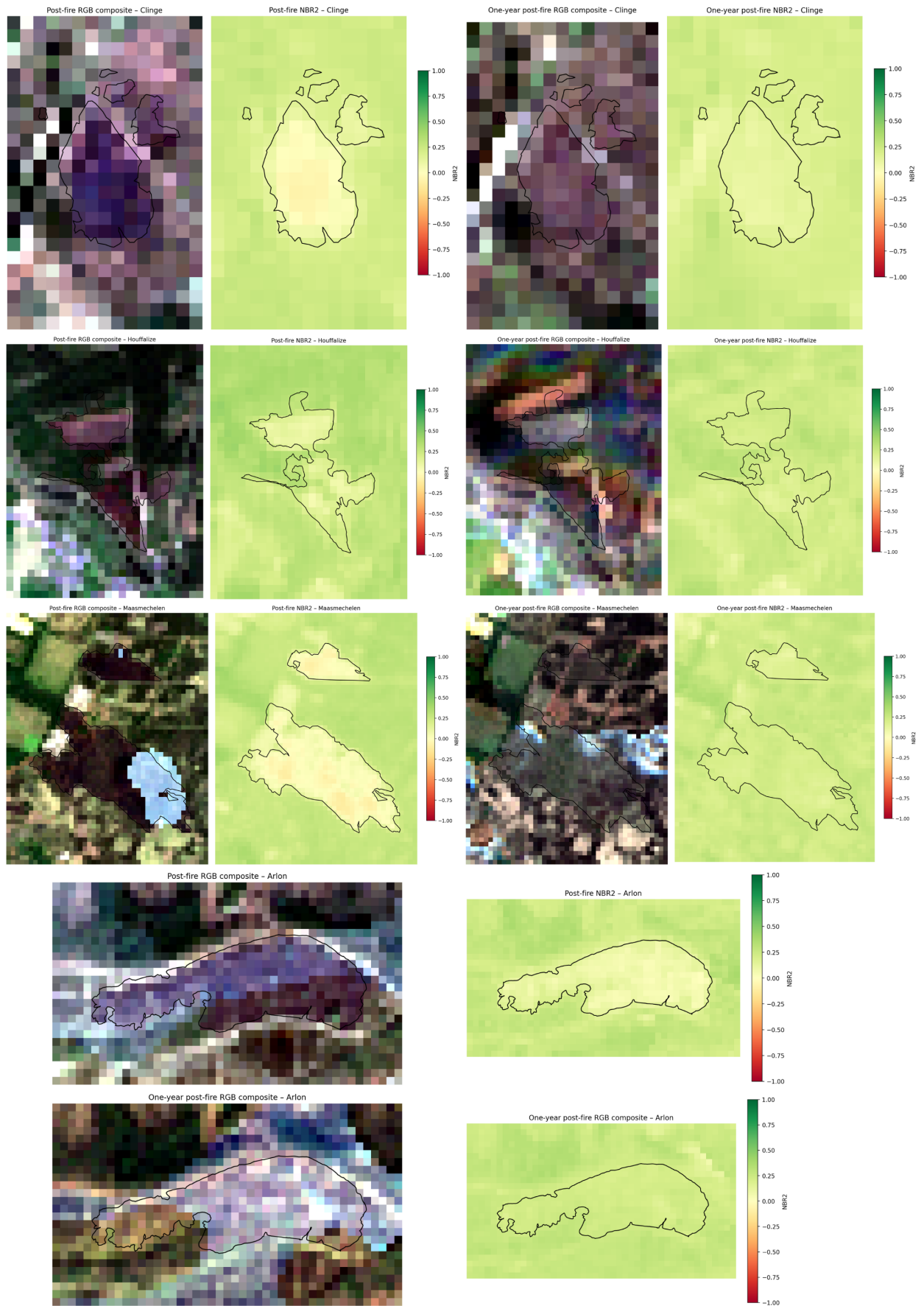


Figure A.23: RGB composites and NBR2 maps for the Clinge, Houffalize, Maasmechelen and Arlon fire sites.

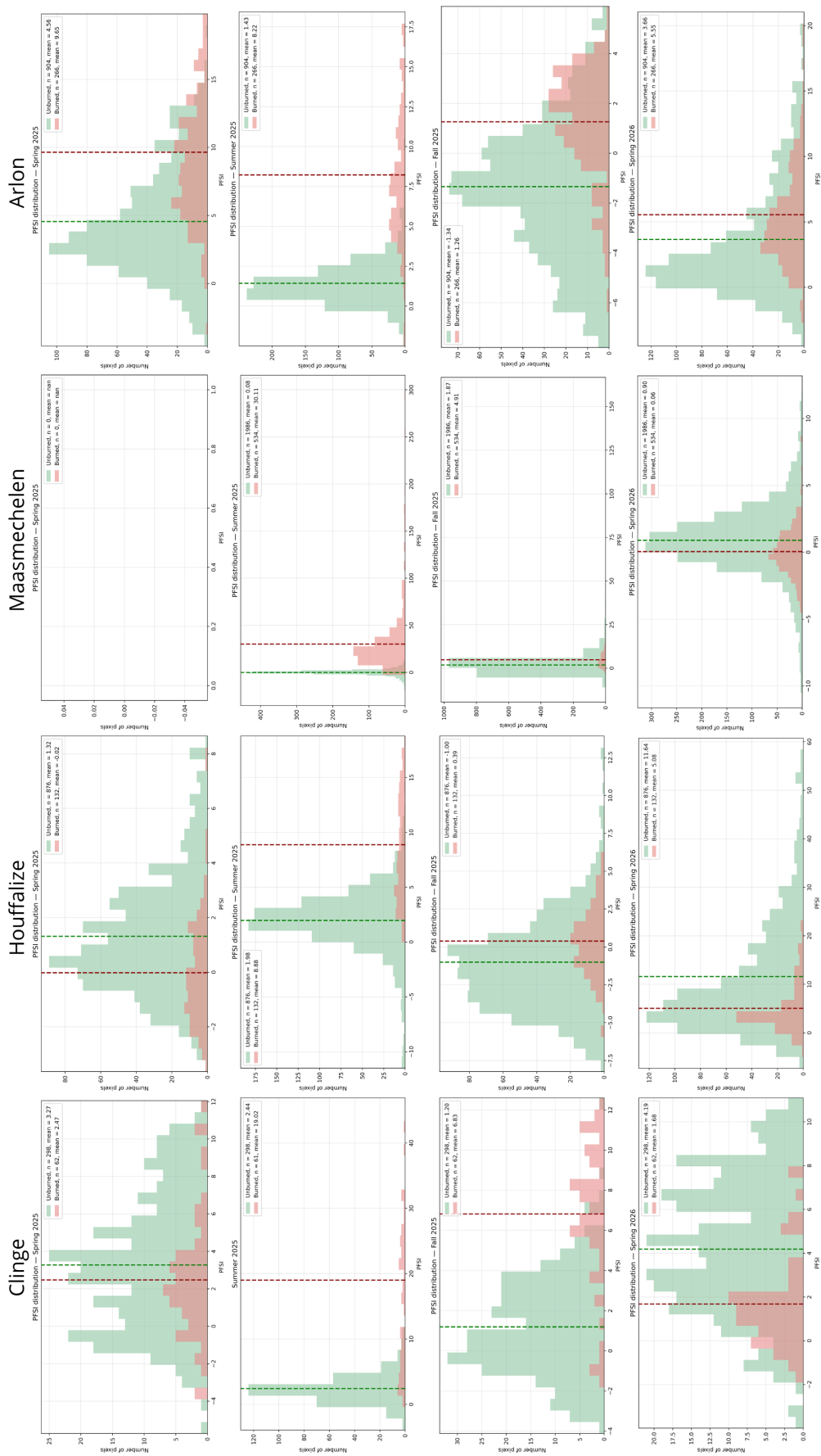


Figure A.24: Seasonal PFSI distributions within burned and unburned areas for the four study sites.

The histograms shown in Figure A.25 illustrate the distribution of PFSI values inside and outside the fire perimeters and demonstrate that the index is relatively sensitive to outliers. Several study areas contain individual pixels with extremely high positive values, particularly in Maasmechelen and Arlon. Despite these outliers, the overall spatial patterns and mean statistics still provide a coherent representation of early post-fire recovery dynamics across the different sites.

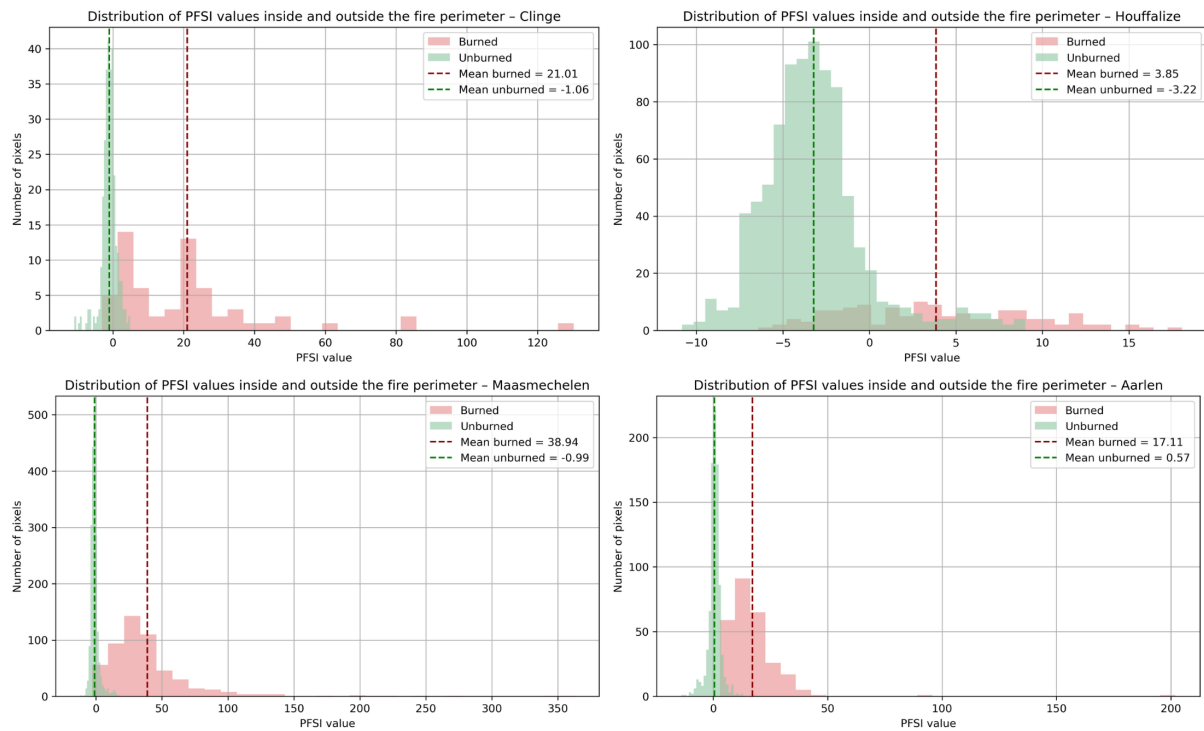


Figure A.25: Distribution of one-year post-fire PFSI values inside and outside the fire perimeter.