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Remote sensing assessment of wildfire severity and early vegetation recovery in a Mediterranean mountain landscape (NW Spain)

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Abstract

Wildfire severity assessment and vegetation recovery monitoring are essential for sustainable forest management, particularly in Mediterranean mountain ecosystems increasingly affected by climate change. This study evaluates the severity and short-term regeneration of vegetation following the July 2022 fire in Montes de Valdueza (Ponferrada, Spain), using Landsat 8 OLI imagery and two spectral indices: differenced Normalized Burn Ratio (dNBR) and differenced Normalized Difference Vegetation Index (dNDVI). Burn severity was classified into four categories, validated against PlanetScope high-resolution imagery as ground truth. The classification achieved an overall accuracy of 87.2% and a Kappa coefficient of 0.83, indicating strong agreement. Moderate severity dominated the burned area (69.4%), followed by low severity (22.8%). Vegetation recovery analysis conducted eight months after the fire revealed that 49.0% of the area showed low vegetation loss, 26.8% remained unchanged, and 7.8% experienced moderate loss. These findings highlight the resilience of shrub-dominated Mediterranean mountain landscapes and demonstrate the viability of low-cost remote sensing approaches for post-fire monitoring. The methodology provides replicable tools for managers to design long-term protocols that integrate vulnerability and resilience assessments in fire-prone regions.

1. Introduction

Wildfires are among the most significant natural disturbances affecting terrestrial ecosystems worldwide, with increasing frequency and intensity under global climate change scenarios (Pausas, 1999; Szpakowski & Jensen, 2019). In Mediterranean regions, recurrent fires interact with land-use changes, rural abandonment, and climatic extremes, producing complex impacts on vegetation dynamics, soil stability, and biodiversity. Understanding fire severity and post-fire vegetation recovery is therefore essential to evaluate ecosystem resilience and to design effective management and restoration strategies.

Fire severity is defined as the degree of organic matter consumption and vegetation mortality resulting from fire (Keeley, 2009). Its assessment requires knowledge of pre-fire vegetation composition and the ecological response of dominant species (Navarro et al., 2014). In Mediterranean mountain environments, high-intensity fires can cause canopy destruction, soil exposure, and delayed regeneration, while moderate-severity fires often allow resprouting of shrubs and partial survival of tree stands (Botella-Martínez & Fernández-Manso, 2017; Lentile et al., 2006). These differences in severity directly influence long-term ecosystem vulnerability and resilience.

Remote sensing has become a cost-effective and reliable tool for mapping fire perimeters, quantifying severity, and monitoring vegetation recovery (Eidenshink et al., 2007; Fernández-Guisuraga et al., 2019). Spectral indices such as the differenced Normalized Burn Ratio (dNBR) and the differenced Normalized Difference Vegetation Index (dNDVI) are widely used to evaluate fire impacts and regeneration dynamics. While dNBR is effective for distinguishing severity classes, dNDVI provides robust measures of short-term vegetation recovery, particularly in heterogeneous Mediterranean ecosystems dominated by mixed forests and resprouting shrublands (Veraverbeke et al., 2012; Szpakowski & Jensen, 2019). Their combined use allows managers to assess both immediate fire damage and early vegetation resilience.

Although numerous studies have applied these indices in coastal or low-altitude Mediterranean ecosystems (Botella-Martínez & Fernández-Manso, 2017; Gómez-Sánchez et al., 2017; Vales et al., 2020), fewer investigations have focused on high-mountain contexts, where steep slopes, mixed vegetation, and climatic variability may produce distinct severity and recovery patterns. Montes de Valdueza (Ponferrada, Spain) represents such a landscape, characterized by pine plantations, oak forests, and dense shrublands (*Erica australis*, *Genista tridentata*), and recurrently affected by wildfires. The July 2022 fire, which burned ~ 1,400 ha, provides a relevant case to evaluate severity and short-term recovery using accessible remote sensing methods.

The objective of this study is to map fire severity and assess vegetation recovery in Montes de Valdueza using dNBR and dNDVI derived from Landsat 8 imagery, validated with high-resolution PlanetScope data. By focusing on a Mediterranean mountain ecosystem, this work contributes to the development of replicable monitoring protocols and provides insights into ecosystem vulnerability and resilience under climate change.

2. Material and Methods

2.1 Study area

The study area comprises the forest region affected by the wildfire in Montes de Valdueza, municipality of Ponferrada, province of León, Spain (Fig. 1). The fire began on Sunday, July 17, 2022, as a result of an electrical discharge at approximately 15:47 h (Real Time Lightning Map, n.d.) and was declared extinguished on August 3. According to the Köppen–Geiger climate classification in the Iberian Climate Atlas (AEMET, 1971–2000), the burned area corresponds to the Csb variant (warm-summer Mediterranean climate). This climate type is characterized by markedly dry summers, with the warmest month averaging ≤ 22.0°C and at least four months exceeding 10.0°C (AEMET, 2011; Frey et al., 2020). July is the driest month, with only 29 mm of precipitation, while August is the warmest, with a mean temperature of 19.3°C. Meteorological conditions that favored ignition and fire spread included westerly winds with gusts of 20–25 km h^{-1}, high temperatures approaching 40°C, and low relative humidity (32%).

The burned area is characterized by diverse vegetation types, including *Pinus sylvestris* plantations (3.26 km²), chestnut groves (*Castanea sativa*, 0.072 km²), oak forests (*Quercus pyrenaica*, 1.49 km²; Q. ilex, 0.73 km²), and extensive shrublands dominated by *Genista tridentata* and *Erica australis* (5.72 km²). Elevation ranges from 705 to 2005 m above sea level, with an average slope of 53.4%. The predominant slope orientation is north, covering 13.8 km². In addition to vegetation, the fire-affected landscape also includes roads, firebreaks, and rocky outcrops, albeit to a lesser extent.

Beyond its biophysical attributes, Montes de Valdueza holds significant ecological and cultural value. The area is partially included in the Natura 2000 network (SCI ES4130005 “Valle de Valdueza”), which protects priority Mediterranean mountain habitats. It also contains important historical heritage, such as medieval monasteries and traditional villages. These characteristics highlight the relevance of assessing post-fire vegetation recovery to safeguard biodiversity and prevent long-term ecosystem degradation in this vulnerable high-mountain landscape.

2.2 Mapping and quantification of affected area

To achieve an accurate delimitation and quantify the area affected by the fire, a high-resolution PlanetScope image (3 m pixel, processing level 1B) was used. The image dated August 9, 2022—six days after the fire was declared extinguished—served as the basis for manual on-screen digitization of the burned perimeter. A false-color RGB composite (bands NIR–Red–Green, i.e., 4-3-2) was employed, in which burned areas appear in dark brown to black tones due to reduced NIR reflectance and increased red reflectance from exposed soil and ash. In contrast, unburned vegetation appears in bright red, while non-vegetated surfaces such as rocks and roads are displayed in gray or light brown.

Pixels were classified as burned according to three visual criteria: (i) abrupt tonal changes compared to adjacent unburned areas, (ii) homogeneous dark textures typical of ash and charcoal, and (iii) absence of high NIR reflectance characteristic of live vegetation. These criteria were adapted from Parsons et al. (2010) and Botella-Martínez & Fernández-Manso (2017), and are widely applied in high-resolution imagery as an alternative to field surveys. The resulting perimeter measured 86,689.45 m, encompassing a total burned area of 14.01 km².

2.3 Severity assesment

The main dataset used to assess the severity of the Montes de Valdueza fire was derived from Landsat 8 OLI imagery. Pre-fire and post-fire scenes correspond to July 7 and August 9, 2022 (WRS Path 203, Row 30), downloaded from the

USGS Earth Explorer portal. These products belong to Level-2 Collection 2, atmospherically corrected using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS), thus requiring no additional preprocessing. Pre-fire and post-fire Landsat images were selected considering minimal cloud cover, phenological consistency, and temporal proximity to the wildfire event. The pre-fire image represents vegetation conditions immediately prior to the fire season, while the post-fire image captures burn effects shortly after fire containment, minimizing potential spectral interference caused by vegetation regrowth.

The Normalized Burn Ratio (NBR) index was applied to quantify fire severity. NBR exploits the spectral contrast between near-infrared (NIR, band 5) and shortwave infrared (SWIR, band 7) reflectance, highlighting vegetation and soil changes induced by fire. The formula used is:

$$NBR=(B5-B7)/(B5+B7) \quad \text{(Eq. 1)}$$

The delta Normalized Burn Ratio (dNBR) was applied to evaluate the severity of burned areas (Key and Benson, 2006; Lutes et al., 2006). This operation enhances the separation between burned and unburned zones (Botella-Martínez and Fernández-Manso, 2017; Vales et al., 2020). The dNBR was selected due to its extensive use in wildfire severity assessments and its demonstrated reliability for detecting vegetation and soil changes caused by fire in Mediterranean ecosystems. The index is calculated as follows:

$$dNBR=NBRpre-NBRpost\times1000 \quad \text{(Eq. 2)}$$

Where NBRpre corresponds to the pre-fire image and NBRpost to the post-fire image. Multiplication by 1000 is applied to scale the values for classification purposes.

The severity thresholds applied in this study were those adapted by Botella-Martínez and Fernández-Manso (2017) for Mediterranean ecosystems of the Iberian Peninsula, specifically validated in the Valencia region (low-altitude coastal Mediterranean area) using Landsat 8 imagery and aerial photography. These thresholds define the following classes (Table 1):

Table 1
Burn severity classification thresholds based on dNBR values. Thresholds adapted from Botella-Martínez and Fernández-Manso (2017) for Mediterranean ecosystems of the Iberian Peninsula, compared with standard USGS guidelines (Key and Benson, 2006).

Severity class	**dNBR range**
Unburned / Low severity	< 160
Low severity	160–260
Moderate severity	260–481
High severity	> 481

Although the standard USGS thresholds (Key and Benson, 2006) provide a general guideline (dNBR < 100: unburned/low; 100–269: low; 270–659: moderate; >660: high), regional adjustments are often necessary due to differences in vegetation type, fuel structure, and topography, as dNBR sensitivity varies across ecosystems (Miller and Thode, 2007; Cansler and McKenzie, 2012).

In this high-mountain Mediterranean context (Csb climate, steep slopes, mixed pine plantations, oak forests, and shrublands), the thresholds proposed by Botella-Martínez and Fernández-Manso (2017) were selected because they

better account for the flammable shrub-dominated strata (e.g., *Erica australis* and *Genista tridentata*) and Quercus-dominated forests typical of the Iberian Peninsula, where fire behavior and spectral response differ from boreal or North American coniferous systems. This choice is further supported by subsequent studies in similar Mediterranean settings (e.g., Fernández-Guisuraga et al., 2020). Ecologically, these dNBR thresholds reflect the degree of fire-induced change in vegetation and soil (Keeley, 2009; Key and Benson, 2006) (Table 2):

Table 2
Burn severity thresholds based on dNBR values. Classes adapted from Botella-Martínez and Fernández-Manso (2017) for Mediterranean ecosystems of the Iberian Peninsula, with comparison to standard USGS guidelines (Key and Benson, 2006).

Severity class	Ecological interpretation
Unburned / Low severity	Minimal consumption of litter/duff; surface fire with scorched but living understory herbs/shrubs; tree canopies largely intact; low tree mortality; soil organic layer preserved, reducing erosion risk.
Moderate severity	Partial consumption of understory and some canopy; moderate charring of litter/duff and small fuels; variable tree mortality (especially in pines); mineral soil exposed, increasing erosion potential but enabling rapid resprouting in resilient Mediterranean shrubs (*Erica*, *Genista*).
High severity	Complete consumption of understory and much of the canopy; deep burning of duff/organic soil; high tree mortality (crown fire); extensive bare soil and ash, leading to higher post-fire erosion, hydrophobicity, and delayed regeneration, often requiring active restoration in oak/pine areas.

These ecological interpretations align with fire effects on organic matter loss, vegetation mortality, and soil exposure, which directly influence ecosystem resilience and post-fire recovery patterns in Mediterranean mountain environments.

2.4 Validation

To validate the accuracy of the severity thresholds, the sample size was calculated from Eq. 1, which takes into account the binomial probability theory. An expected accuracy of 85% was established for all classes, as well as an admissible error of 10%. Thus, a sample size of 51 points was obtained for each of the classes, for 204 points (Eq. 3).

$$N = \frac{Z^2(p)(q)}{E^2}$$ (Eq. 3)

Where:

p: expected accuracy of the validation sample for that class (p),

q = (100-p),

E: admissible error in the classification of that class.

Z = 2, normal standard deviation approximation of 1.96 for 95% confidence interval (two-tailed).

The validation points were established using a stratified sampling approach (Anaya et al., 2023; Casal and Mateu, 2003; Olofsson et al., 2013) (Fig. 2). With this procedure, points were randomly generated across pixels segmented by the different severity thresholds. A limitation of this method arose from the uneven distribution of severity classes within the burned area. For the high-severity class, the calculated sample size (51 points per class, totaling 204 points across four classes) exceeded the actual number of available pixels (only 35). Consequently, all 35 pixels in the high-severity class

were selected as validation points, while random points were generated only for the remaining classes. This adjustment resulted in a total of 188 validation points effectively used instead of the initially planned 204.

For the “Unburned” class, validation points were deliberately placed outside the burned perimeter, following established protocols (Botella-Martínez and Fernández-Manso, 2017; Vales et al., 2020; Key and Benson, 2006). This ensured true unburned conditions as reference, avoiding potential misclassification of unburned islands within the fire scar. Points were selected in areas adjacent to the perimeter with vegetation cover types similar to those dominant inside the burned area (e.g., *Pinus sylvestris* plantations, *Quercus* spp. forests, and *Erica/Genista* shrublands), while excluding dissimilar land covers such as bare rock, water bodies, or agricultural fields to maintain spectral and ecological comparability.
For validation, the PlanetScope image of August 9, 2022 was used as ground truth. The use of high-resolution imagery as an alternative to compensate for the absence of field sampling has been widely documented (Botella-Martínez and Fernández-Manso, 2017; Cansler and McKenzie, 2012; Quintano et al., 2013; Stehman and Czaplewski, 1998), and serves as a substitute for other procedures such as the Composite Burn Index (CBI) of Key and Benson (2006). The visual criteria for determining severity on the high-resolution image followed those proposed by Botella-Martínez and Fernández-Manso (2017), adapted from Parsons et al. (2010).

The ground truth analysis enabled the numerical determination of error levels in the resulting cartography. Reliability measures included the confusion matrix, the Kappa statistic, overall accuracy (OA), producer’s and user’s accuracy, and the F1 score (Gómez-Sánchez et al., 2017; Pérez et al., 2017; Chuvieco Salinero, 2008). From the confusion matrix, overall accuracy, producer’s and user’s accuracy, omission and commission errors, and F1 scores were derived for each severity class.

Although Pontius and Millones (2011) highlighted significant limitations of the Kappa index—such as redundancy with overall accuracy, reliance on a hypothetical random chance agreement model often inappropriate for remote sensing classifications, and lack of insight into spatial allocation of errors—Kappa remains widely adopted in burn severity mapping studies, including recent publications (e.g., Franco et al., 2020; Saulino et al., 2020; Picotte et al., 2020). It provides a standardized measure of agreement corrected for chance, facilitating direct comparison with numerous prior dNBR-based assessments in Mediterranean and Iberian ecosystems (Botella-Martínez and Fernández-Manso, 2017; Vales et al., 2020).

2.5 Regeneration of vegetation

For the study of vegetation recovery in the burned region, a multi-temporal analysis was conducted over a short period of time, eight months after the fire. Landsat 8 OLI images used for recovery assessment correspond to July 17, 2022 (date of the fire), and the post-fire dates of September 8, 2022, and May 4, 2023.

The Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974) was applied to evaluate vegetation regeneration. NDVI provides a quantitative measure of photosynthetic activity, responding to the amount of green biomass regardless of species, and is widely used for monitoring ecosystem health (Blackburn and Milton, 1995; Gamon et al., 1995). Although NDVI may saturate in dense vegetation and be influenced by soil background in sparsely vegetated areas, it remains one of the most robust indices for post-fire recovery, particularly in heterogeneous Mediterranean ecosystems (Veraverbeke et al., 2012; Szpakowski and Jensen, 2019). In comparative evaluations of 13 spectral indices, NDVI consistently outperformed others (including SAVI) in areas with mixed vegetation and variable soil types, effectively capturing initial regrowth without requiring soil adjustments.

Given the short-term focus (~ 8 months post-fire), the mixed vegetation composition (pine plantations, oak forests, and resilient shrublands), and the need for a simple, species-independent metric, NDVI and its differenced form (dNDVI) were deemed the most appropriate choice. The differenced NDVI was calculated as:

dNDVI= NDVIa – NDVIb (Eq. 4)

Where NDVIa corresponds to the image closest to the fire event and NDVIb to subsequent post-fire images. This operation allowed the identification of positive and negative anomalies in vegetation recovery, stratified according to the initial severity level assigned.

The differenced NDVI (dNDVI) was reclassified into seven categories using thresholds based on the mean and standard deviation (σ) of dNDVI values across the burned area, following the methodology successfully applied by Vales et al. (2020) in a similar Mediterranean ecosystem affected by a large wildfire. This statistical approach (mean ± multiples of σ) is widely used in post-fire recovery studies because it adapts thresholds to the specific distribution of spectral changes in each fire event, avoiding fixed arbitrary values that may not reflect local variability in pre-fire vegetation and fire effects (Gómez-Sánchez et al., 2017; Sun et al., 2017; Hislop et al., 2018).

In this study, the short-term assessment (~ 8 months post-fire) and the heterogeneous vegetation composition justified the adoption of these relative, data-driven thresholds, which provide an objective and reproducible classification tailored to the observed range of dNDVI values. The seven recovery classes and their ecological interpretation, adapted from Vales et al. (2020) and aligned with common post-fire regeneration patterns in Mediterranean ecosystems (Keeley et al., 2008; Calvo et al., 2012), are summarized in Table 3.

Table 3
Post-fire vegetation recovery classes derived from dNDVI thresholds (mean ± σ). Categories adapted from Vales et al. (2020) and aligned with Mediterranean ecosystem regeneration patterns, distinguishing persistent damage (loss classes) from active regrowth (recovery classes).

Recovery class	Ecological interpretation
High loss	Strong negative dNDVI; persistent severe damage or delayed regeneration; typical of crown fires in pine plantations or dense oak stands, with high tree mortality and limited resprouting.
Moderate loss	Notable decrease in green biomass; partial mortality of overstory and understory; common in moderate severity areas where some individuals survive but photosynthetic activity remains reduced.
Low loss	Slight decline; surface fire effects with rapid recovery of herbaceous layer and scorched but living shrubs/trees.
No change	dNDVI ≈ 0; marginally affected areas or immediate compensation between loss and early regrowth.
Low recovery	Modest positive dNDVI; initial resprouting of obligate seeder shrubs (*Erica australis*, *Genista tridentata*) or herbaceous cover, still below pre-fire levels.
Moderate recovery	Clear increase in green biomass; vigorous resprouting of resprouter species and/or pioneer herbs, approaching pre-fire photosynthetic activity.
High recovery	Strong positive dNDVI; rapid, dense regeneration, often exceeding pre-fire NDVI values due to opportunistic shrubs and herbs thriving in nutrient-enriched ash beds.

These categories reflect ecologically meaningful gradients in post-fire vegetation resilience and trajectory, distinguishing between persistent damage (loss classes) and active regeneration (recovery classes), which is critical for management decisions in Mediterranean mountain ecosystems.

3. Result

3.1 Fire severity

The spatial distribution of burn severity derived from the dNBR classification is shown in Fig. 3. Moderate severity was the dominant class within the burned area, covering 9.71 km² (69.35%), followed by low severity with 3.20 km² (22.81%). High-severity areas were limited in extent and occurred mainly in patches associated with Quercus pyrenaica and Quercus ilex forests. Moderate severity was relatively evenly distributed across the burned region and affected primarily shrubland formations (4.63 km²) and *Pinus sylvestris* plantations (1.86 km²), with smaller contributions from Quercus pyrenaica (0.98 km²) and Quercus ilex (0.46 km²).

The accuracy assessment of the burn severity classification is presented in Table 4. Validation using the stratified sample of 188 reference points resulted in an overall accuracy of 87.23% and a Kappa coefficient of 0.828, indicating strong agreement between the dNBR-derived classification and the reference data obtained from the high-resolution PlanetScope imagery. Among the severity classes, the Unburned category achieved the highest classification accuracy, with 100% producer accuracy and 98.04% user accuracy. The Low severity class showed a producer accuracy of 86.96% and user accuracy of 78.43%, whereas the Moderate severity class obtained 73.77% producer accuracy and 88.24% user accuracy. The High severity class reached 93.55% producer accuracy and 82.86% user accuracy. Most classification errors occurred between the Low and Moderate severity classes. In particular, 11 pixels classified as low severity corresponded to moderate severity according to the reference data, reflecting the spectral similarity between these categories.

The analysis of disagreement metrics also indicated satisfactory performance of the classification. Overall omission and commission errors reached 10.76%, while overall agreement was 89.24%. Quantitative disagreement accounted for 5.85%, whereas exchange and shift errors represented 6.38% and 0.53%, respectively.

The resulting spatial pattern of burn severity across the study area is illustrated in Fig. 3, while the detailed confusion matrix and accuracy metrics are provided in Table 4.

Table 3
Confusion matrix obtained from the validation with the 188 sampling points implemented on the PlanetScope image.

Segmentation result	Ground truth							
		Unburned	Low	Moderate	High	Total	UA	F1- Score
	Unburned	50	1	0	0	51	98.04%	100%
	Low	0	40	11	0	51	78.43%	91.85%
	Moderate	0	4	45	2	51	88.24%	74.38%
	High	0	1	5	29	35	82.86%	87.61%
	Total	50	46	61	31	188		
	PA	100%	86.96%	73.77%	93.55%			

3.2 Pos-fire vegetation recovery

The spatial distribution of vegetation recovery derived from the dNDVI classification is presented in Fig. 4, while the proportional area of each recovery class and its correspondence with burn severity levels are summarized in Table 5.

Among the seven recovery categories, Low loss represented the largest proportion of the burned area, accounting for 49.02%. This was followed by No change, which covered 26.80% of the area, and Low recovery, representing 10.89%. Areas classified as Moderate loss accounted for 7.81% of the burned area. In contrast, categories indicating more pronounced vegetation recovery were less extensive, with Moderate recovery covering 2.40% and High recovery representing only 0.73% of the total burned area.

The spatial distribution of recovery classes showed clear associations with pre-fire vegetation types. Areas classified as Low loss and Moderate loss were mainly located in zones previously occupied by *Pinus sylvestris* plantations and forests dominated by *Quercus ilex* and *Quercus pyrenaica*. In contrast, areas categorized as Low recovery and Moderate recovery were primarily associated with shrubland communities dominated by *Erica australis* and *Genista tridentata*.

Field observations within the burned region support these patterns. As illustrated in Fig. 5, several areas previously occupied by *Pinus sylvestris* plantations showed regeneration dominated by shrub species, particularly *Erica australis* and *Genista tridentata*, which were observed colonizing the burned surface and contributing to the initial stages of post-fire vegetation recovery.

Table 5
Area occupied by each of the classes of post-fire vegetation recovery levels in Montes de Valdueza, Ponferrada and concordance with the severity classes estimated in the study in percentage.

Classes	**Ocupied area (%)**	**Unburned (%)**	**Low (%)**	**Moderate (%)**	**High (%)**
High loss	2.14	0.20	0.60	1.33	0.01
Moderate loss	7.81	0.17	0.60	7.13	0.01
Low loss	49.02	0.94	5.96	41.98	0.14
Not changes	26.80	1.76	8.94	16.07	0.03
Low recovery	10.89	2.38	4.38	4.13	-
Moderate recovery	2.40	0.57	1.13	0.70	-
High recovery	0.73	0.21	0.38	0.14	-

4. Discussion

4.1 Fire severity patterns

The predominance of moderate burn severity observed in Montes de Valdueza reflects the heterogeneous structure typical of Mediterranean mountain ecosystems. Moderate-severity fires usually involve partial canopy consumption and incomplete burning of understory vegetation, generating intermediate levels of ecological disturbance that still allow the persistence of surviving vegetation elements and facilitate subsequent regeneration processes.

The spatial distribution of burn severity classes suggests that fire effects were influenced by the heterogeneous composition of the landscape, which includes shrublands, pine plantations, and mixed oak forests. In particular, moderate severity was largely associated with shrub-dominated areas and *Pinus sylvestris* plantations, where surface and crown fire effects can coexist due to variable fuel loads and vertical vegetation structure. Such structural heterogeneity is characteristic of Mediterranean fire-prone ecosystems and often leads to mosaics of burn severity across the landscape (Miller and Thode, 2007; Cansler and McKenzie, 2012; Parks et al., 2014; Saulino et al., 2020).

Topographic conditions may also have contributed to the spatial variability observed in burn severity. In the study area, large portions of the burned landscape are located on steep slopes exceeding 50% and at elevations above 1000 m, conditions that can influence fire behavior by facilitating rapid fire spread and intensifying combustion processes. These factors may increase the vulnerability of high-mountain Mediterranean ecosystems to post-fire degradation processes such as soil erosion and vegetation loss.

Despite these environmental constraints, the predominance of moderate severity suggests that complete canopy destruction was relatively limited, which may favor natural regeneration processes, particularly in shrubland communities and mixed forest stands. Similar burn severity patterns have been documented in Mediterranean landscapes where mixed vegetation structures and spatial variability in fuel loads generate intermediate fire impacts rather than uniformly high-severity fires (Miller and Thode, 2007; Cansler and McKenzie, 2012).

The accuracy assessment obtained in this study (overall accuracy = 87.23%; Kappa = 0.828) indicates that the dNBR thresholds adapted for Mediterranean ecosystems (Botella-Martínez and Fernández-Manso, 2017) performed satisfactorily in the study area. Comparable accuracy levels have been reported in previous burn severity assessments based on dNBR in Mediterranean environments, confirming the reliability of this index for mapping fire effects in heterogeneous landscapes (Fernández-García et al., 2018).

The main classification errors occurred between the Low and Moderate severity classes, a limitation frequently reported in studies based on spectral burn indices. Transitional fire effects—such as partial canopy scorching, variable consumption of understory shrubs (e.g., *Erica australis* and *Genista tridentata*), and incomplete burning of litter and duff layers—often produce spectral responses that fall near classification thresholds, making the separation between adjacent severity classes more difficult (Miller and Thode, 2007; Cansler and McKenzie, 2012).

Additional factors may also influence the spectral response captured by the dNBR index. Pre-fire vegetation heterogeneity, including the coexistence of pine plantations, oak forests, and dense shrublands with different fuel structures, can affect reflectance patterns and occasionally lead to underestimation of burn severity in dense forest stands (Kokaly et al., 2007; Miller and Thode, 2007). Furthermore, rapid post-fire vegetation greening and topographic variability may reduce the spectral contrast between severity classes, particularly in Mediterranean environments characterized by strong seasonal dynamics (Cansler and McKenzie, 2012).

Despite these limitations, the validation results demonstrate a strong agreement between the dNBR-derived classification and the independent reference data derived from PlanetScope imagery. The use of high-resolution satellite imagery as a substitute for field-based validation has been widely applied in remote sensing studies, particularly in areas where direct field surveys are difficult to implement (Botella-Martínez and Fernández-Manso, 2017; Cansler and McKenzie, 2012; Quintano et al., 2013; Stehman and Czaplewski, 1998).

Nevertheless, this approach does not fully replace direct field measurements. Methods such as the Composite Burn Index (CBI) proposed by Key and Benson (2006) remain the most robust approach for assessing fire severity because they incorporate detailed information on vegetation mortality, soil exposure, and organic matter consumption (Delegido et al., 2017; Fang et al., 2018; Martínez-García et al., 2013). Future studies integrating field observations with remote sensing analyses would therefore provide a more comprehensive assessment of fire impacts in Mediterranean mountain ecosystems.

One limitation of this study is the absence of field-based burn severity measurements, such as Composite Burn Index (CBI) plots, which would allow a more detailed validation of the satellite-derived severity classes.

4.2 Vegetation recovery dynamics

The post-fire vegetation recovery analysis conducted approximately eight months after the wildfire indicates a landscape dominated by low vegetation loss and limited early recovery, reflecting the short temporal window considered in this study. It should be noted that the recovery assessment was conducted only eight months after the wildfire, which represents an early stage of post-fire vegetation dynamics. Longer temporal analyses would be necessary to fully characterize ecosystem recovery trajectories.

The predominance of the Low loss (49.02%) and No change (26.80%) categories suggest that a substantial proportion of the burned area retained partial vegetation cover or experienced early stages of regrowth. Such patterns are common during the initial months following wildfire events, when vegetation recovery processes are still developing and photosynthetic activity has not yet fully returned to pre-fire levels.

Recovery dynamics appear to be strongly influenced by pre-fire vegetation composition. Areas dominated by shrub species such as *Erica australis* and *Genista tridentata* showed clearer signals of early regeneration, which can be explained by the strong resprouting capacity of these species. Shrub communities in Mediterranean ecosystems are well known for their resilience to fire disturbances and frequently dominate the initial stages of post-fire succession.

In contrast, areas previously occupied by *Pinus sylvestris* plantations tended to exhibit slower recovery signals in the short term. Pine species often depend on seed-based regeneration processes, which may require longer time periods to become detectable through spectral vegetation indices. Consequently, artificial reforestation or active management interventions may be required in some pine-dominated areas to accelerate canopy recovery and reduce the risk of soil degradation, as documented in Mediterranean post-fire environments (Calvo et al., 2012).

Similarly, the relatively limited recovery observed in Quercus-dominated stands suggests that tree regeneration processes in Mediterranean mountain forests may occur at slower rates than shrub regeneration during the early post-fire phase. In many Mediterranean ecosystems, early post-fire recovery is initially dominated by herbaceous and shrub species, while tree regeneration becomes more evident over longer temporal scales.

These findings are consistent with recent studies conducted in Iberian ecosystems, which emphasize the key ecological role of shrub dynamics in shaping post-fire recovery trajectories and influencing ecosystem resilience (Pérez-Romero et al., 2025). The rapid resprouting ability of Mediterranean shrub species contributes to soil stabilization, nutrient cycling, and the gradual restoration of ecosystem structure following wildfire disturbances.

From a management perspective, the coexistence of rapid shrub recovery and slower tree regeneration highlights the need for differentiated restoration strategies. Natural regeneration may be sufficient in shrub-dominated areas where vegetation recovery occurs rapidly, whereas active restoration measures may be required in pine plantations or degraded forest stands to ensure long-term forest resilience and reduce erosion risks.

The integration of satellite-based burn severity assessment and vegetation recovery monitoring provides valuable information for post-fire management planning and ecological restoration strategies in Mediterranean mountain landscapes.

5. Conclusion

The severity mapping of the burned area in Montes de Valdueza, based on dNBR and thresholds proposed for Mediterranean climates in the Iberian Peninsula (Botella-Martínez and Fernández-Manso, 2017), revealed that *moderate severity* was the most extensive class, covering 9.71 km² (69.3% of the affected area), followed by *low severity* with 3.20 km² (22.81%). Within the low-severity regions, most of the area corresponded to shrublands (4.63 km²) and *Pinus sylvestris* plantations, while high-severity patches predominantly coincided with *Quercus pyrenaica* and *Quercus ilex* forests.

Validation of the selected thresholds yielded satisfactory results, with an overall segmentation accuracy of 87.23% and a Kappa statistic of 0.828, indicating almost perfect agreement (Landis and Koch, 1977). These outcomes confirm that the thresholds were well-suited to the study area and demonstrate that high-resolution imagery (PlanetScope) can serve as a reliable and cost-effective proxy ground truth in remote mountainous regions, although it does not fully replace direct field observations.

The dNDVI-based mapping of post-fire vegetation recovery (~ 8 months after the event) showed that 49.02% of the area was classified as *low loss*, 26.80% as *no change*, and 7.81% as *moderate loss*. Areas exhibiting low and moderate loss largely overlapped with zones previously occupied by *Pinus sylvestris* plantations and *Quercus ilex/Quercus pyrenaica* forests, whereas regions showing initial recovery were dominated by resilient resprouting shrublands (*Erica australis* and *Genista tridentata*).

These results underscore the importance of integrating remote sensing into regional geographic policies for monitoring resilience in Mediterranean landscapes, particularly in steep-sloped, high-mountain areas like Montes de Valdueza, where regeneration patterns vary significantly according to altitude, slope orientation, and pre-fire vegetation type. This spatially explicit approach provides valuable information and operational tools for implementing long-term management protocols in climate change-vulnerable regions of northwest Spain. It highlights the need for region-specific monitoring to assess both ecosystem vulnerability and resilience, supporting sustainable forest management, erosion control, and targeted restoration interventions in fire-prone Mediterranean mountain environments.

This study represents an initial step; continued multi-temporal monitoring of the affected area is recommended to better understand medium- and long-term recovery trajectories and to refine adaptive management strategies in the context of increasing wildfire frequency and intensity across the Iberian Peninsula.

Declarations

Credit Authorship Contribution Statement

Alexey Valero-Jorge: Conceptualization, Data Curation, Processing Data, Formal Analysis, Visualization, Writing – original draft and editing;**Angel Luis Becerra González:** Conceptualization, Writing – original draft and editing; **Roberto González-DeZayas**: Conceptualization, Formal Analysis, Visualization, Writing – original draft and editing.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

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Clinical Trial Registration

Not applicable.

Ethics and Consent to Participate Declaration

Not applicable.

Consent to Publish Declaration

Not applicable.

Data availability statement

The datasets generated and analysed during the current study are available in the “Dataset: Remote sensing assessment of wildfire severity and early vegetation recovery in a Mediterranean mountain landscape (northwestern Spain)” repository, https://zenodo.org/records/19110406.

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Figures

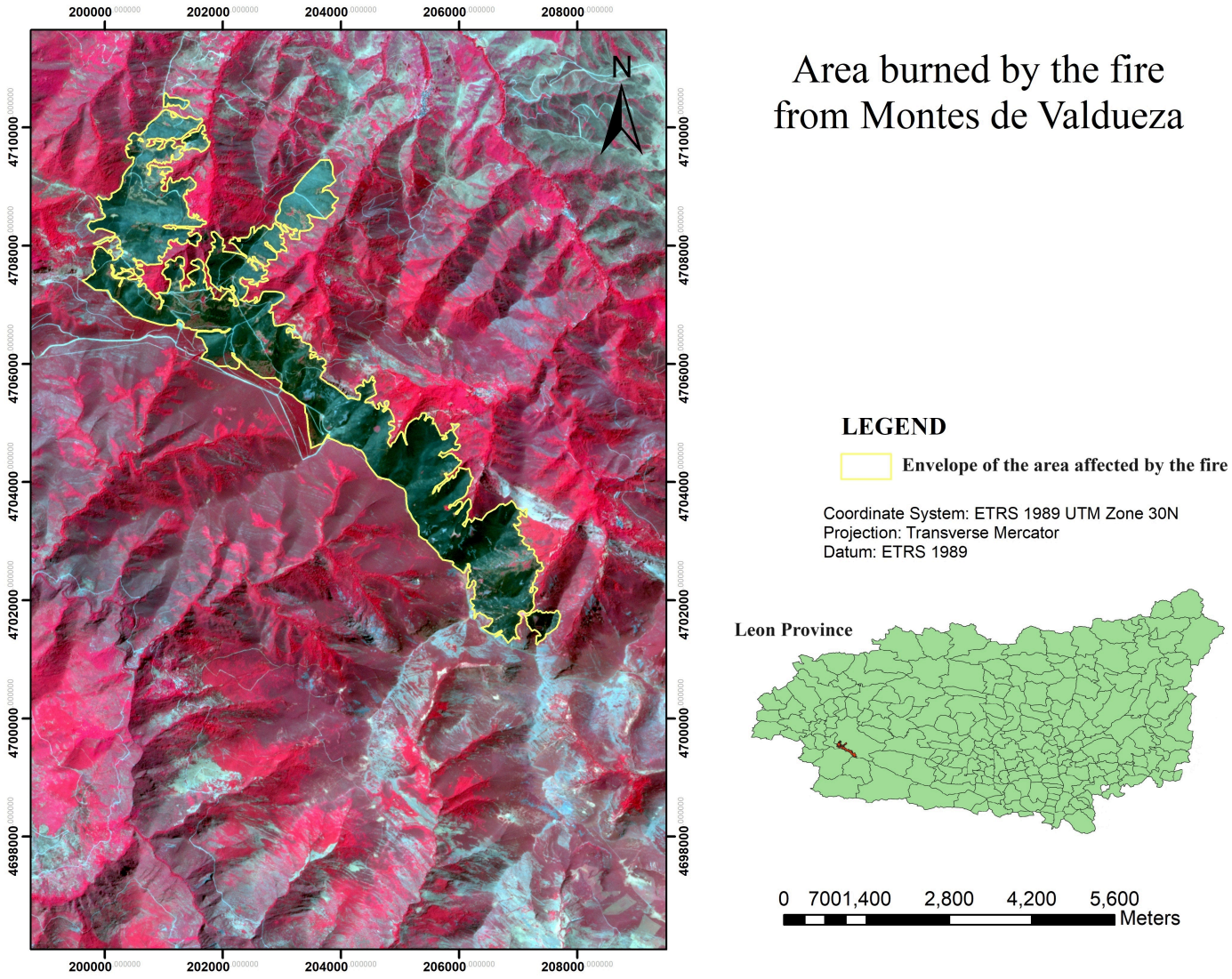


Figure 1

Location of the study area in Montes de Valdueza, Ponferrada (León Province, NW Spain). The map shows the spatial extent of the wildfire analyzed in this study within the Mediterranean mountain landscape.

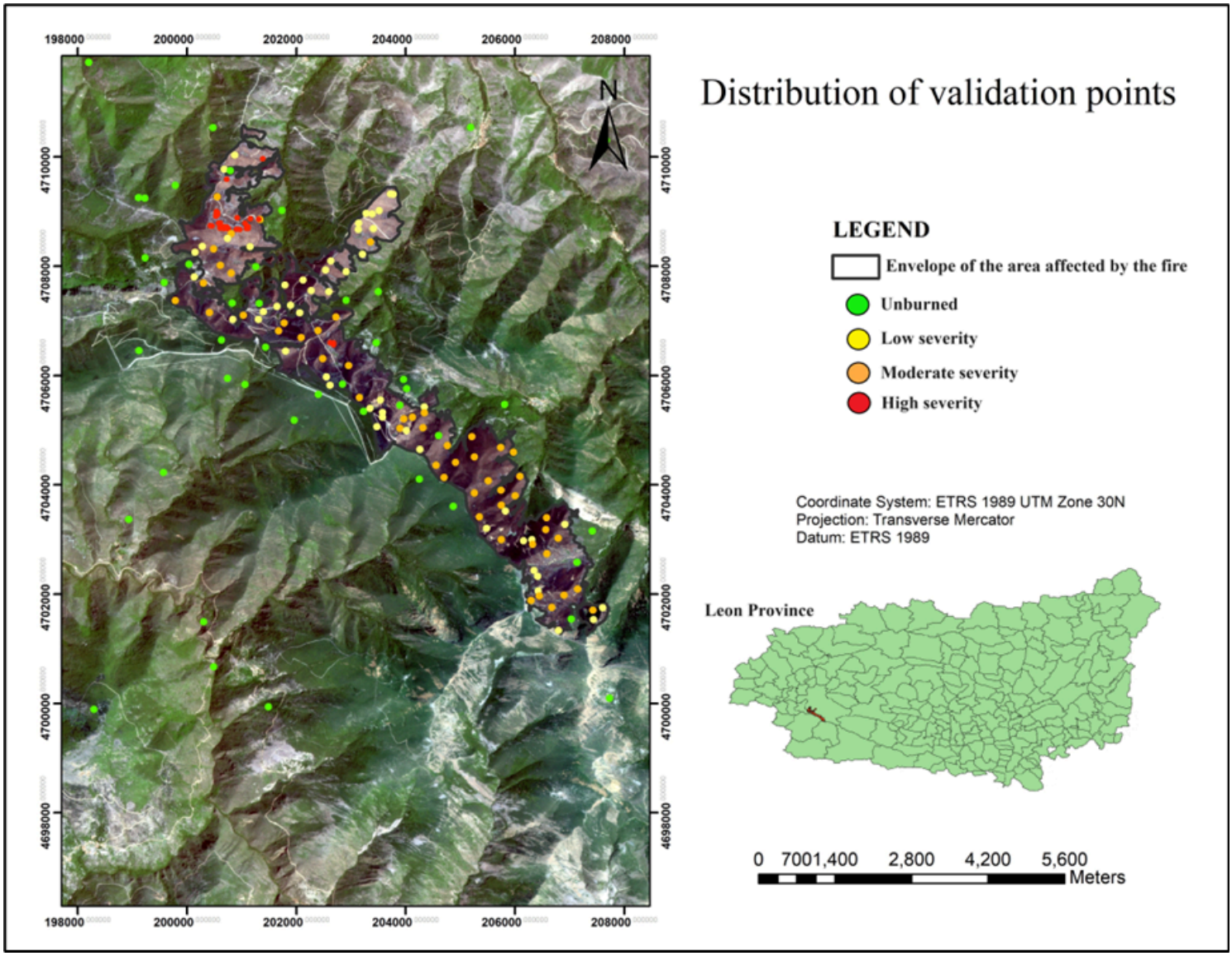


Figure 2

Spatial distribution of validation points generated by the stratified random method.

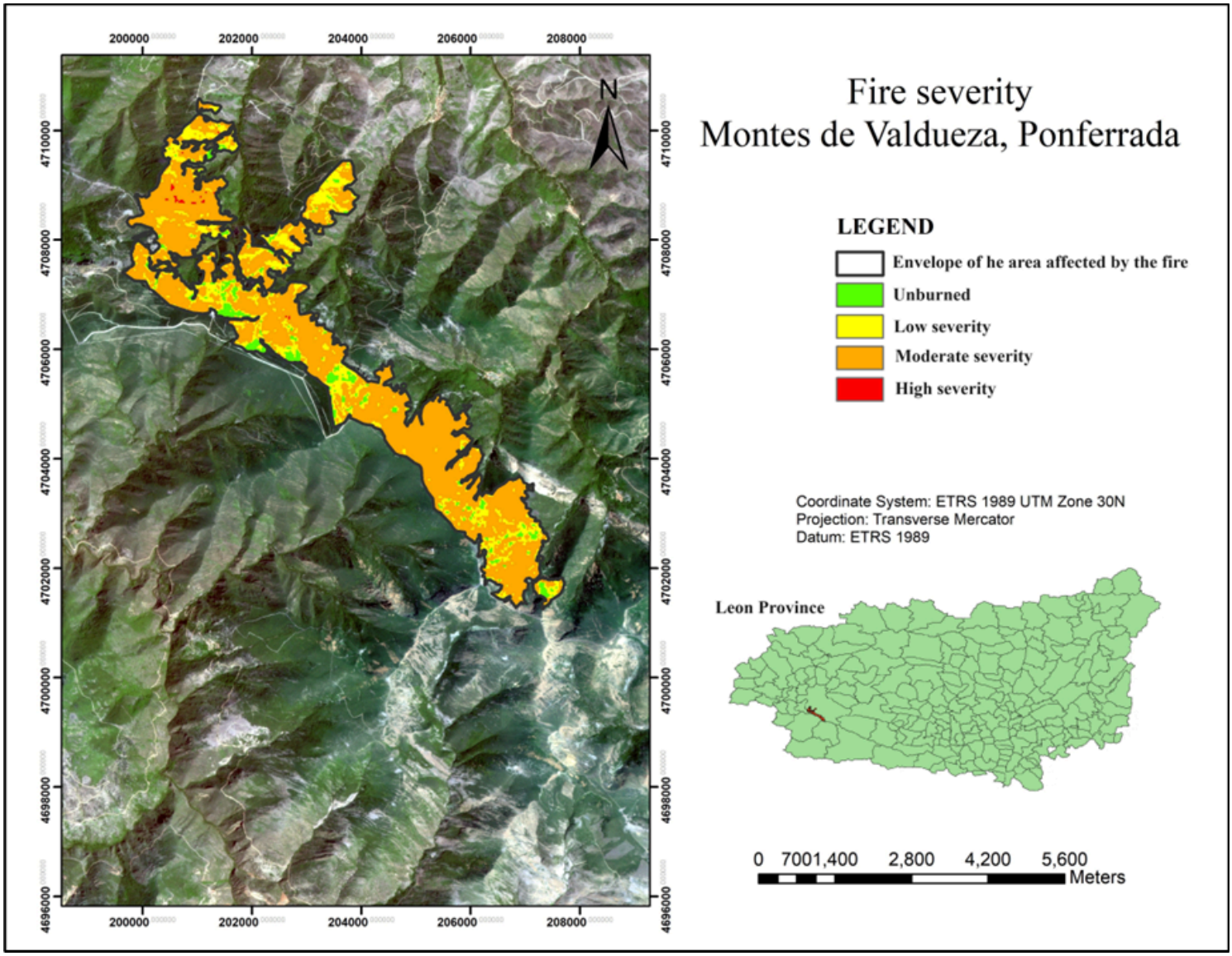


Figure 3

Mapping of the severity of the fire in Montes de Valdueza, Ponferrada.

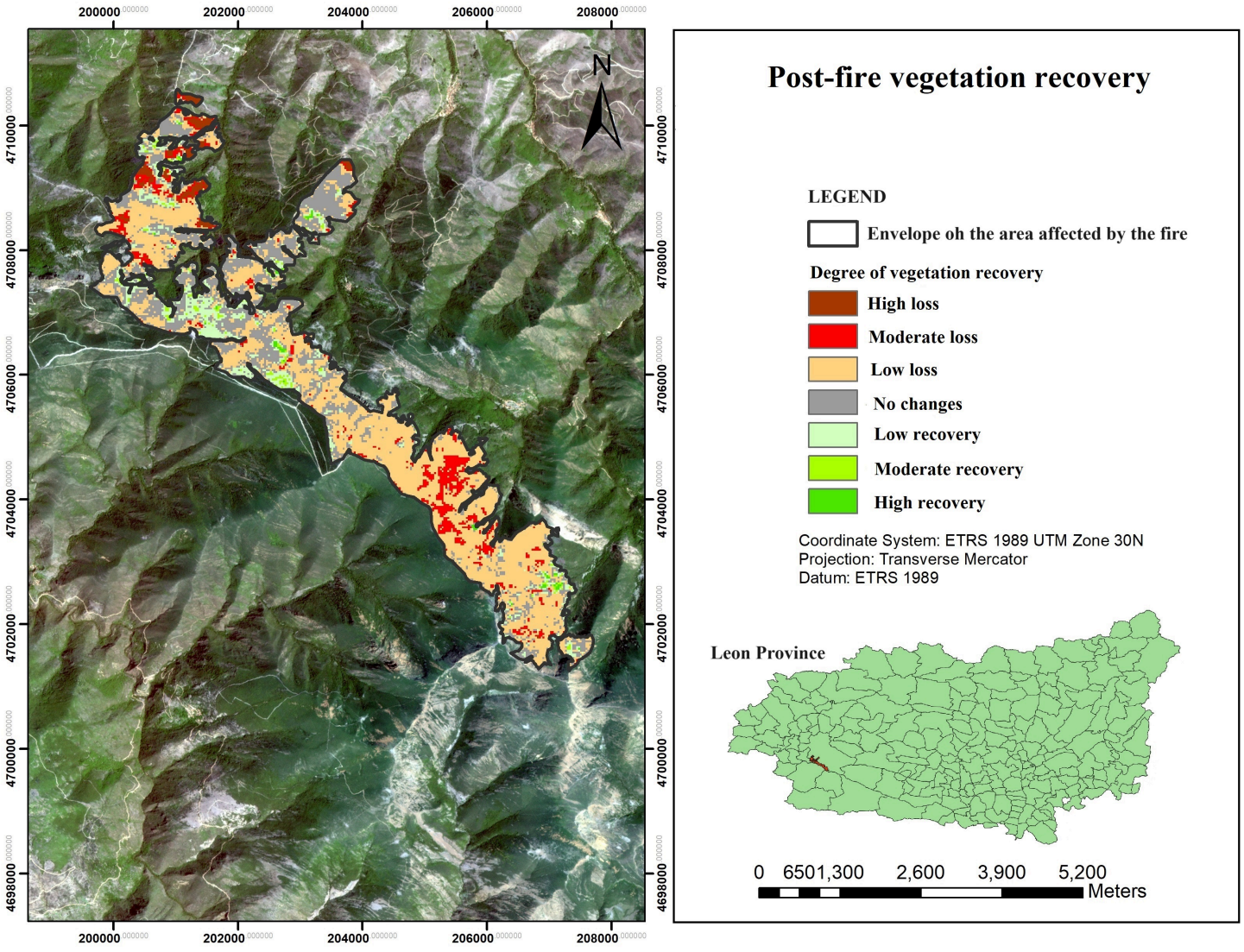


Figure 4

Post-fire vegetation recovery map derived from the differenced Normalized Difference Vegetation Index (dNDVI). The map illustrates spatial patterns of vegetation loss and early regeneration eight months after the wildfire.



Figure 5

Areas of young *Pinus sylvestris* plantations within the burned region, where a regeneration of mostly *Erica australis* and *Genista tridentata* can be observed.