DATA PRODUCTS & DATA PORTAL MANUAL

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Abstract (EN)

The SeverusPT project aims to periodically and timely provide relevant and standardized information on burn severity supported by satellite and field observations. Key objectives include developing a spatially explicit framework for assessing, mapping, and predicting burn severity and delivering a co-designed product/service to enhance institutional and operational capacity for fire hazard management and post-fire ecosystem restoration.

The project currently provides standardized satellite-based datasets on mainland Portugal's observed/historical burn severity, leveraging multiple satellite missions (Sentinel-2, Landsat, MODIS), spectral indices (e.g., Normalized Burn Ratio – NBR, Tasseled Cap Transformation – TCT), and burn severity indicators. The datasets are derived from pre-calculated severity products through algorithms that integrate satellite image time series (SITS) in two main approaches: (i) a delta-based pipeline, employing "classical" severity measurements (e.g., delta NBR) and focused primarily on high spatial resolution satellites; and (ii) a trajectory-based pipeline supported by SITS and the analysis of post-fire trajectories for multiple dimensions of ecosystem functioning and primarily focusing on high-temporal/moderate spatial resolution satellites.

Field assessments, critical for validating satellite products and obtaining nuanced results regarding post-fire effects, were used to provide information on burn severity across different structural components of vegetation. The project used a purposive stratified approach for field surveys, focusing on the 2022 fire season across mainland Portugal. Selection criteria based on fire size, location, main vegetation type, and other ancillary layers enabled comprehensive coverage and diversity in post-fire conditions. Approximately 111 sites in 28 burned areas were surveyed in north and centre Portugal (the wildfire foci in the country) using the Geometrically Structured Composite Burn Index (GeoCBI) protocol. Two methods were used to validate the delta-based products by comparing in situ GeoCBI and satellite burn severity estimates: (i) non-parametric linear correlation (Spearman method) and nonlinear correlation; and (ii) a nonlinear exponential model adapted from pre-existing studies.

Delta-based SeverusPT products agreed well with GeoCBI field measures of burn severity. The best linear correlation results were bounded between 0.64 and 0.71. Sentinel-2 and the NBR spectral index with RBR generally ranked higher when compared to Landsat-8. For nonlinear correlation, results were between 0.65 and 0.76, with the best results for Landsat-8 TCTG, closely followed by Sentinel-2 NBR spectral index with RDT or RBR indicators. The results for the nonlinear model validation were similar, with the best marks attained by the RdNBR, RBR, and dNBR indicators ($R2$= 0.64, 0.62, and 0.60, respectively).

The project's data portal is a centralized gateway for accessing and downloading project data and metadata. It offers two primary levels of data access: Level 1 includes

the products, and Level 2 comprises image data files along with metadata. The trajectory-based pipeline and products are still under active development and will be added to the SeverusPT Data Portal.

SeverusPT builds on a comprehensive approach combining satellite data with rigorous field validation, yielding significant insights into wildfire severity. The project's innovative methodologies and the data portal's accessibility contribute to the field of wildfire severity assessment, offering valuable data and tools for fire management and prioritizing post-fire mitigation and recovery strategies.

Resumo (PT)

O projecto SeverusPT tem como objetivo disponibilizar, de forma regular e atempada, informação relevante e pradonizada da severidade da área ardida, baseada em dados de satélite e observações no terreno. Os principais objetivos incluem o desenvolvimento de uma moldura de análise espacialmente explícita para avaliar, mapear e prever a severidade da área ardida, fornecendo um produto/serviço resultante de co-desenho para melhorar a capacidade institucional e operacional para a gestão do risco de incêndio e o restauro dos ecossistemas pós-incêndio.

Atualmente este projeto disponibiliza conjuntos de dados derivados de imagens de satélite para Portugal Continental acerca da severidade histórica/observada da área ardida. Estes conjuntos de dados fazem uso de informação proveniente de múltiplas missões espaciais (Sentinel-2, Landsat, MODIS), índices espetrais (p.ex. "Normalized Burn Ratio" – NBR, "Tasseled Cap Transformation" – TCT), e indicadores da severidade da área ardida. Os conjuntos de dados derivam de produtos pré-calculados de severidade através de algoritmos que integram séries temporais de imagens de satélite (SITS) em duas abordagens principais: (i) a cadeia de processamento ("pipeline") baseado em deltas, que implementa medidas "clássicas" de severidade (p.ex. delta-NBR) e que se foca principalmente em satélites de alta resolução espacial; e (ii) a cadeia de processamento baseado em trajetórias, que se baseia na análise de trajetórias pós-incêndio para múltiplas dimensões do funcionamento dos ecossistemas e que se foca em dados de satélite de alta resolução temporal e resolução espacial moderada.

No sentido de fornecer informação acerca da severidade da área ardida em vários componentes estruturais da vegetação, foram utilizados dados recolhidos no terreno, os quais são cruciais para validar produtos derivados de imagens de satélite e obter resultados pormenorizados relativamente a efeitos pós-incêndio. No âmbito do projeto foi usada uma abordagem estratificada para efetuar os levantamentos no terreno, focada na época de incêndios de 2022 em Portugal Continental. Critérios de seleção baseados no tamanho da área ardida, localização, tipo de vegetação principal e outras camadas auxiliares de informação permitiram cobrir uma maior diversidade de condições pós-incêndio. Foram visitados aproximadamente 111

locais pertencentes a um total de 28 áreas ardidas no Norte e Centro de Portugal Continental (as zonas do país mais afetadas por incêndios), usando o protocolo "Geometrically Structured Composite Burn Index" (GeoCBI). Foram utilizados dois métodos para validar os produtos baseados em deltas, através da comparação do GeoCBI in situ com estimativas obtidas por satélite: (i) correlações lineares não paramétricas (método de Spearman) e correlações não-lineares; e (ii) um modelo exponencial não-linear adaptado de estudo pré-existentes.

Os produtos SeverusPT baseados em deltas apresentaram elevada concordância com as medidas de severidade da área ardida recolhidas no terreno através do GeoCBI. Os valores resultantes mais elevados para a correlação linear situaram-se entre 0,64 e 0,71. Foram obtidos valores geralmente mais elevados para Sentinel-2 e para o índice espetral NBR e o indicador de severidade RBR, em comparação com os resultados obtidos para Landsat-8. Relativamente às correlações não-lineares, foram obtidos valores entre 0,65 e 0,76, tendo os valores mais elevados sido obtidos para o índice espetral TCTG derivado de Landsat-8, seguido do índice espetral NBR derivado de Sentinel-2 com os indicadores de severidade RDT ou RBR. Foram obtidos resultados semelhantes para a validação através de modelo não-linear, com os valores mais elevados correspondendo aos indicadores de severidade RdNBR, RBR e dNBR (R2 = 0,64, 0,62 e 0,60, respetivamente).

O portal de dados do projeto constitui uma via de acesso centralizada para a visualização e descarregamento de dados e metadados do projeto, oferecendo dois níveis primários de acesso: o Nível 1 inclui os produtos e o Nível 2 é constituído por ficheiros de imagens e metadados. Os produtos provenientes da cadeia de processamento baseada em trajetórias estão ainda em desenvolvimento activo e serão adicionados posteriormente no Portal de Dados do SeverusPT.

O SeverusPT assenta numa abordagem abrangente que combina dados provenientes de satélites com uma rigorosa validação baseada em dados recolhidos no terreno, oferecendo uma melhor compreensão da severidade dos incêndios. As suas metodologias inovadoras e a acessibilidade do seu portal de dados contribuem para o campo da avaliação da severidade dos incêndios, providenciando dados e ferramentas valiosos para a gestão do fogo e para a priorização de estratégias de mitigação e recuperação pós-incêndio.

1. Introduction

Using satellite and field data, the SeverusPT project aims to provide, in a periodic and timely manner, relevant and standardized information on the evaluation and prediction of fire severity. By including national entities engaged in fire management, emergency response, land planning and Earth Observation, the project aims to monitor post-fire ecosystems and contribute to their assessment, resilience and restoration.

Main objectives:

- Develop a spatially explicit framework to assess, map, and predict fire severity;
- Deliver a co-designed product/service that enhances institutional and operational capacity for fire hazard management and post-fire restoration;
- Foster collaboration with key stakeholders for long-term sustainability and continuous improvement of the product/service;
- Contribute to advancing the state-of-the-art in fire severity mapping and modelling and understanding its driving factors and links to fire hazard management.

Key features:

- Robust framework: The project implements a spatially explicit framework that assesses, maps, and predicts burn severity, considering the effects of fires on ecosystems under a changing climate;
- Satellite data analysis: Spectral and ecosystem functioning indicators extracted from satellite remote sensing time series are leveraged to assess fire severity and provide detailed characterizations on a large scale;
- Web-based services: A user-friendly Data Portal is implemented to access and share the project's data, and web services are being developed to provide continuous and standardized fire severity products, facilitating preventive fire risk management, monitoring, and post-fire restoration efforts.

1.1. SeverusPT product calculation approaches

SeverusPT provides standardized satellite-based datasets on mainland Portugal's observed/historical burn severity. These datasets are based on multiple satellite missions (Sentinel-2, Landsat and MODIS), spectral indices (e.g., Normalized Burn Ratio, NBR; Tasseled Caps Transformation, TCT) and burn severity indicators. These datasets are based on pre-calculated severity products (i.e., rather than on-demand calculation) through algorithms integrating satellite image time series (SITS) and taking a multi-temporal aggregation or a time series analysis approach.

The project encompasses a rigorously defined data organization and distribution structure for easy access and sharing. The data is available in raster format compatible with any GIS or Remote Sensing software.

The products have been validated through rigorous *in situ* surveys in more than 100 sites across mainland Portugal and nearly 30 burned areas for the focal years of 2021 and mostly 2022 (as of October 2023).

Two complementary calculation approaches were used to obtain observed burn severity products:

- Delta approach – based on "classical" severity measurements (e.g., delta NBR) and using high spatial resolution satellites – primarily Sentinel-2 (20 meters) but also harmonized Landsat-5, 7 and 8 (30 meters). This product already has a preliminary version available through the project's data platform (see section 5);

- Trajectory approach – based on SITS and the analysis of post-fire trajectories for multiple dimensions of ecosystem functioning (see Marcos et al. (2023)). This framework was applied to satellite data of moderate spatial resolution – MODIS (500 to 1000 meters).

1.2. Some concepts: fire intensity vs. burn severity

As described by Keeley (2009), fire intensity encapsulates the measure of energy released from the combustion of organic matter. This metric quantifies the power of a wildfire and refers to while the fire is active. It serves as a fundamental parameter in understanding the immediate dynamics of a fire event. Fireline intensity, a frequently employed metric in assessing fire intensity and behaviour, quantifies the rate of heat transfer per unit length of the fire line (expressed in kWm^{-1}). It serves as a direct indicator of the radiant energy release at the flaming front. Fireline intensity plays a pivotal role in evaluating the likelihood of fire propagation and the challenges involved in containment efforts. As such, it is a vital component within fire behaviour models, providing essential insights to guide and inform effective wildfire suppression strategies (see e.g., Aparício et al. 2022, Sil et al. 2023).

Burn severity, on the other hand, extends our comprehension beyond the raw intensity of the fire. It delves into the aftermath and describes how the fire intensity impacts environmental conditions and functions in the affected area. It is a multidimensional concept, as Keeley (2009) emphasizes, with its impacts often exhibiting spatial and temporal variability both within the burned area and across diverse ecosystems.

Furthermore, burn severity can be viewed as a measure of the extent to which an ecosystem has been transformed or its functioning disrupted by the passage of a fire. It reflects the enduring alterations and ecological consequences that fires can leave in their wake, encompassing factors like soil damage, vegetation loss, and changes in hydrological processes. It also extends to effects on biodiversity and overall ecosystem functioning.

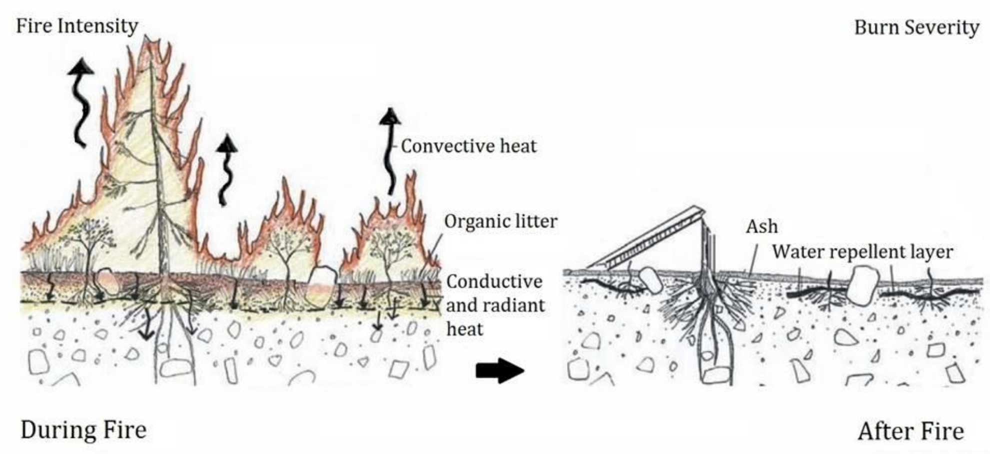


Figure 1– Illustration of fire intensity versus burn severity (Source: U.S. Forest Service, Gen. Tech. Rep. RMRS-GTR-243. 2010).

To better illustrate the contrast between these two critical concepts, Figure 1 visually portrays the difference between fire intensity and burn severity, highlighting the dynamic interplay between the immediate fire event and the ecological consequences that unfold in its aftermath.

Burn severity typically exhibits variations depending on the specific ecosystem under consideration. Spatial variations in burn severity also form what is known as the post-fire mixed severity landscape, with unburnt to low severity "islands" in which biological legacies have high importance in its post-fire recovery (Torres et al. 2018, Santos et al. 2022). Typically, larger wildfires (with a higher probability of having more heterogeneous fuel types, conditions, and continuity) show higher spatial heterogeneity in burn severity levels.

In forested environments, burn severity is generally assessed through parameters such as tree mortality, canopy damage, and the scorching of boles and crowns (Keeley 2008). These metrics are often employed as proxies for quantifying the intensity of a fire, and they are presumed to reflect the fire's influence on the ecosystem's ability to recover. However, it is essential to note that these forest-specific measures of burn severity are not universally applicable to other ecosystems, such as grasslands or shrublands, where crown fires can result in the total consumption of aboveground biomass. In such cases, alternative indicators of burn severity become relevant, particularly those that gauge the ecosystem's ability to rebound. These indicators include resprouting success and the survival of seed banks (Keeley 2008), often challenging as well as time/resource-intensive to estimate in the field.

The relationship between fire intensity and burn severity is a multifaceted research area with still aspects to clarify and uncover. Understanding how different ecosystems respond to varying fire intensities and their resulting severities is a complex endeavour involving a wide array of ecological factors and interdependencies. Further research in this domain is crucial for comprehending the intricate dynamics of wildfires in diverse environments and for developing more targeted and effective management strategies.

2. Delta-based approach

2.1. Introduction to satellite-based estimation of burn severity

Several satellite-based spectral indices have been created to quantify the burn severity in a standardised and systematic manner over diverse spatiotemporal scales. One well-known example of such spectral indices is the Normalized Burn Ratio (NBR). NBR is a valuable index designed to identify and delineate burnt areas and estimate burn severity. NBR employs a mathematical formula similar to the well-known Normalized Difference Vegetation Index (NDVI), with a unique twist: the NBR combines spectral information from both the near-infrared (NIR) and shortwave infrared (SWIR) wavelengths, where the contrast of spectral signatures between burned vs unburned vegetation is more evident.

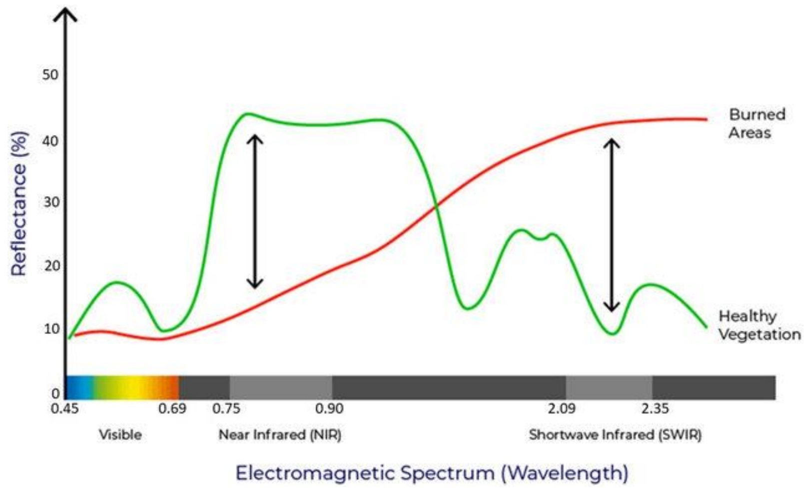


Figure 2 – Comparison of the spectral response of healthy vegetation and burned areas (image source: Alcaras et al. (2022)).

Under "normal" conditions, "healthy" vegetation exhibits a distinctive pattern in its spectral reflectance characteristics (hereafter, spectral signature). It tends to show a very high reflectance in the NIR region, related to non-photosynthetic electromagnetic radiation, while displaying low reflectance in the SWIR portion of the electromagnetic spectrum, typically linked to vegetation and soil water content (Figure 2).

However, this pattern sharply contrasts with the spectral signature of areas affected by wildfires. These areas typically feature low reflectance in the NIR and high reflectance in the SWIR. This pronounced disparity in spectral responses between "healthy" vegetation and recently burned regions – chiefly in the NIR and SWIR regions – is featured in the NBR spectral index to portray burn severity by comparing pre- and post-fire conditions. The NBR is calculated through a normalized ratio involving the NIR and SWIR bands by leveraging the substantial contrast in spectral characteristics. A high NBR value is a robust indicator of healthy vegetation, whereas a low NBR value points to artificial, bare ground or recently burned areas. The index by itself is not an indicator or allows a "direct" classification of burned areas; instead, comparing at least two images (i.e., pre- vs post-fire) points to changes in Earth's surface reflectance that can be attributed to wildfire effects. Within the SeverusPT platform, to overcome this issue, only burned areas (obtained from validated and publicly available sources) are assessed to avoid false detections and thus target severity assessments (only) within fire perimeters.

Overall, the NBR is a valuable index for assessing burn severity in post-fire areas, and one way to quantify this is by calculating the delta NBR (dNBR or ΔNBR). The delta NBR represents the difference between the pre-fire and post-fire NBR values obtained from remote sensing images (or multitemporal composites of images such as the case of SeverusPT). It is a widely known and commonly used metric for estimating the degree of burn severity.

In this context, a higher dNBR value indicates more severe damage to the landscape, with the affected area showing a significant departure from its pre-fire state. Values around zero usually translate to "normal" seasonal shifts related to phenology and weather variation. Conversely, areas with negative dNBR values often suggest regrowth or recovery following a fire. These negative values often indicate positive changes in post-fire vegetation cover compared to the pre-fire conditions.

There are several methods for calculating the difference based on NBR (or other similar spectral indices):

$$NBR = \frac{NIR - SWIR}{NIR + SWIR}$$

Eqn. 1 – Calculation formula for the Normalized Burn Ratio (NBR) spectral index. NIR is the reflectance in the Near Infrared region, and SWIR is the reflectance in the Shortwave Infrared.

- Delta NBR (dNBR):

  $$dNBR = NBR_{pre-fire} - NBR_{post-fire}$$

- Relative Difference NBR (RdNBR):

  $$RdNBR = \frac{dNBR}{\sqrt{\left|NBR_{pre-fire}\right|}}$$

- Relativized Burn Ratio (RBR):

$$RBR = \frac{dNBR}{(NBR_{pre-fire} + 1.001)}$$

Eqns. 2 - 4: Equations for delta (d), the relativized difference (Rd) and relative burn ratio (RBR) used to estimate burn severity indicators comparing pre- and post-fire satellite images (or multi-temporal mosaics).

All these severity indicators are currently available through the SeverusPT Project.

Delta NBR (dNBR) values indeed exhibit variability depending on the specific characteristics of each fire event and targeted ecosystem. For this reason, it is advisable to compare remotely sensed data with on-the-ground field assessments to obtain more accurate and nuanced results regarding fire effects. Field assessments provide more context and information on burn severity across different structural components of vegetation (from the ground to tall trees) and can support the validation of remotely sensed estimates.

The USGS's classification table typically categorizes dNBR values into several burn severity classes (Table 1) to aid in interpreting burn severity based on dNBR values. This classification system provides a standardized framework for assessing the ecological impacts of wildfires and categorizing them into different levels of severity. It serves as a useful reference guide for land managers, researchers, and emergency response teams. By using these burn severity categories, professionals can quickly understand and communicate the ecological consequences of a fire event, allowing for more efficient allocation of resources and prioritization of rehabilitation efforts in areas with the greatest need. While field assessments are essential for fine-tuning the evaluation, the USGS classification system is a valuable starting point for interpreting dNBR data.

Table 1– Burn severity categories for dNBR proposed by USGS.

Severity Level	dNBR Range (scaled by 10^3)	dNBR Range (not scaled)
Enhanced Regrowth, high (post-fire)	-500 to -251	-0.500 to -0.251
Enhanced Regrowth, low (post-fire)	-250 to -101	-0.250 to -0.101
Unburned	-100 to +99	-0.100 to +0.99
Low Severity	+100 to +269	+0.100 to +0.269
Moderate-low Severity	+270 to +439	+0.270 to +0.439
Miderate-high Severity	+440 to +659	+0.440 to +0.659
High Severity	+660 to +1300	+0.660 to +1.300

Low severity: This category often corresponds to dNBR values close to zero or slightly positive. It suggests minimal ecological impact, potential for post-fire regrowth, and relatively mild soil and vegetation damage.

Moderate severity: Moderate burn severity may be associated with dNBR values that are moderately negative. It indicates a more substantial impact on the landscape, with a moderate reduction in vegetation cover and possible soil disturbance.
High severity: severity is typically linked to strongly positive dNBR values. This class denotes significant vegetation damage, including canopy, understory, and notable soil alterations. Post-fire recovery may be more challenging in high-severity areas.
Very-high severity: The highest burn severity level, often represented by highly positive dNBR values, suggests severe impacts on vegetation, including widespread mortality of trees and shrubs and potentially severe soil damage. Recovery in these areas may be prolonged and challenging.

Burn severity data and corresponding maps are pivotal in formulating post-fire emergency rehabilitation and restoration strategies. Beyond assessing the immediate impact of a fire, these data sets offer a comprehensive toolkit for estimating the severity of soil damage and the probability of consequential downstream repercussions, such as flooding, landslides, and soil erosion.

Burn severity data and maps provide a detailed assessment of how much the fire has affected the soil. This information is critical for understanding how the soil's physical and chemical properties have been altered. Soil burn severity data can guide post-fire mitigation and restoration actions, aiding in decisions about reseeding, soil stabilization, and nutrient management to facilitate ecosystem recovery. The significance of burn severity data goes beyond the immediate burn area. By considering the potential downstream effects, such as increased runoff and sedimentation, these data enable the assessment of risks related to flooding, landslides, and soil erosion in the aftermath of a fire. This foresight is invaluable for emergency planning and developing measures to mitigate these secondary impacts. With standardized and comprehensive burn severity data and maps, land management authorities can allocate resources more effectively. This targeted approach ensures that the most critical ecological and environmental preservation areas receive the necessary attention and resources for restoration. On the other hand, by understanding the potential risks of flooding, landslides, and soil erosion following a fire, this data aids in safeguarding communities and infrastructure. Emergency responders, urban planners, and disaster management agencies can make informed decisions to protect public safety and infrastructure integrity.

In essence, burn severity data and maps are indispensable tools in the post-fire landscape, offering a multifaceted view of the environmental consequences of wildfires. Integrating these data into rehabilitation and restoration planning makes it possible to rehabilitate damaged areas, safeguard against secondary environmental threats, and mitigate risks to communities and ecosystems.

2.2. Delta-based product calculation in Google Earth Engine platform

SeverusPT employs Google Earth Engine (GEE) to generate delta products and process large satellite image time series. GEE facilitates data pre-processing, spectral index calculations, spatiotemporal aggregations, and merging image mosaics across large areas.

In a nutshell, GEE is a cloud-based geospatial platform that simplifies access to a vast array of Earth observation data and provides in-depth analysis and visualization tools (Gorelick et al. 2017). It operates through a JavaScript or Python API, allowing users to interact with geospatial data stored in Google's cloud infrastructure. Key features include its distributed computing architecture, enabling users to process large datasets without significant local computing resources. Earth Engine excels at handling temporal data, making it useful for monitoring changes over time. Users can also create maps, export analysis outputs to local computing resources, and develop animations to visualize analysis results.

Additionally, the platform encourages sharing and collaboration within the Earth Engine community. It can be integrated with other Google services and tools (e.g., Google Drive, Google Cloud), enhancing its versatility and convenience for various geospatial applications, from environmental monitoring to disaster management and urban planning. GEE's capabilities in accessing, analyzing, and visualizing geospatial data and its powerful temporal analysis tools make it an invaluable resource for post-fire analysis. It aids in understanding the dynamics of wildfires, assessing their impacts, and facilitating informed decision-making for both immediate post-fire response and short to long-term recovery.

Despite its many advantages and benefits, GEE holds some caveats mainly tied to its Terms of Service (ToS) and limitations due to the lack of analytical features/algorithms or limited computing resources allocated to each user. Long-term usage is also a concern since unpredictable alterations in the ToS may eventually limit the platform's access and usability. Additional cloud space in Google Drive to overcome limitations in data storage and paid access to Google's Cloud Computing infrastructure needs to be purchased to take full advantage of GEE. Nevertheless, it is important to note that alternatives to the use of GEE can imply much higher computation times and resources that may not be readily available.

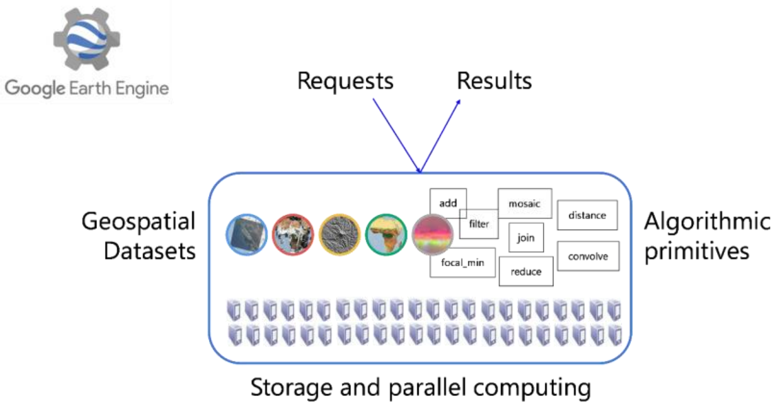


Figure 3- Google Earth Engine main workflow (source: Google | https://docs.google.com/presentation/d/1hT9q6kWigM1MM3p7IEcvNQlpPvkedW-lgCCrlqbNeis/htmlpresent).

To fully access GEE capabilities, we use the R package rgee (Aybar 2023), which serves as a bridge between R and Google Earth Engine (GEE). It enables R users to access GEE's vast geospatial data catalogue and conduct complex analysis tasks in the cloud. Users authenticate with their Google accounts to link R with GEE. Using rgee, users write R code for geospatial analysis, which is sent to GEE's servers for processing. After analysis, users can retrieve results back to R for further processing and visualization. This integration allows R to harness GEE's geospatial capabilities, making it a powerful tool for wildfire-related applications.

Processes in rgee use reticulate (Ushey et al. 2023), an R package designed to allow seamless interoperability between R and Python. When an Earth Engine request is created in R, reticulate will translate it into Python and pass it to the Earth Engine Python API, which converts the request to JSON. Finally, the GEE Platform receives the request through a Web REST API, and the response will follow the same path back in reverse.

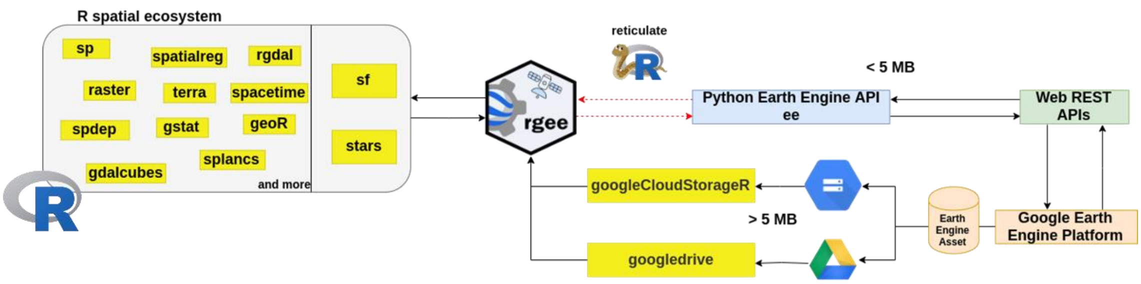


Figure 4 – The rgee package main workflow (source: https://r-spatial.github.io/rgee).

2.3. FAQ – Burn severity products with the delta-based approach

Delta-based products from SeverusPT map burn severity levels through different spectral indices (e.g., NBR, TCTs) and for different indicators comparing pre- vs-fire conditions (Delta, RDT and RBR). SeverusPT also uses multiple satellites (MODIS, Landsat and Sentinnel-2) to provide a more nuanced understanding of wildfire effects, profiting from different spatiotemporal resolutions and the rich image archive provided by these missions. This multifaceted approach, entailing multiple dimensions, indices and satellite missions, also enhances the accuracy and reliability of burn severity assessments.

Each burn severity layer shows all wildfires that occurred for a given year at different temporal horizons (or windows) 3, 6, 9 and 12 months after the wildfire date. This way, SeverusPT delta-based products provide an integrated and seamless method of comparing severity levels for all wildfires occurring within a given year, independently of the actual start/ignition date, and at the same comparable timeframe.

Delta-based products use multitemporal quarterly composites to aggregate image data (i.e., from three up to twelve months after the fire). This approach aims to improve image quality and remove clouds or other potential artefacts. The pre-fire reference is always based on the same period as the post-fire but for the year before (i.e., homologous year).

The main workflow used to calculate the burn severity products in Google Earth Engine is shown in Figure 5. The first step consists of selecting the pre- and post-fire satellite images for each fire perimeter (for a given year) based on the ignition date annotated in the burned areas dataset. A cloud mask is applied to the images, and then the spectral indices are calculated for each image in the stack. Multitemporal aggregation follows by determining the median composites to establish baselines for the pre- and post-fire conditions. Burn severity indicators (delta, RdNBR, RBR) are then computed and spatially aggregated in the image product for each burned site. This process is iteratively repeated for all burned areas until the dataset is complete.

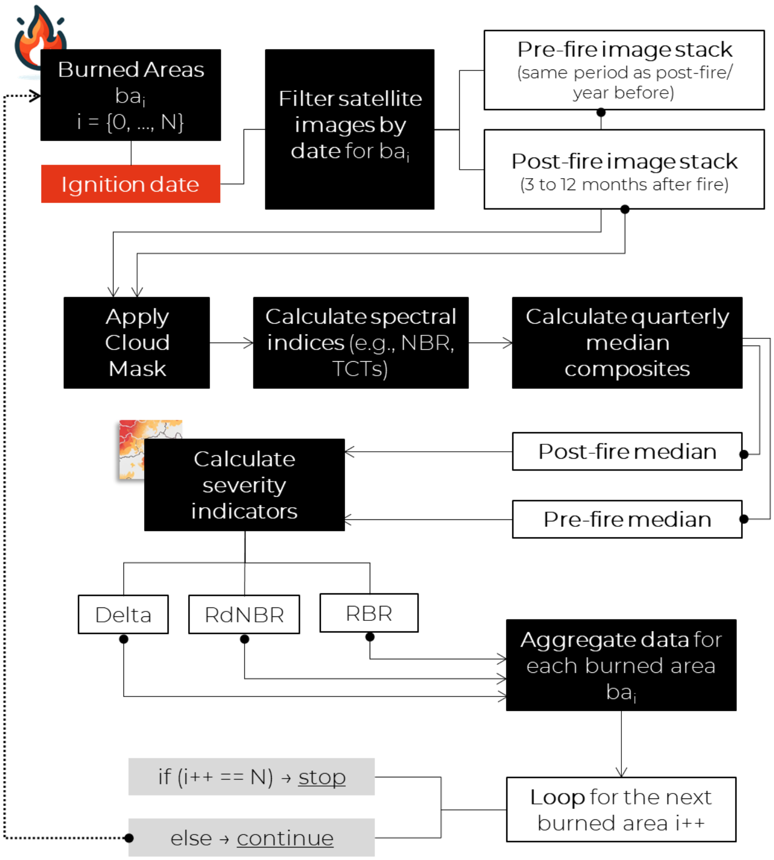


Figure 5 – Main workflow used to calculate burn severity products in Google Earth Engine for the "Delta-pipeline".

The main workflow is then applied at several quarterly time steps from 3 to 12 months after the fire. The following figures illustrate in more detail the calculation workflow for SeverusPT delta products at different time steps:

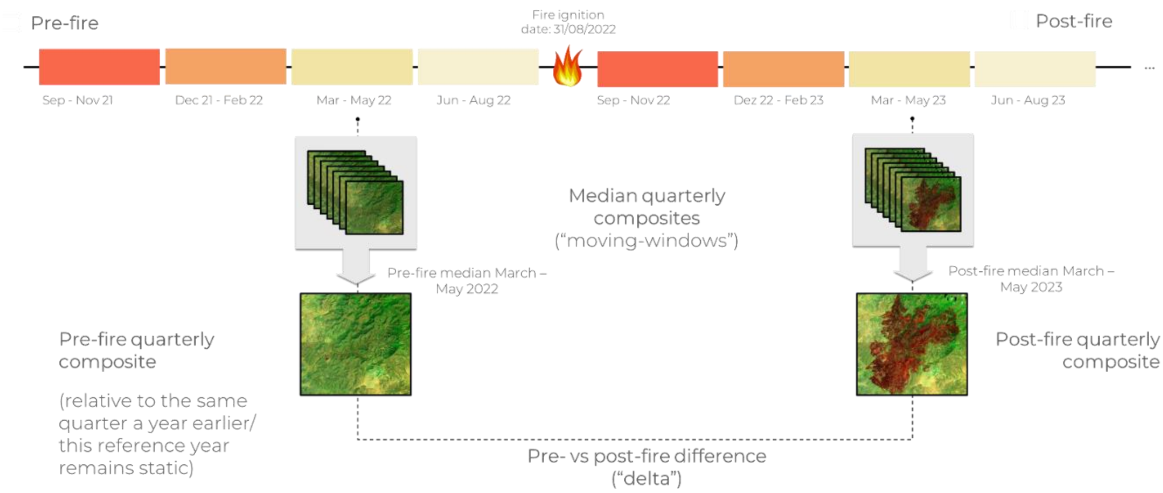


Figure 6 – Comparing pre- and post-fire quarterly image composites in the SeverusPT mapping system with the delta-based framework. Initial assessment (i.e., up to 12 months after the date of fire).

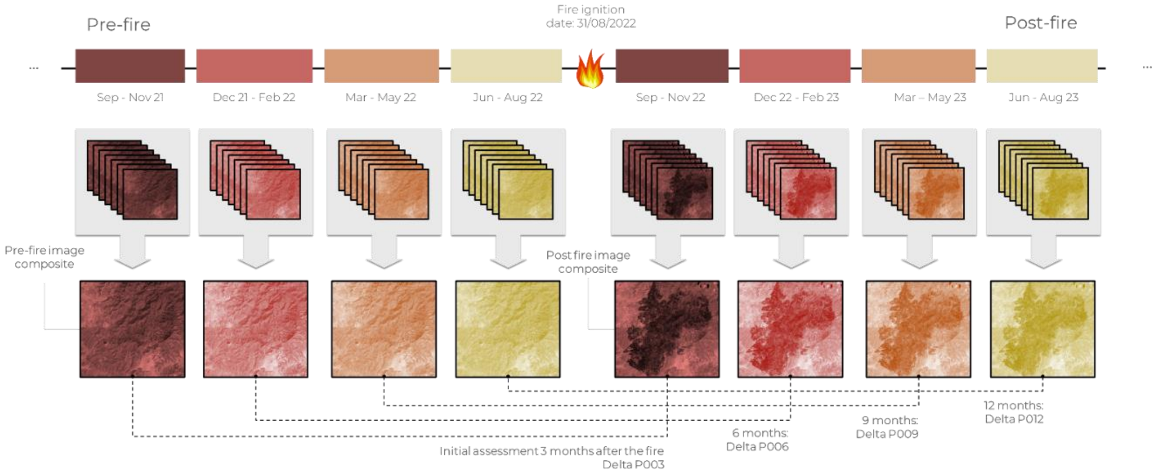


Figure 7 – Example of comparing pre- and post-fire images: multiple sequential windows are used to compare pre- vs post-fire situations in the initial assessment (from 3, 6, 9 to 12 months after the fire)

In essence, SeverusPT's products offer a comprehensive and standardized means of assessing the impacts of wildfires, aiding in the understanding, monitoring, and managing these critical environmental events.

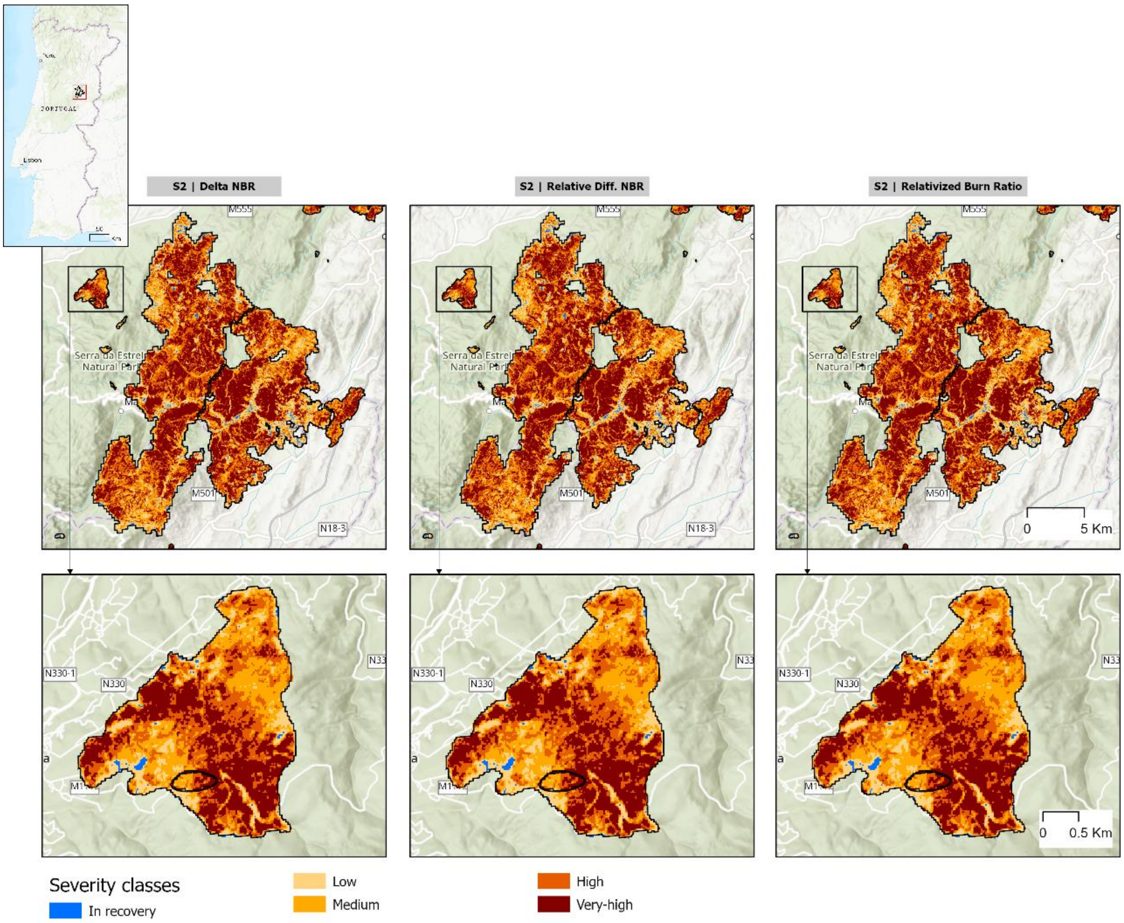


Figure 8 – Comparison between burn severity indicators for 20-m resolution Sentinel-2 for the Serra da Estrela wildfire (2022), including the delta Normalized Burn Ratio (NBR), the Relativized Difference NBR (RdNBR) and the Relative Burn Ratio (RBR). Severity classes were estimated using empirical percentiles for mainland Portugal approximated to the values proposed by US Forest Service/USGS/NASA.

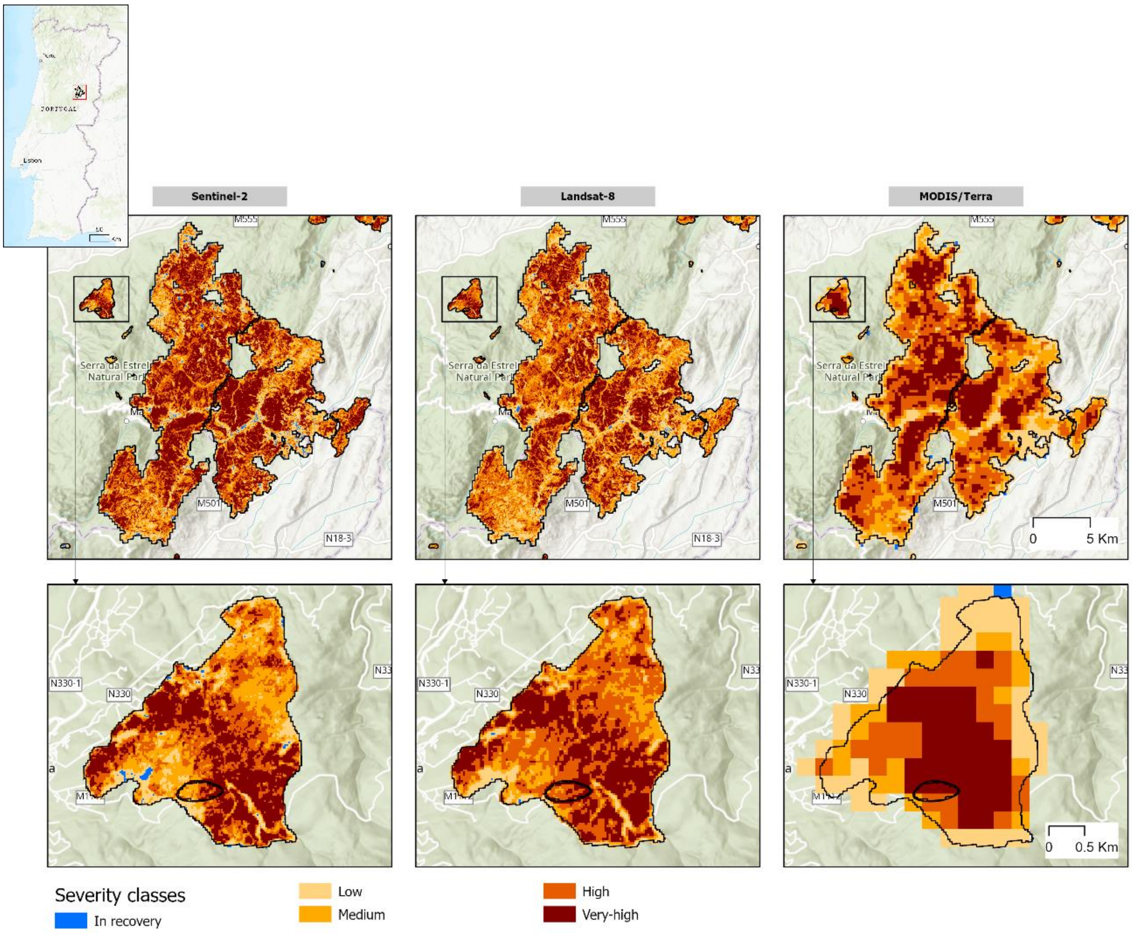


Figure 9 - Comparison between Sentinel-2, Landsat-8 and Terra/MODIS for the Serra da Estrela wildfire (2022), the delta Normalized Burn Ratio (NBR). Severity classes were estimated using empirical percentiles for mainland Portugal approximated to the values proposed by US Forest Service/USGS/NASA.

Q&A

Q: To calculate the pre- vs post-fire difference, what is the pre-fire reference used?

R: The year before the fire is used for the same period (i.e., homologous year reference).

Advantages | Minimises intra-annual or seasonal phenological differences.

Disadvantages | It enhances inter-annual differences, resulting in differences due to the "climatic year".

Q: How many images are used to calculate the pre- and post-fire difference?

R: Multiple images are combined to generate multitemporal composites with three-month (or quarterly) moving windows (i.e., up to 3 months, 4 to 6 months, 7 to 9 months and 10 to 12 months). Median aggregation is used to make image composites. The actual number of images used in composites depends on the temporal resolution of the satellite mission and image availability.

Advantages | Increased probability of finding the best pixel without cloud cover. In the literature, the best results for analyzing post-fire severity were found using temporal aggregation/composite methods.

Disadvantages | Computationally more complex, it requires temporal aggregation of multiple images. This process may not capture the "maximum" severity by aggregating multiple images.

Q: Does the fact that severity products use quarterly composites mean that users must wait that amount of time to access the data?

R: No. As soon as satellite images are available on the Google Earth Engine platform, it is possible to calculate the burn severity products. However, considering Sentinel-2's revisit frequency, this could take a maximum of 5 days (depending on the date of occurrence). Cloud cover may, however, decrease the quality of fast assessments or their feasibility.

On the other hand, for fast burn severity assessments, it is recommended to use SeverusPT analysis and mapping apps ("Fire Severity Analyst").

Q: Is cloud removal performed before calculating the quarterly median?

R: Yes. For all satellites currently available in SeverusPT products, a cloud removal filter is applied in each original image based on the masks available for this purpose.

Although it is not a process capable of completely removing cloud cover, it can at least reduce their influence.

Q: What is the level of processing of the optical images used in calculating the products?

R: Level 2 (L2) – Surface Reflectance (SR) images, sometimes called Bottom-Of-Atmosphere (BOA), are used.

Due to the "double" interaction of the Earth's atmosphere with the light coming from the Sun to/from the Earth's surface, this results in distortions in the images captured by satellite sensors. These distortions can be caused by the transmission, absorption and scattering of light by atmospheric components, such as aerosol particles, water vapour and other gases. Satellite optical L2 SR images seek to correct these atmospheric effects, removing or reducing their influence. These corrections use models and algorithms that consider spectral information from images and measured or estimated atmospheric parameters, such as aerosol composition and optical thickness.

Q: Does the SeverusPT project aim to map or detect burned areas?

R: No. The project uses updated data on burned areas from official databases in the analysis and severity mapping processes, including Copernicus EFFIS (link) or ICNF National Forest Fires Database for Portugal (link).

Advantages | Official data is used. Less complexity in terms of data processing. Focus on measuring severity rather than detecting burned areas by satellite.

Disadvantages | Less control over the severity mapping process. Unavailability of fire dates in the ICNF databases (only from 2014 onwards did the database have ignition/start dates), and there is no access to recent data (~one year gap). In the case of EFFIS, it focuses on larger fires and has a more "generalist" design. For EFFIS only from 2006, the database has ignition/start dates for wildfires (Figure 7).

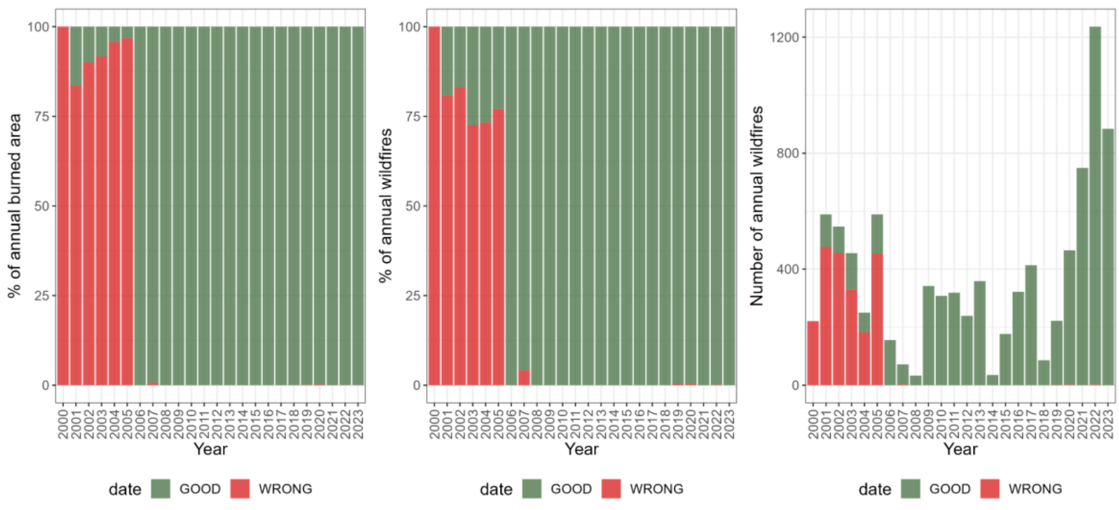


Figure 10 – Comparison between wildfires with ('good') and without correct dates ('wrong') in the Copernicus EFFIS dataset of burned areas. Comparisons, from left to right, are for the % of annual burned area, % of annual wildfires and the number of occurrences. From 2006, ignition/fire start dates are fully recorded in EFFIS database.

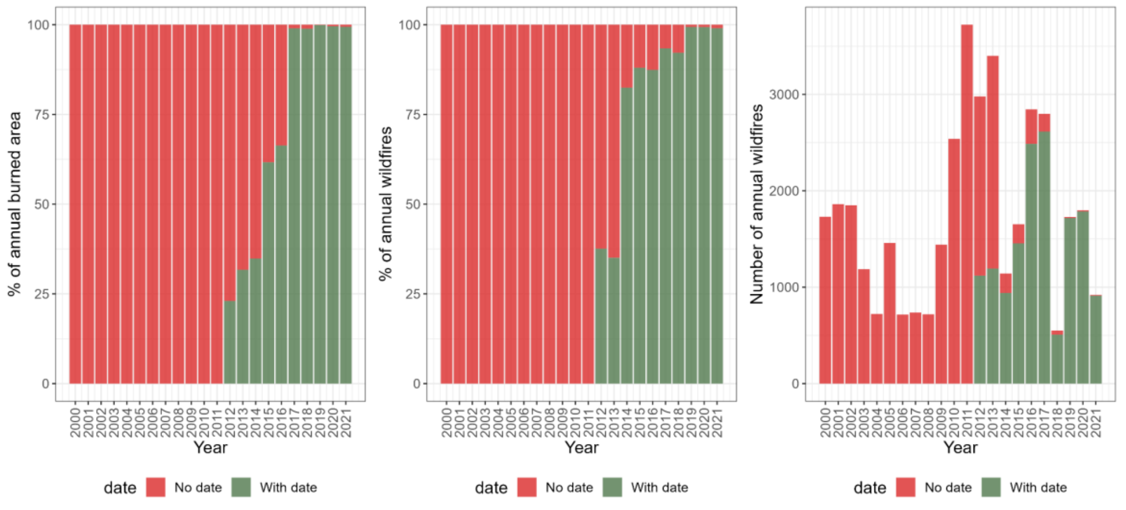


Figure 11 – Comparison between wildfires with ('no date) and without start/ignition dates ('with date) in the ICNF National Burnt Areas Database for Portugal. Comparisons, from left to right, are for the % of annual burned area, % of annual wildfires and the number of occurrences. Only from 2014, >50% of annual burned area and >75% of occurrences have ignition dates in this database.

Q: Is the fire date explicitly used?

R: Yes. The specific dates of each fire are used (i.e., "fire or event-specific severity assessment"). This means that products contain temporally standardized data. In other words, for products based on the "delta" approach, despite the different dates of each fire, all pixels in the severity products represent the difference between the pre-fire and 3, 6, 9 or 12 months after the fire.

Advantages | Burn severity is calculated in a specific way for the event, thus minimizing differences related to the timing or phenology of the fire (i.e., much higher comparability between events is obtained). Allows the user to compare all fires inside or outside the "fire season" for a given year. Better for understanding severity as a fundamental variable for fire regime.

Disadvantages | Requires knowledge of the dates of occurrences. Unfortunately, there are many information gaps and uncertainties about fire dates (especially concerning ICNF data; see Figure 10 and Figure 11).

Q: What is the minimum size of the burned areas considered for severity mapping purposes?

R: The minimum area considered is 10 hectares. Based on a consultation carried out through questionnaires (Task 1 – co-design) and considering the spatial resolutions of the three satellites used (MODIS: 250 – 1000m, Landsat: 30m and Sentinel-2: 10 – 20m), this value was the one that achieved the greatest consensus.

Advantages | Less complexity in terms of processing (less fire perimeters to handle). Focus on measuring the severity of fires with a significant impact and size equal to or greater than the national average. Considering the size of the burned areas, fires >= 10 ha total ca. 90% of the national burned area (on average per year).

Disadvantages | Information about smaller occurrences is lost.

Q: Are satellite-based severity products evaluated in the field?

R: Yes (see section 6 for details). SeverusPT data products are evaluated in the field using a standardized multi-stratum protocol called GeoCBI (modified Composite Burnt Area Index).

The GeoCBI protocol and index evaluates the severity of the burned area for several factors in each of the following strata: (a) soil (including litter, duff, fine and coarse fuels), (b) herbaceous cover, shrubs and trees below one meter, (c) shrubs and trees between 1 and 5 meters, (d) tall trees from 5 to 20 meters and (e) very tall trees above and 20 meters. The severity of each factor is evaluated from 0 (no effect) to 3 (very high severity). The final GeoCBI value is determined by the weighted average of the various factors weighing the coverage proportion of each stratum.

As of the date of this document (October 2023), 111 validation points were collected from mainland Portugal's north-to-centre regions. More surveys are planned to complement this assessment.

3. Trajectory-based approach

i INFO: The trajectory-based pipeline and products are still under active development and will be added in the future to the SeverusPT Data Portal

3.1. The multidimensional ecosystem functioning framework

As an integral part of the natural dynamics of ecosystems in several biomes, fire can profoundly impact many aspects of their structure, composition, and functioning (San-Miguel-Ayanz et al. 2013, Adámek et al. 2016). Post-fire assessment and monitoring based on attributes of ecosystem functioning are of particular interest since fire can cause rapid modifications in multiple di-mensions of matter and energy flows in ecosystems. Furthermore, attributes of ecosystem functioning exhibit quicker responses to disturbances than structural or compositional ones and are more directly connected to ecosystem services (Alcaraz-Segura et al. 2008).

Wildfires play a crucial role in the terrestrial biosphere carbon cycle (Wei et al. 2018) – e.g., in biomass (Pellegrini et al. 2018, Sparks et al. 2018) and primary production (Leys et al. 2016). Furthermore, water supply and quality (Smith et al. 2011, Santos et al. 2015, Carvalho-Santos et al. 2019), as well as soil moisture and vegetation water content (Ebel and Martin 2017, McGuire and Youberg 2019, Senf and Seidl 2020), can also be directly or indirectly affected by wildfire disturbances. Moreover, different aspects of energy balances, such as albedo (e.g., Gatebe et al. 2014, French et al. 2016, Saha et al. 2017, Quintano et al. 2019), latent heat (e.g., Sun et al. 2019), and sensible heat (e.g., Liu et al. 2018, Maffei et al. 2018) can also suffer profound alterations induced by wildfires.

In summary, post-fire processes and the effects of wildfires on ecosystems are multidimensional (Donohue et al. 2013, Donohue et al. 2016), with post-fire trajectories of different dimensions of ecosystem functioning exhibiting different patterns (Ryu et al. 2018). To tackle this challenge, remote sensing techniques have been increasingly employed to assess and monitor different aspects of the post-fire period due to lower costs and improved technology for providing up-to-date information on the status of ecosystems. Indeed, indicators derived from satellite image time series (SITS) can provide information on the dynamics of multiple dimensions of ecosystem functioning, thus enabling the ability to assess and map the spatially and temporally heterogeneous effects of wildfire disturbances on ecosystems (Smith et al. 2011).

To that end, a comprehensive framework based on remotely sensed data was established by Marcos et al. (2019, 2021, 2023) that provides several indicators of both burn severity and post-fire recovery in short-, medium-, and long-term in an integrative way. These indicators are extracted from metrics computed from SITS-derived post-fire trajectories informing on each of the following key attributes of ecosystem functioning:

i) primary productivity;
ii) water content in vegetation and soil;
iii) surface albedo; and
iv) sensible heat.

3.2. General approach and input data

The SeverusPT trajectories-based burn severity product takes advantage of the framework for enhanced multidimensional satellite-based post-fire assessment and monitoring based on ecosystem functioning described in Marcos et al. (2019, 2021, 2023). In this product, per-pixel estimates of burn severity are obtained through a complementary approach to the more "traditional" one employed in the delta-based product by extracting key features of a curve that is constructed from de-noised and de-seasonalized post-fire observations – i.e., the post-fire trajectory.

To that end, satellite image time-series (SITS) with high temporal resolution (i.e. low revisiting times) are preferable since enhanced precision is paramount for obtaining timing-related estimates. In this sense, data products from the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard the Terra and Aqua satellites offer high temporal resolutions – ranging from 8- or 16-day composites to a maximum of four observations per day –, with an archive spanning more than two decades (starting in 2000), despite their moderate to coarse spatial resolutions (250-1000 m).

i NOTE: Despite the Terra orbit drift, starting in late October 2022 and affecting all MODIS products derived from this satellite, the MODIS sensor onboard the Aqua satellite will predictably continue operating at least until 2026 (see https://aqua.nasa.gov/, consulted in 2023-11-28).

In any case, other missions – e.g., Sentinel-2, Sentinel-3, VIIRS – can provide SITS data meeting the data requirements (e.g. spectral, spatial, and temporal resolutions) of the framework employed in the SeverusPT trajectory-based burn severity product.

To derive proxies for the first three of the four abovementioned key attributes of ecosystem functioning, SITS were extracted from the Terra-MODIS Surface Reflectance product MOD09A1 (8-Day L3 Global 500 m, Collection 6; (Vermote

2015)) by applying the *Tasseled Cap Transformation* (TCT; see (Lobser and Cohen 2007, Marcos et al. 2019, 2021)). This transformation consists of rotating principal component axes derived from a global sample to maximize the association of each axis with the bio-physical parameters of photosynthetically active vegetation, vegetation water content and soil moisture, and albedo (Mildrexler et al. 2009). In this way, three sensor-specific linear combinations of bands in the visible, near-infrared, and shortwave infrared regions of the electromagnetic spectrum (Lobser and Cohen 2007), are derived: *Greenness* (TCTG), *Wetness* (TCTW), and *Brightness* (TCTB). Finally, land surface temperature (LST) – a well-known proxy of sensible heat – is a calibrated measure of the thermal emissivity of the land surface (Duan et al. 2019). For the SeverusPT trajectory-based burn severity product, the day-LST from the MODIS-Terra Land Surface Temperature/Emissivity product MOD11A2 (8-Day L3 Global 1000 m, Collection 6; (Wan et al. 2015)) was used, rescaled to degrees Celsius. All four abovementioned satellite-based proxies of ecosystem functioning – i.e., TCTG, TCTW, TCTB, and LST – have been successfully used for fire-related applications (Coops et al. 2008, San-Miguel-Ayanz et al. 2013, Bowman et al. 2015, Marcos et al. 2019, Quintano et al. 2019, Marcos et al. 2021).

3.3. Trajectory-based product calculation

The SeverusPT trajectory-based burn severity product's processing pipeline was mainly undertaken within the R statistical programming environment (R Core Team 2021). First, the *MODIStsp* R package (Busetto and Ranghetti 2016) was used to download MODIS SITS, reproject them to the WGS84/UTM29N coordinate system (EPSG: 32529) and convert the native HDF files into GeoTIFF files. The ensuing processing tasks currently use functions from the *raster* package (Hijmans 2020) – however, future versions of the pipeline will use the *terra* package (Hijmans 2023) instead. The Python package *rasterio* (Gillies et al. 2013) was also used for faster implementations of some specific tasks involving operations with large SITS.

To minimize the influence of spurious values, locally extreme values (i.e. minima/maxima) were filtered from all SITS using the Hampel identifier (Hampel 1971, 1974), with the identified values replaced with local medians. Although quality control/assessment (QC/QA) layers (e.g., cloud cover) are included with MODIS products, the current version of the SeverusPT trajectory-based burn severity product does not explicitly use that information due to much-increased processing times and unsatisfactory results in a preliminary analysis. However, future versions of the processing pipeline are planned to add this step for thoroughness.

To extract meaningful post-fire resilience metrics from SITS, seasonal variations (i.e., fluctuations in the data with a fixed and known frequency) must first be separated from long-term changes due to fire disturbances. To that end, the *Seasonal and*

Trend decomposition using Loess (STL; (Cleveland et al. 1990, Hyndman and Athanasopoulos 2018)) algorithm was used for decomposing time series through a loess smoother to extract the seasonal, trend, and remainder components of time series, as described by the following expression:

$$y_t = S_t + T_t + R_t$$

where, at period t, y_t is the original time series, S_t is the seasonal component, T_t is the trend component, and R_t is the remainder component, all with the same units. More specifically, the STL decomposition was employed to obtain:

i) seasonally adjusted time series (A_t); i.e., the original time series with the seasonal component removed:

$$A_t = y_t - S_t = T_t + R_t$$

to establish pre-fire reference conditions; and

ii) isolated long-term trend component time series, used for calculating incremental median values (i.e., stepwise medians based on moving windows) in the post-fire period:

$$T_t = y_t - S_t - R_t = A_t - R_t$$

The pre-fire reference conditions were those within the range of one median absolute deviation from the median (i.e., median ±1 M.A.D.) of A_t (i.e., in the yy-axis) within the three years prior to the date of the fire occurrence.

Following the trajectory-based approach, the first post-fire directionality inflection point (t_{INF}; Figure 12) must be determined to derive burn severity estimates from SITS. This moment in the post-fire trajectory corresponds to a shift in the values of the trend component change from divergent from- to convergent with the pre-fire reference conditions. The t_{INF} thus translates into an estimate of the date when the disturbance period ends, and the recovery starts. Conversely, the duration of the period between the date of the fire occurrence (t_{FIRE}) and t_{INF} (i.e., in the time axis) can be regarded as an estimate of short-term recovery speed (Marcos et al. 2023). Burn severity metrics can then be extracted based on the difference (i.e., distance along the y-axis) between the pre-fire conditions and some (simple or aggregated) values at or around t_{INF}, translating into the magnitude of the break in the time series.

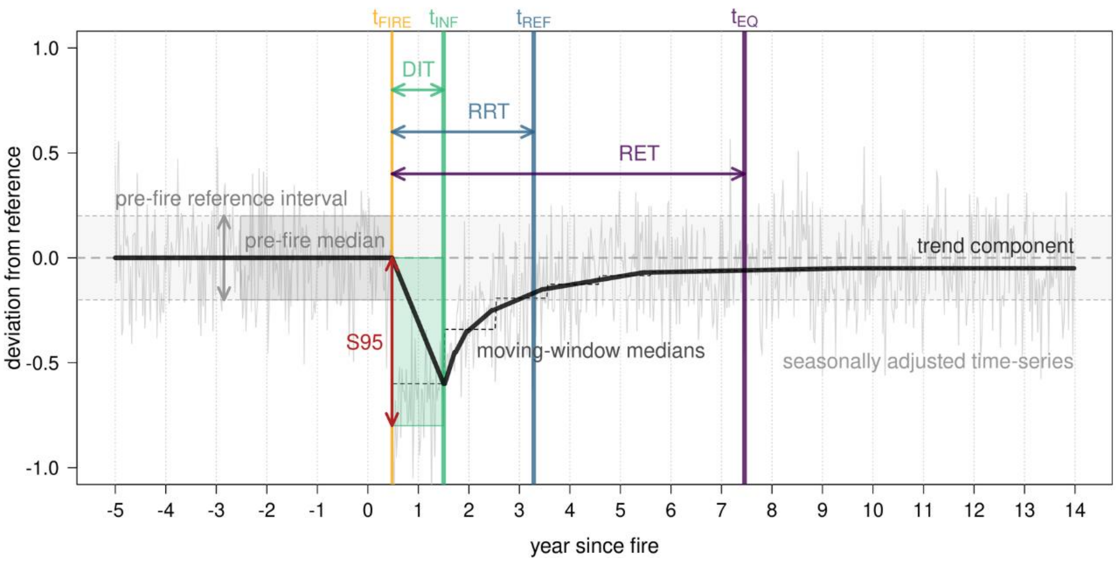


Figure 12 – Generic illustration of metrics extracted from post-fire trajectories, derived from SITS, that can be related to different ecosystem functioning dimensions, such as the S95 burn severity metric used in the trajectory-based burn severity product.

Among those metrics, the simplest one can be defined by the difference between the pre-fire median and the single value of A_t at t_{INF}. However, more robust alternatives can be obtained from the difference between the pre-fire median and an aggregated value extracted from applying a given statistic to a finite subset of values of A_t after t_{INF}. Following Marcos et al. (2023), the *S95* burn severity indicator (see Figure 12) is based on the metric calculated using the 95% percentile of A_t values up to one year after t_{FIRE} (see Figure 11). Alternative indicators can instead be derived based on, e.g., the 99% percentile or even the maximum value within the same period. These indicators aim to translate the (near-)maximum short-term impact of the wildfire disturbance on each dimension of ecosystem functioning and can also be regarded as approximate measures of the level of ecosystem resistance to those disturbances (De Keersmaecker et al. 2015, Meng et al. 2021).

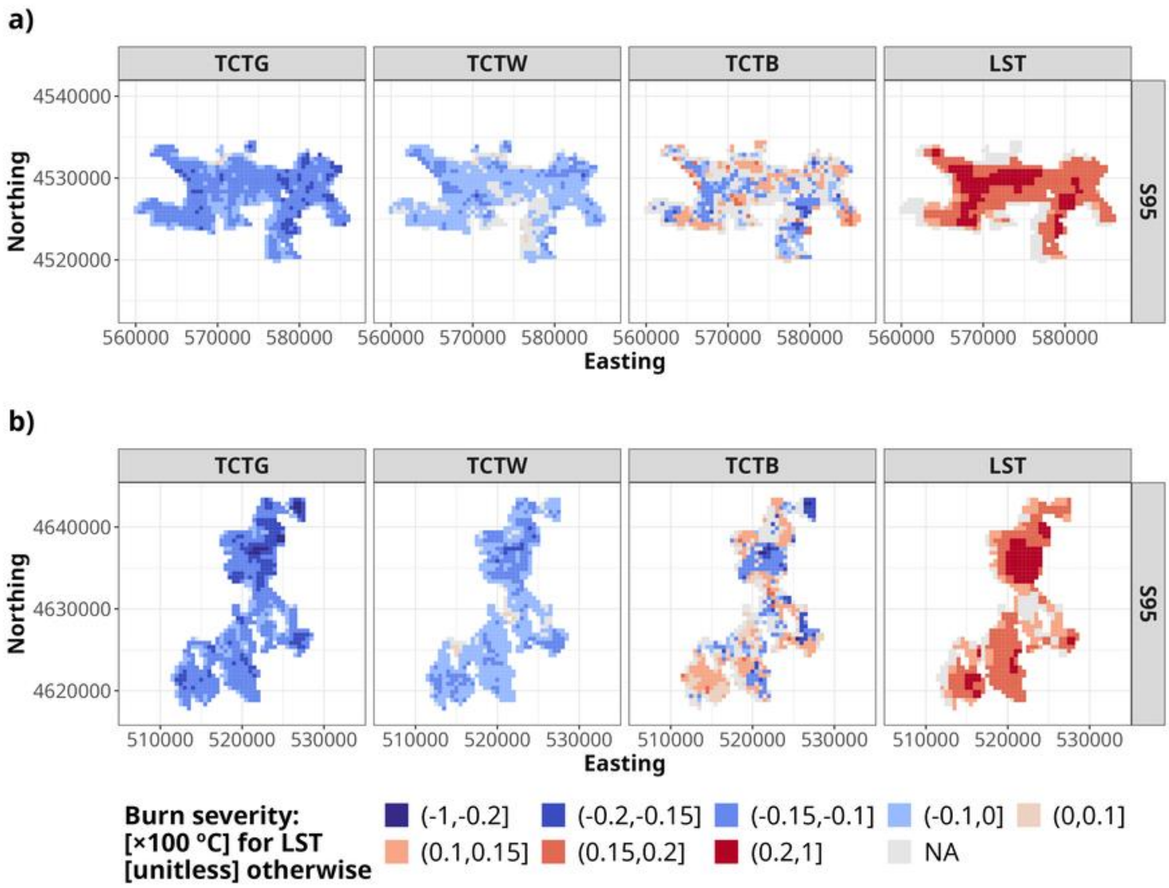


Figure 13 – Example of the S95 burn severity indicator for two burned areas in mainland Portugal (a and b), extracted from SITS related to the following key attributes of ecosystem functioning: (i) primary productivity (TCTG); (ii) water content in vegetation and soil (TCTW); (iii) surface albedo (TCTB); and (iv) sensible heat (LST). (Note that burn severity, as translated by the S95 indicator, can exhibit either (or both) negative and/or positive values, depending on the specific satellite-based proxy variable – however, in this figure, darker colors always translate higher burn severity than lighter colors, regardless of sign.)

4. SeverusPT Data Portal

The SeverusPT data portal provides a centralized gateway to access and download the project's data and metadata. Data access has two primary levels:

- Level 1: includes the main products, which can be defined as directories with datasets with specific calculation approach/pipeline, severity indicator, satellite spectral/biophysical index, satellite mission, burned area dataset and version;

- Level 2: image data files in GeoTIFF format containing each product's burn severity estimates and accompanying metadata. Beyond the elements identified within a specific product (i.e., approach, severity indicator, spectral index, etc.), each file pertains to a specific year, post-fire temporal assessment window (up to 3, 6, 9 or 12 months after the fire), and coordinate system.

4.1. Level 1 – data products

In a nutshell, products are a set of directories in the SeverusPT data portal with datasets by calculation approach/pipeline, severity indicator, satellite spectral/biophysical index, satellite mission, burned area dataset and version.

Product names follow specific rules and conventions for organizing data repositories (the full version of the name description can be found at the link https://bit.ly/spt_product_names). At the product level, the following name components are used:

ProjectAccronym - ApproachCode - SeverityIndicator - BaseIndex - PlatformCode - BurnedAreaDataset - VersionNumber

Example:

SPT-D-DELTA-NBR-L8-E-v01

Description of name components:

SPT – Project acronym used as a prefix for every product and filename;

D – 'Delta' method or pipeline;

DELTA – Uses the simple difference severity indicator (DELTA = pre_fire – post_fire);

NBR – Normalized Burn Ratio (NBR) spectral index;

L8 – Landsat-8 satellite;

EFFIS – Copernicus EFFIS burned areas dataset for mainland Portugal.

v01 – The major version number is 1.

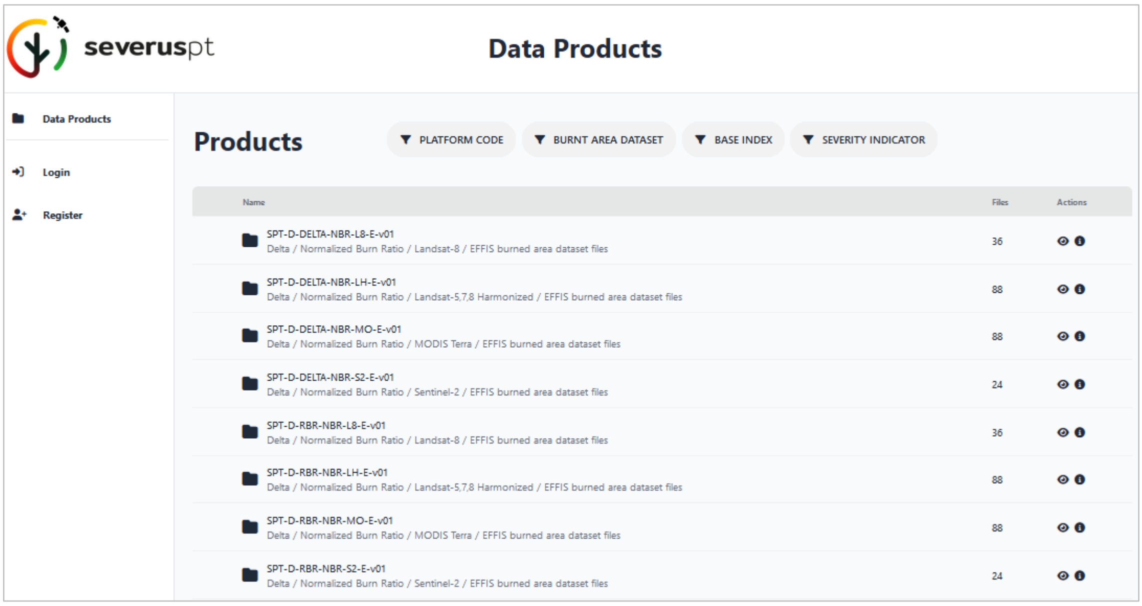


Figure 14 – SeverusPT Data Portal showing the list of products. Filters by satellite mission, burnt area dataset, spectral index and severity indicator are shown on the top. Login and registration are located on the left side.

4.2. Level 2 – data and metadata files

SeverusPT data products are available in single-band GeoTIFF raster format containing each product's burn severity estimates along with metadata. Beyond the elements identified within a specific product (i.e, approach, severity indicator, spectral index, etc.), each file pertains to a specific year, post-fire temporal assessment window (up to 3, 6, 9 or 12 months after the fire), and coordinate system.

The image data format has the following specifications:

• The number format is of the signed integer type with 32-bits / INT4S with values between -2,147,483,647 to 2,147,483,647 (written in Little-endian; Intel, II)
• The scale factor (multiplicative) is 0.0001 (allowing to obtain decimal values for each indicator in the "correct" scale)
• "No Data" Value: -2,147,483,648
• Spatial resolution is variable: 20-m Sentinel-2 / 30-m Landsat / 250-m MODIS
• Two designed coordinate systems are used to make the data available: o WGS 1984/UTM 29 N (SRID ID: 32629) o ETRS 1989/PT TM06 (SRID ID: 3763)
• Units in meters

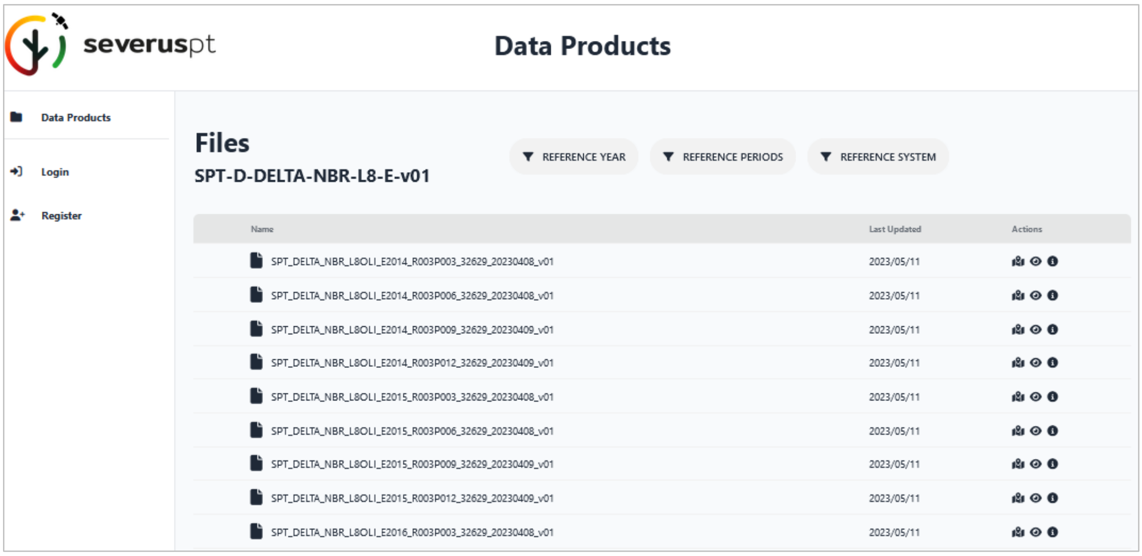


Figure 15 – SeverusPT Data Portal showing the list of files contained in a product.

At Level 2 – Data files – the name components are as follows (separated by underscores):

ProjectAccronym _ SeverityIndicator _ BaseIndex _ SatCode _ BurntAreaDataset _ ReferenceYear _ RefPeriods _ ReferenceSystem _ CalculationDate _ VersionNumber

Example:

SPT_DELTA_NBR_S2MSI_E2017_R003P006_32629_20221001_v01

Description of name components:

SPT – Project acronym used as a prefix for every product and filename;

DELTA – Severity image of the burned area (observed/historical) obtained by the 'Delta' method using the

NBR – Spectral index used, in this case the Normalized Burn Ratio (NBR)

S2MSI – Sentinel-2/MSI images.

E2017 – The burned area dataset is EFFIS for year 2017.

R003P006 – Severity estimates were obtained by comparing composite images quarterly (R003) and up to 6 months post-fire (P006). That is, the quarter that includes months 4, 5 and 6 after the fire (and compared with the same quarter for the previous year)

32629 – The coordinate system uses the EPSG code corresponding to the projected coordinate system Datum WGS 1984 UTM 29N projection.

20221001 – Data was processed on October 1, 2022.

v1 – The major version number is 1.

4.2.1. Metadata

Metadata is available for each raster file in several formats, including JSON, txt and csv. Each metadata file includes information regarding the aspects displayed in Table 2.

Table 2 - List of metadata fields included along with product files.

Parameter	Description
ProjectAcronym	SeverusPT
ProjectName	A web-based data product and service for fire severity assessment and prediction in mainland Portugal
ProjectWebsite	Project portal/website: https://severus.pt/en/
ContactEntity	CIBIO/InBIO/BIOPOLIS/ECOCHANGE Team - University of Porto
ContactEmail	The main email for contact: geral@severus.pt
ProductName	Product name in extended form
ProductType	Observed historical severity or predicted potential severity
SpatialResolution	Spatial resolution
TemporalResolution	Temporal resolution
CoordRefSystem	Coordinate Reference System used to represent data
CalculationDate	Calculation date in year, month, day format
CalculationPlatforms	R/RStudio, Google Earth Engine or both. Version code is appended if needed
BurntAreaDataset	The reference dataset used to obtain burned area polygons

BurntAreaDatasetURL	Link for the reference dataset used to obtain burned area polygons
ReferenceYear	Reference year for the burned area dataset
MinFireSize	Minimum fire size threshold (in hectares)
SatCollectionData	Satellite data used for calculations
SatProcLevel	Processing level for optical data, e.g., L1C - TOA reflectance, L2A - surface reflectance
SatColVersion	Version of the satellite data collection
CloudMaskUsed	Does the product use cloud masking? From where?
CloudMaskMethod	Cloud masking method employed in pre-processing
OtherCorrections	Other corrections applied in pre-processing (e.g., peak filtering, smoothing, time-series decomposition). Parameters may be added if needed
BaseIndex	Acronym and a short description of the spectral index or biophysical parameter used
BaseIndexFormula	Formula of the spectral index
SeverityIndicator	Acronym name and a short description of the severity indicator calculated
SeverityIndicatorForm	Formula for the severity indicator such as delta or relative delta
CompAggMeasure	The statistical measure used to make the image composite, e.g., Median or Average
PreFireType	Type of the pre-fire period used: fixed/static or relative/moving in reference to the previous/homologous year
PreFireRefPeriod	The number of months used to calculate the pre-fire period (should be equal when using option

	PreFireType=relative/moving but it can be different when using option PreFireType=fixed/static)
PostFireType	Indicates the type of post-fire period used, either as a moving window with fixed months or variable for trajectory-based methods
PostFireRefPeriod	The number of months used to calculate the post-fire period, or the number of months used to search the 95% percentile in the trajectory-based method
ScaleFactor	The scale factor applied to the product
VersionNumber	Version number of the product/collection. Composed of a single digit which denotes changes only to the major version (e.g., v01, v02, etc.).
VersionFullNumber	Full version number of the product/pipeline only presented at metadata level. Composed of three digits which denote the major.minor.patch versions (e.g., v0.1.0).

Table 3 – An example of txt metadata accompanying data files from SeverusPT with a table formatted in markdown style.

Parameter	Value
ProjectAcronym	SeverusPT
ProjectName	A web-based data product and service for fire severity assessment and prediction in mainland Portugal
ProjectWebsite	https://severus.pt/en/
ContactEntity	CIBIO/InBIO/BIOPOLIS/ECOCHANGE Team - University of Porto
ContactAddress	U. Porto, Campus de Vair<e3>o, R. Padre Armando Quintas 7, 4485-661 Vair<e3>o
ContactEmail	geral@severus.pt<a0>
ProductType	Observed/historical severity
ProductName	Fire/burn severity / Indicator: RBR BAI / moving window 3 months composite
SpatialResolution	20 meters
TemporalResolution	3 months composite
CoordRefSystem	Primary CRS: ETRS1989/PTTM06 (EPSG: 3763)
CalculationDate	2023-06-25 15:21:26 Lisbon GMT +00:00
CalculationPlatforms	Google Earth Engine; R/RStudio; EE-API-version: 0.1.339 / rgee-version: 1.1.6
BurntAreaDataset	EFFIS
BurntAreaDatasetURL	https://effis.jrc.ec.europa.eu/applications/data-and-services
ReferenceYear	2022
MinFireSize	10 hectares
SatCollectionData	S2MSI / Sentinel-2a/b/MSI
SatProcLevel	Level L2/L2A: Surface reflectance (SR)
SatColVersion	
CloudMaskUsed	Yes
CloudMaskMethod	Pixel QA band: Cirrus, clouds and/or cloud shadows removed
OtherCorrections	
BaseIndex	BAI - Burned Area Index
BaseIndexFormula	1 / (pow(0.1 - RED,2) + pow(0.06 - NIR,2))
SeverityIndicator	RBR
SeverityIndicatorForm	RBR = (BAI_prefire - BAI_postfire) / (BAI_prefire + 1.001)
CompAggMeasure	Median
PreFireType	moving / considers the year before fire, i.e., homologous year
PreFireRefPeriod	3 months
PostFireType	moving
PostFireRefPeriod	Start post-fire window: 0 months / End: 3 months , i.e., 1 to 90 days after ignition date
ScaleFactor	Multiply by 0.0001
VersionNumber	v01
VersionFullNumber	v0.1.2

4.3. Data Portal tutorial and guidelines for use

SeverusPT Data Portal is characterized by its user-friendly interface and robust functionality, allowing for various user roles. This section provides a comprehensive guide on the usage of the SeverusPT platform, detailing the capabilities and permissions associated with each user role.

User Roles and Permissions

The SeverusPT platform accommodates four distinct user roles, each with a unique set of permissions:

1. *Guest*: Unregistered users who have access to basic viewing and filtering capabilities.
2. *Consult*: Registered users who, besides Guest permissions, can download data products or their data files.
3. *Manager*: Users who can add Data Products, manage data files, and Consult permissions.
4. *Admin*: Users with the same permissions as the Manager and complete control over the platform.

Guest role

Guest, or unregistered users, can:

- View data products and their associated names, as well as descriptions of components. (Figures Figure 14 and Figure 15)
- Filter data products based on Platform Code, Burnt Area Dataset, Base Index, and Severity Indicator. (Figure 16)
- Access the content of data products, including data and metadata files. (Figure 17)
- View a description of the components of the data file names, metadata, and a severity map. (Figure 17)
- Filter data files by Reference Year, Reference Periods, and Reference System. (Figures Figure 18, Figure 19 and Figure 23)

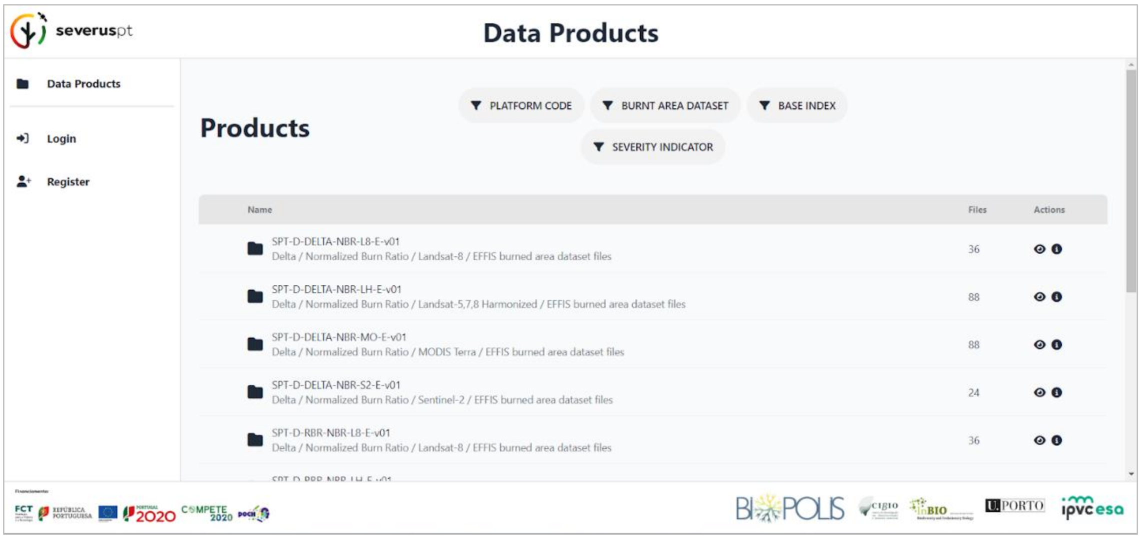


Figure 16 - Visualization of data products and their associated names, as well as descriptions of components.

By clicking the "Name Details" button, users can view the product's description by its name components.

Figure 17 - Visualization of descriptions of components at the Data Product level.

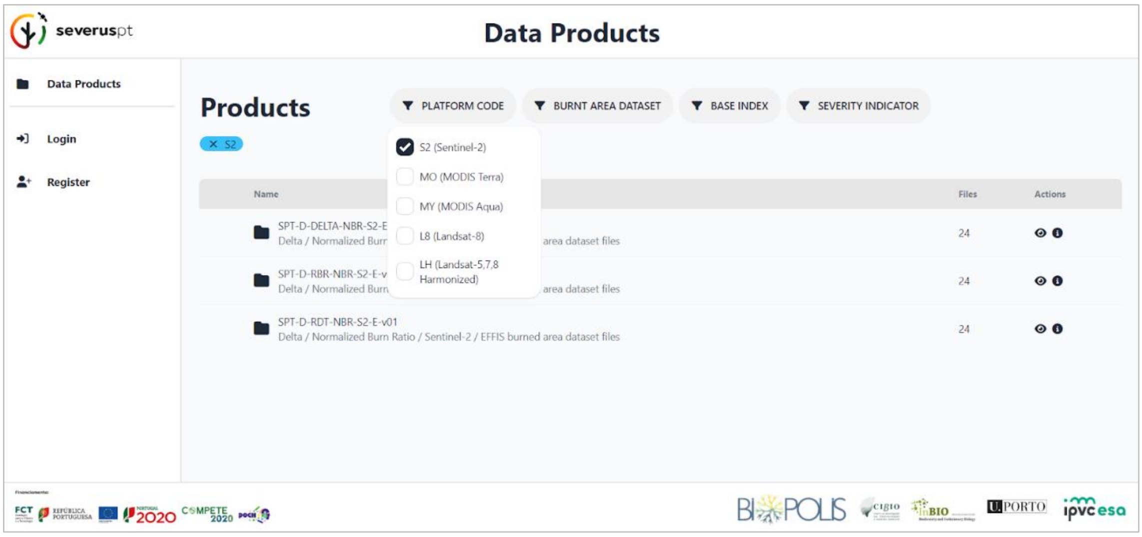


Figure 18 - Example of filtering Data Products, in this case by the satellite platform/mission.

To access the content of data products, users can click on the data product name, double click on the corresponding table row or click the "View Content" button (👁).

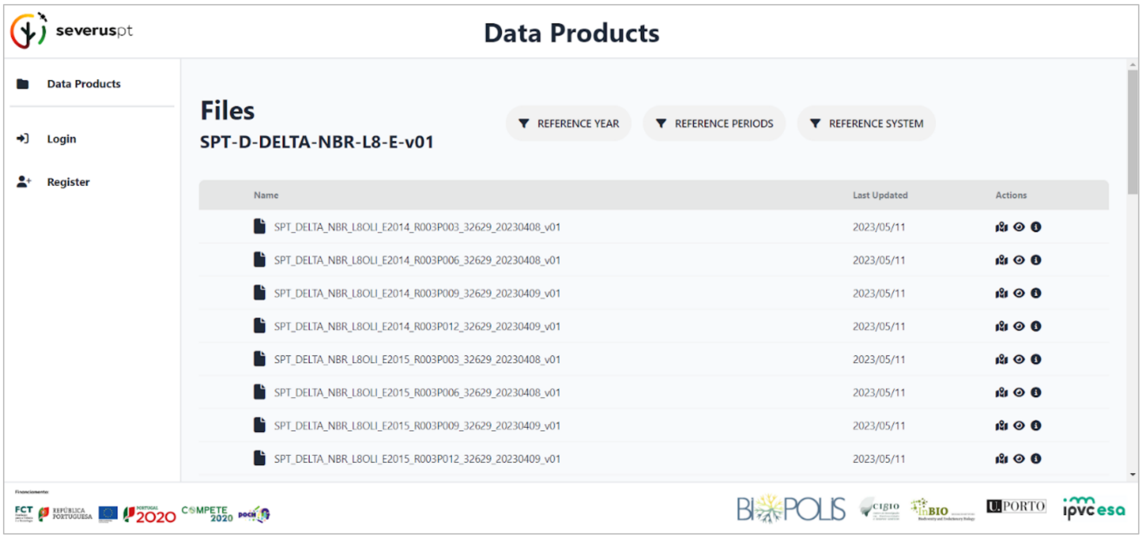


Figure 19 - Visualization of the content of a data product – in the example Delta NBR for Landsat-8 mission based on EFFIS burned areas (version 1).

By clicking on "Name Details" button ( ) users can view descriptions of components.

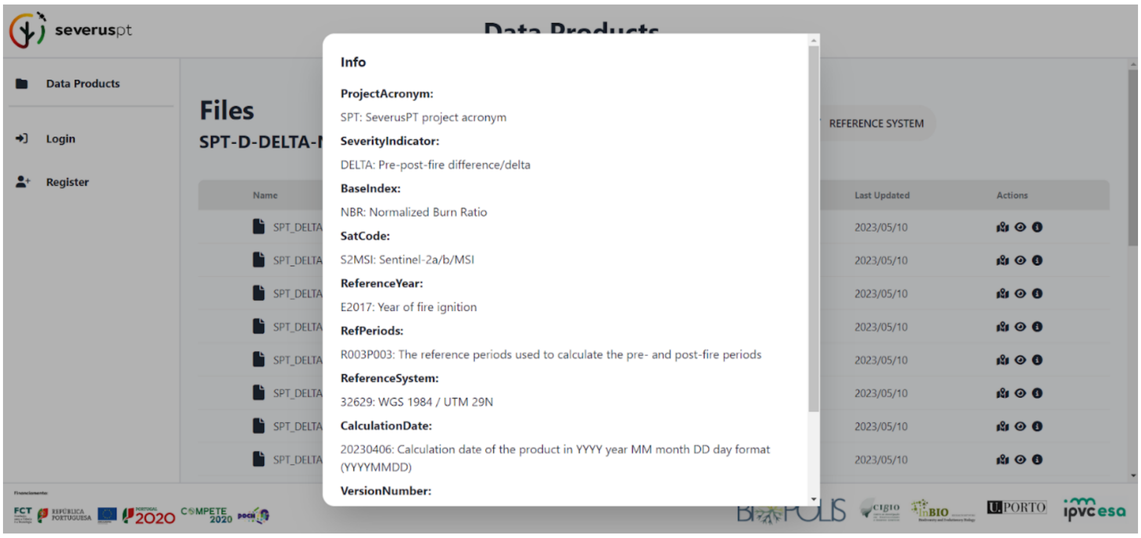


Figure 20 - Visualization of descriptions of components at the data files level.

By clicking on "View Metadata" button ( ) users can view details of metadata files.

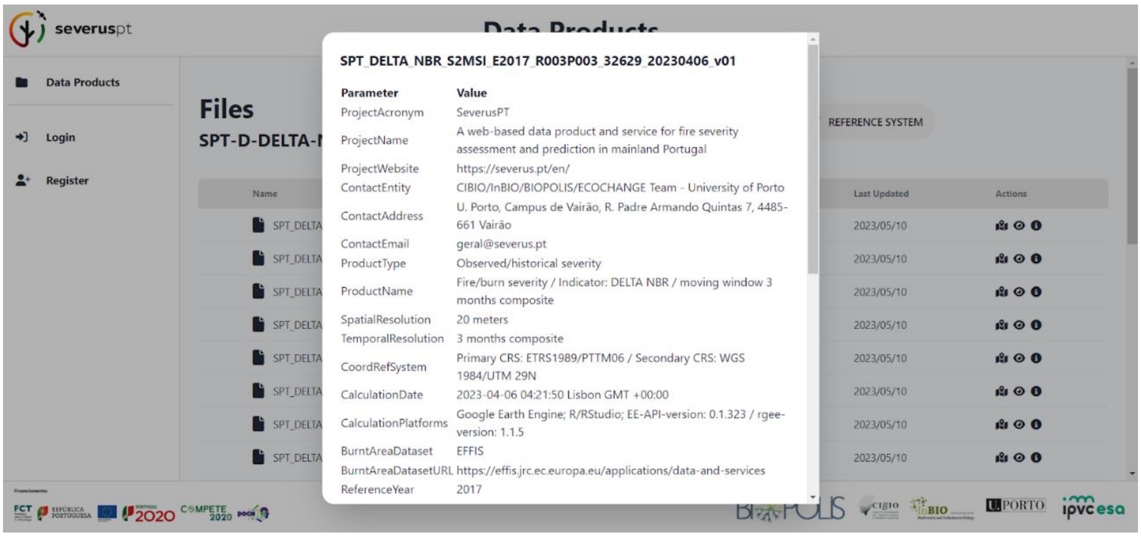


Figure 21 - Visualization of details of metadata files.

By clicking on the "View Map" button (), users can view the burn severity map/product.

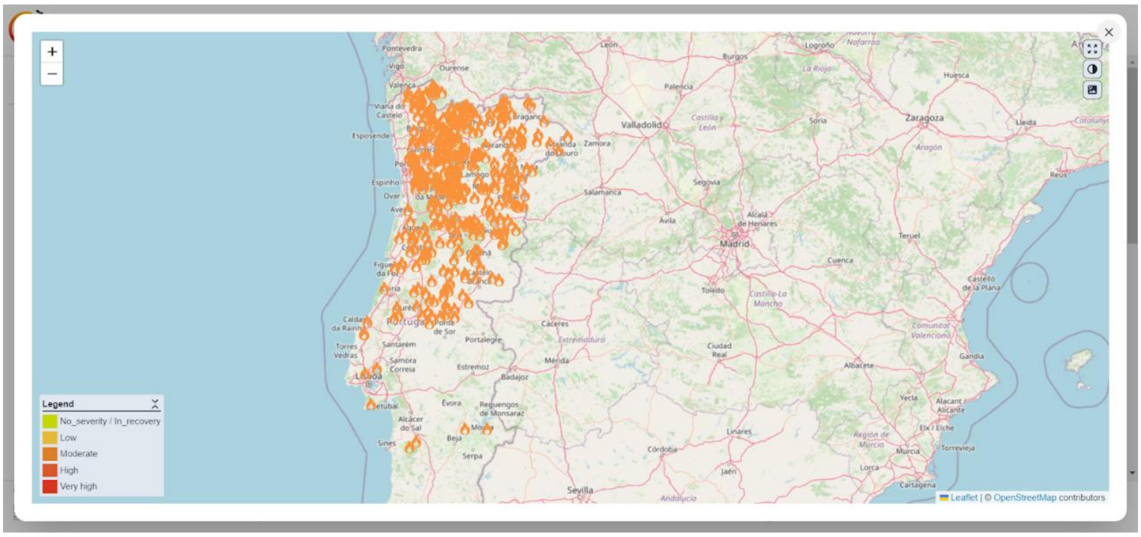


Figure 22 - Visualization of severity map.

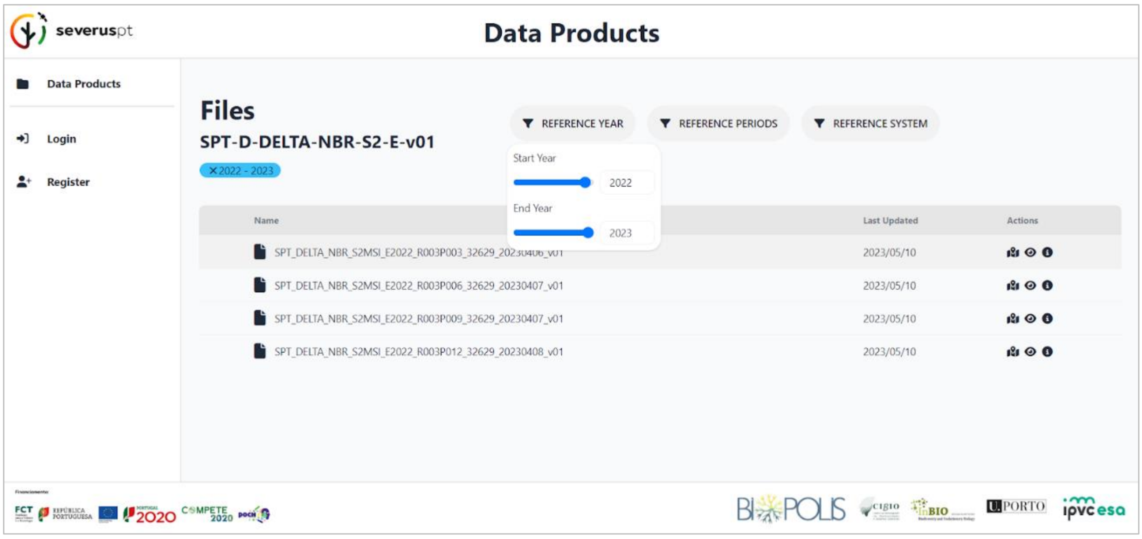


Figure 23 - Example of filtering Data Files – in the example, the filter acts over the year of the data.

Consult role

Registered and authorized users have all the permissions of a Guest, with the added ability to download data products or their data files. Registration requires an email and password, followed by account confirmation through a confirmation email.

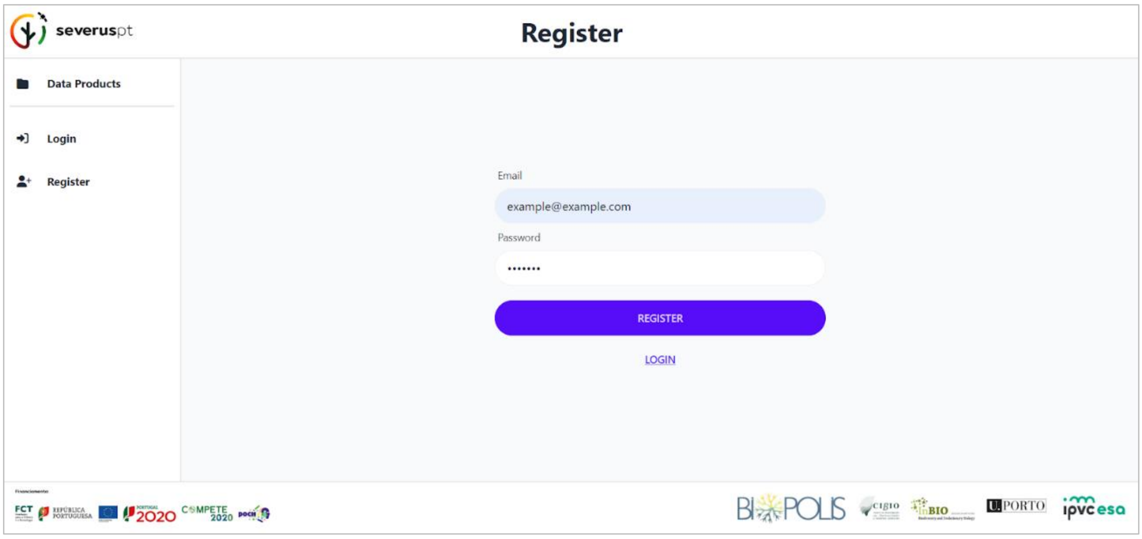


Figure 24 - User registration form.

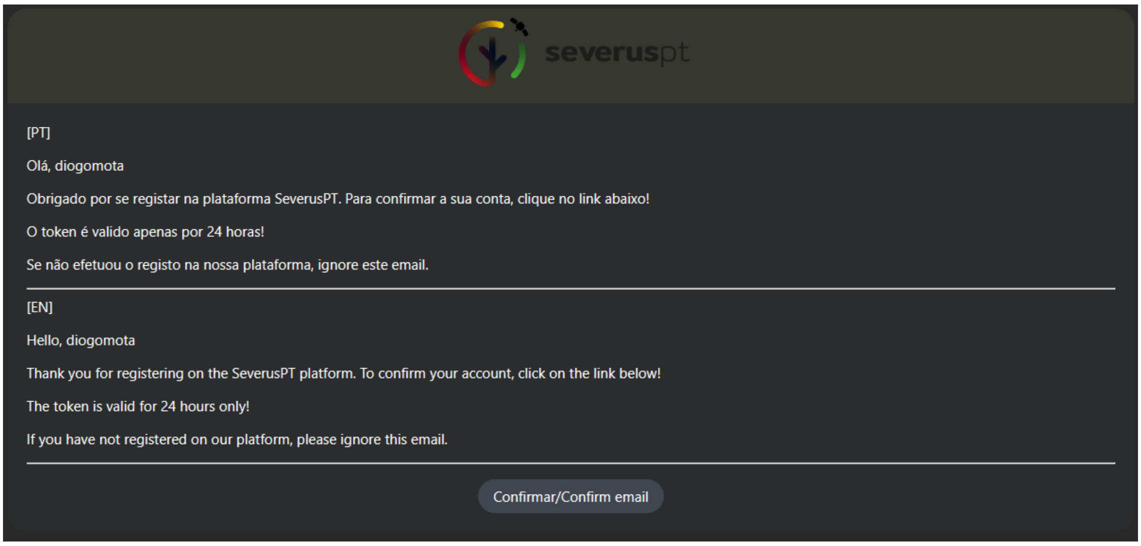


Figure 25 - Confirmation email sent to the user.

After confirming the email the user can access the Data Portal through the following login form:

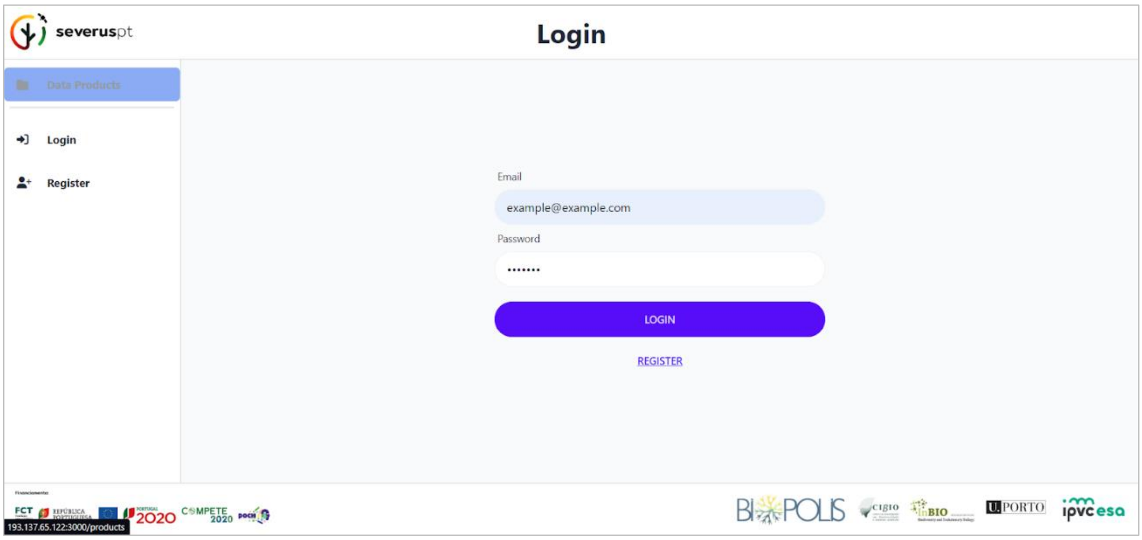


Figure 26 - Registered user login.

To download the burn severity data, registered users can select/check the intended files and download them by pressing the "DOWNLOAD" button in the bottom-right corner:

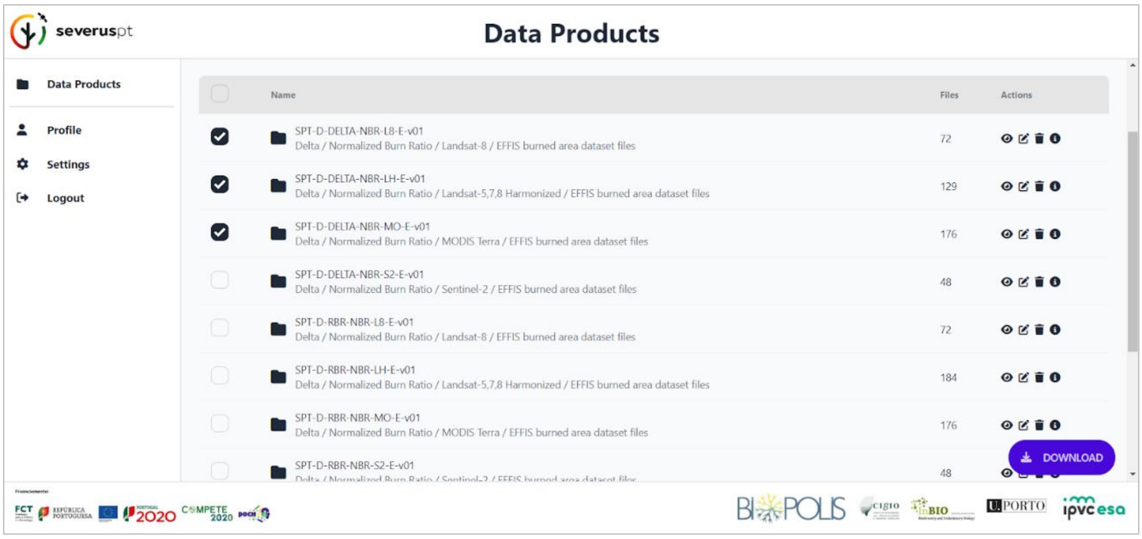


Figure 27 - Selection and download of data products.

Manager role

Managers have all the permissions of the "Consult" role but with additional capabilities to:

- Add Data Products (Figure 28);
- Add data files to the created Data Products (Figure 29);
- View errors that may exist from incorrect nomenclature or missing data files (Figure 30);
- Generate an API key to upload data files and obtain information about the aforementioned errors (Figure 31).

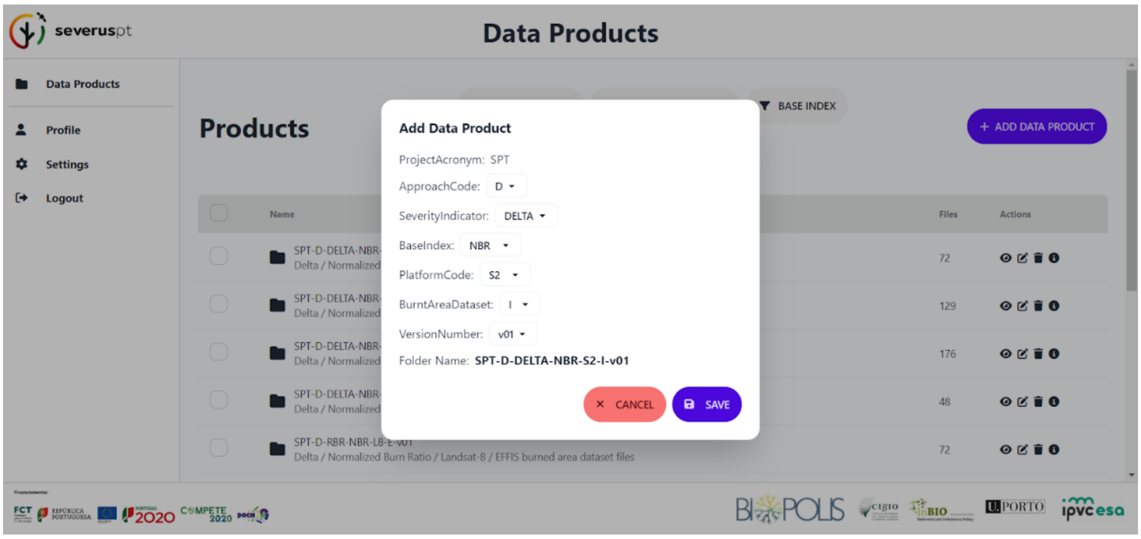


Figure 28 - Creation of Data Product.

Managers can add Data Files to Data Products by dragging and dropping files to the Data Portal or selecting them from local files.

Figure 29 - Upload of data files.

By clicking on the “Name Details” button ( ) Managers can view errors that may exist from incorrect nomenclature or missing data files.

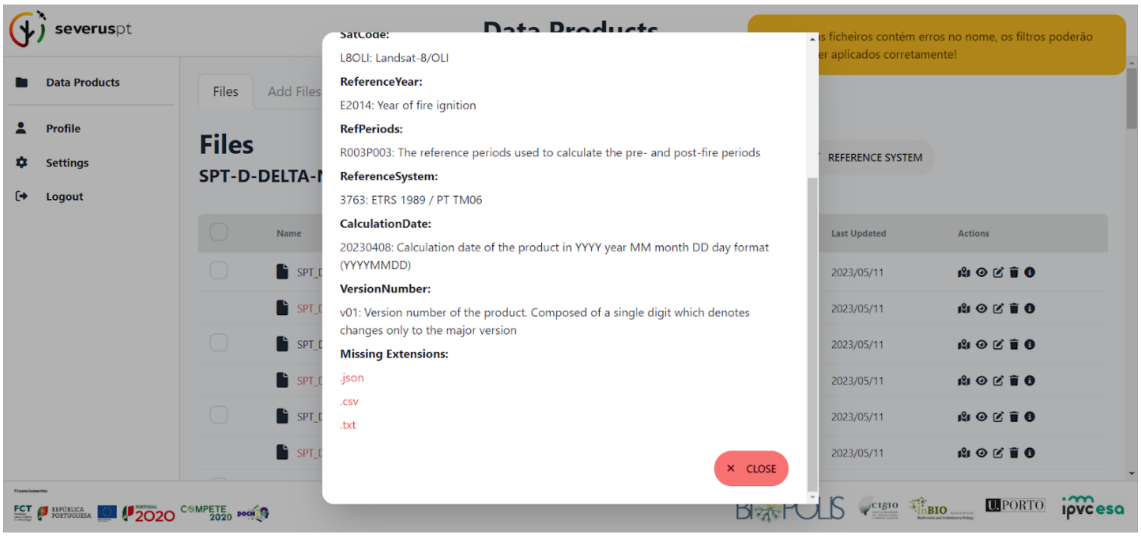


Figure 30 - Visualization of errors that may exist from incorrect nomenclature or missing data files.

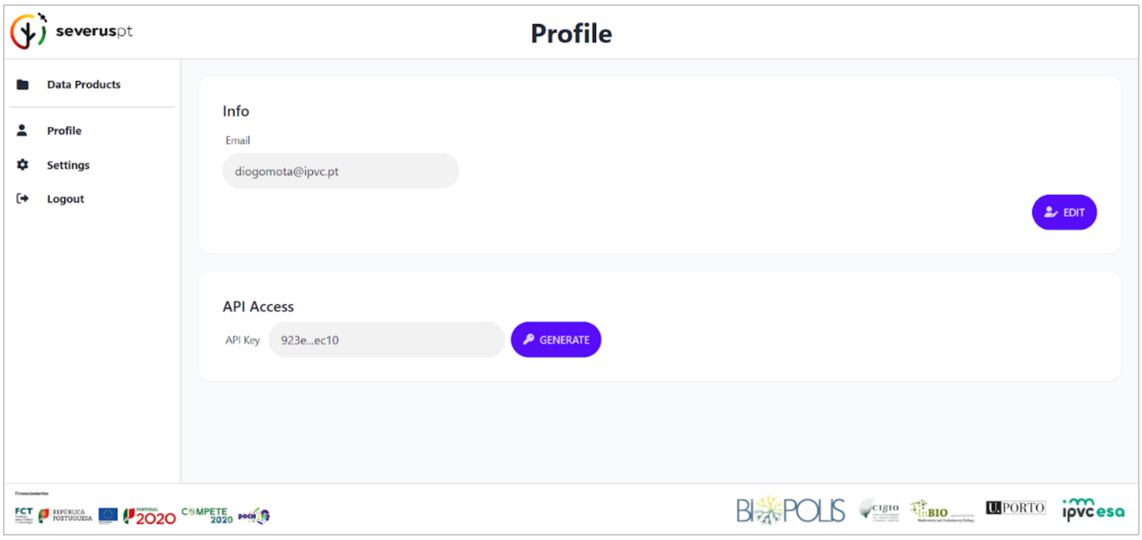


Figure 31 - Generation of API key on the Profile page.

5. In situ assessment and validation of satellite products

5.1. Spatial sampling strategy

Field surveys to assess and validate satellite-based burn severity products were conducted from May 2022 to August 2023. This survey campaign focused on assessing wildfires from the 2022 fire season spread across mainland Portugal.

We implemented a purposive stratified approach considering fire size, location, and main vegetation type to select burned areas. The specific locations to survey were pre-defined using ancillary GIS layers related to roads, vegetation and land cover, topography and burn severity levels and locally adjusted given the access conditions verified in the site. In tandem, these selection criteria allowed us to circumvent limitations related to accessibility to fire perimeters while maximizing national coverage and the diversity of post-fire situations. It also allowed us to cover the diversity of post-fire conditions nationwide instead of focusing our limited resources on specific fire occurrences. For this reason, we stopped surveying a specific burned area once its main conditions (in terms of geomorphology, main vegetation types, and burn severity levels) were mainly covered. Approximately 111 sites were surveyed using the Geometrically Structured CBI (GeoCBI) protocol and index in 28 burned areas from the north to centre and south regions of mainland Portugal.

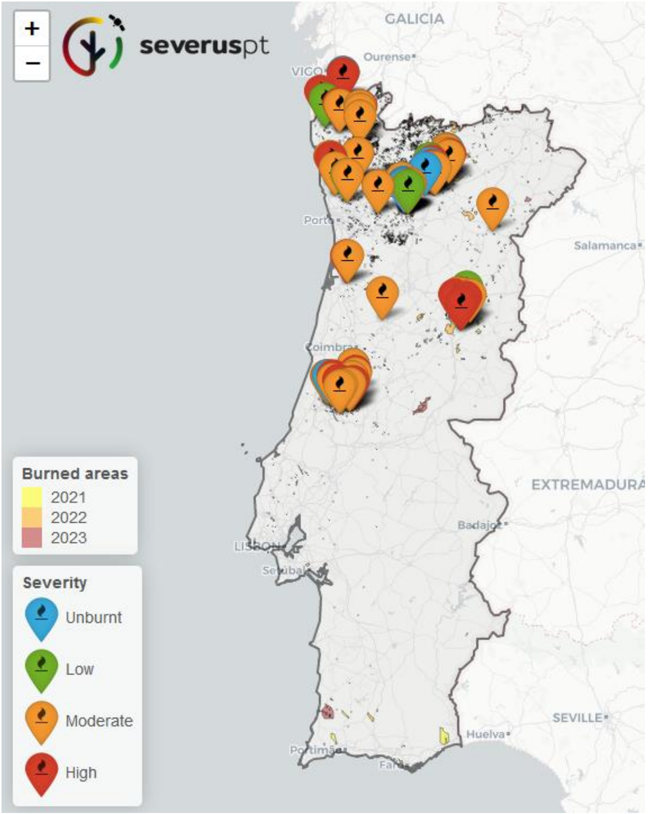


Figure 32 – Plot locations where GeoCBI was estimated in the field. Data can be checked through the SeverusPT web viewer for field data: https://severuspt.bitbucket.io/.

5.2. GeoCBI – Geometrically Structured Composite Burn Index

A modified version of the Composite Burn Index (CBI), known as the Geometrically Structured Composite Burn Index (GeoCBI), was developed to enhance the assessment of burn severity by accounting for the influence of vegetation cover on the reflectance characteristics of different strata within a given burned area (De Santis and Chuvieco 2009). The GeoCBI protocol and index were adopted in the SeverusPT project to obtain *in situ* estimates of burn severity.

In the field, burn severity was visually evaluated using the GeoCBI protocol and aggregate index, employing a continuous numeric scale that spans from 0 to 3. This scale was used to quantify the cumulative effects of fire in relation to pre-fire conditions. The GeoCBI field protocol utilizes a hierarchical and multi-layered sampling approach, segmenting the plot into five distinct strata: (i) substrates – encompassing the ground surface, litter, and duff layers; (ii) herbs, low shrubs, and trees under 1 meter – this category includes vegetation under 1 meter in height (iii) tall shrubs and trees from 1 to 5 meters – comprising vegetation ranging from 1 to 5 meters in height; (iv) intermediate trees from 5 to 20 meters – encompassing trees with heights between 5 and 20 meters, and; (v) tall trees over 20 meters – this category pertains to trees exceeding 20 meters in height. These strata are then subdivided into specific aspects and individually assessed using particular criteria. These criteria encompass factors such as the percentage of soil layer and vegetation consumed, the char height observed on tree boles, and the resprouting capacity of burned vegetation. For each subcategory, decimal values ranging from 0.0 to 3.0 are assigned, representing the full spectrum of possible burn severity, from no discernible impact (0) to a high level of impact (3).

To calculate the GeoCBI for a particular stratum, the scores from all the evaluated items or subcategories are averaged and then weighted by their respective fraction of coverage (Fcov). This comprehensive approach yields a nuanced and detailed assessment of burn severity across the various strata within a burned area, offering valuable insights into the ecological impact of the fire event.

$$GeoCBI_s = \frac{1}{n}\sum_{i=1}^{n} I_{s,i}$$

(Eqn. 5)

$GeoCBI_s$ is the average composite burn index for a given stratum (s), whereas $I_{s,i}$ is an evaluation item or subcategory for a given stratum. The final overall GeoCBI is a weighted average of the five strata scores.

$$GeoCBI_{total} = \frac{\sum_{s=1}^{5} CBI_s \times Fcov_s}{\sum_{s=1}^{5} Fcov_s}$$

(Eqn. 6)

In each particular situation, depending on site vegetation and conditions, we assessed which strata and which evaluation items could be or were relevant to be quantified at the plot level. If it was impossible to accurately assess a particular descriptor, we decided not to include it in the evaluation (e.g., uncertain estimation of the % frequency of living due to the short time since fire).

To avoid differences in the protocol application across surveys, the same team conducted the assessments based on rigorously defined and previously agreed criteria (supported by CBI and GeoCBI literature; e.g., (Key and Benson 2006, De Santis and Chuvieco 2009)) and by obtaining an average consensus of individual scores.

During fieldwork, we employed a centimeter-precision GNSS receiver/station (Stonex® S850A) with RTK-enabled corrections to obtain the central coordinates of the survey plot (averages HRMS=9.7 cm, VRMS=15.1 cm, PDOP=1.0). Tree height was accessed by a laser telemeter (Nikon® Forestry Pro II) to avoid errors when attributing the tree strata.

Plot code / Unique ID (Site code / Plot code)	001 / 001
Examiner(s) name(s)	
Location name/address	
Location coordinates	Lon/X: Lat/Y:
Coord. System	_
Survey date	
Dominant land cover type(s)	
Elevation	
Fire start date	
Fire end date	
Time since fire (days)	
Fire size (hectares)	
Plot size (diameter meters)	

STRATA / RATING	BURN SEVERITY SCALE							FACTOR
A. SUBSTRATES								
% dead leaves on the soil:				Soil depth (cm):				
	No-effect	Low severity		Moderate severity		High severity		
	0.0	0.5	1.0	1.5	2.0	2.5	3.0	
Litter / Light fuel consumed	Unchanged	---	50% litter	---	100% litter	> 80% light fuel	98% light fuel	
Duff	Unchanged	---	light char	---	50% loss / deep char	---	Consumed	
Medium / heavy fuel	Unchanged	---	20% consumed	---	40% consumed	---	> 60% loss / deep char	
Soil / Rock cover/color	Unchanged	---	10% change	---	40% change	---	> 80% change	
A. ∑ = 0.0		N = 0		Average =	0.0			

B. HERBS, LOW SHRUBS AND TREES (less than 1 meter)								
Dominant vegetation type:		Ulex		Fcov =				
	No-effect	Low severity		Moderate severity		High severity		
	0.0	0.5	1.0	1.5	2.0	2.5	3.0	
% foliage altered (blk-brn)	Unchanged	---	30%	---	80%	95%	100% + branch loss	
Freq. % Living	100%	---	90%	---	50%	< 20%	0%	
New sprouts	Abundant	---	Moderate-High	---	Moderate	---	Low - none	
B. ∑ = 0.0		N = 0		Average =	0.0			

C. TALL SHRUBS AND TREES (1 to 5 meters)								
Dominant vegetation type:		Pinpin		Fcov =				
	No-effect	Low severity		Moderate severity		High severity		
	0.0	0.5	1.0	1.5	2.0	2.5	3.0	
% foliage altered (blk-brn)	0%	---	20%	---	60 - 90%	> 95%	Significant branch loss	
Freq. % Living	100%	---	90%	---	30%	< 15%	< 1%	
LAI change %	Unchanged	---	15%	---	70%	90%	100%	
C. ∑ = 0.0		N = 0		Average =	0.0			

D. INTERMEDIATE TREES (5 to 20 meters)								
Dominant vegetation type:		Eucglo		Fcov =				
	No-effect	Low severity		Moderate severity		High severity		
	0.0	0.5	1.0	1.5	2.0	2.5	3.0	
% Green (unaltered)	100%	---	80%	---	40%	< 10%	None	
%Black / Brown	0%	---	20%	---	60 - 90%	> 95%	Signif. branch loss	
Freq. % Living	100%	---	90%	---	30%	< 15%	< 1%	
LAI change %	Unchanged	---	15%	---	70%	90%	100%	
Char height	None	---	1.5 m	---	2.8 m	---	> 5m	
D. ∑ = 0.0		N = 0		Average =	0.0			

E. TALL TREES (> 20 meters)								
Dominant vegetation type:		Eucglo		Fcov =				
	No-effect	Low severity		Moderate severity		High severity		
	0.0	0.5	1.0	1.5	2.0	2.5	3.0	
% Green (unaltered)	100%	---	95%	---	50%	< 10%	None	
%Black / Brown	0%	---	20%	---	60 - 90%	> 95%	Signif. branch loss	
Freq. % Living	100%	---	90%	---	30%	< 15%	< 1%	
LAI change %	Unchanged	---	15%	---	70%	90%	100%	
Char height	None	---	1.8 m	---	4 m	---	> 7m	
E. ∑ = 0.0		N = 0		Average =	0.0			

Notes: Factor scores: bounded within [0.0, 3.0] (one decimal place) Fcov - Fractional cover is bounded within [0.0, 1.0] (one decimal place) Fcov for stratum A is fixed as 1.0	**Factor codes**	Non-relevant/ non-applicable	NA - Non-applicable UC - Uncertain
		Relevant / applicable	Min: 0 Max: 3

CBI by stratum average		Fcov	CBI × Fcov
A. SUBSTRATES	0.0	1.0	0.0
B. HERBS, LOW SHRUBS AND TREES (less than 1 meter)	0.0	0.0	0.0
C. TALL SHRUBS AND TREES (1 to 5 meters)	0.0	0.0	0.0
D. INTERMEDIATE TREES (5 to 20 meters)	0.0	0.0	0.0
E. TALL TREES (> 20 meters)	0.0	0.0	0.0
GeoCBI (Fcov weighted average) =			**0.0**

Figure 33 – Table showing the GeoCBI protocol divided into plot data, A – D strata, evaluation items and criteria. Fcov is the fraction cover of strata B to D. The severity scale attributed to each descriptor is given by the percentage values in each column and assessed locally.

Table 4 – Severity categories for GeoCBI

Severity value	Severity category	Definition obtained from field
0	Unburned	Unburned and unaffected areas, sometimes within a burned perimeter. Vegetation is green, and soils are unaffected.
0.01 – 0.10	Very-low	Vegetation and ground surface are very lightly affected by the fire. Minimal to no vegetation mortality. Limited impacts on soil properties. Very fast recovery of vegetation
0.1 – 1.24	Low	The surface area of the fire has minor changes in its coverage and little mortality in terms of plant structure.
1.25 – 2.24	Moderate	The area displays a mix of effects between the unchanged and high categories.
2.25 – 3.00	High	Vegetation has high mortality rates.

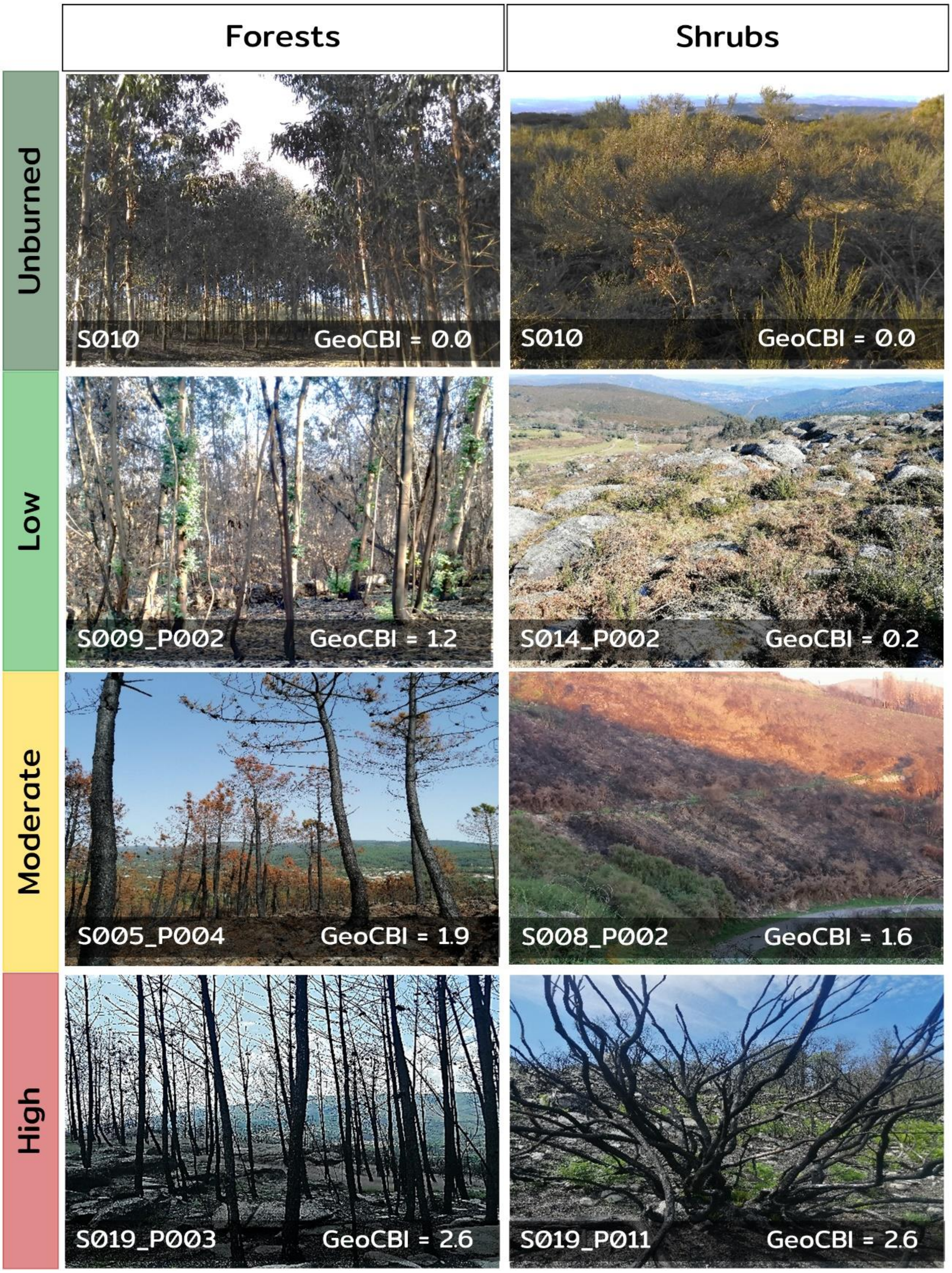


Figure 34 - Examples of GeoCBI from some surveyed areas at three different severity levels (low, moderate and high) and for two main vegetation types: forests vs shrublands.

5.3. Comparison between in situ GeoCBI and satellite burn severity estimates

Two methods were implemented to assess and compare in situ GeoCBI and satellite burn severity estimates:

i. Non-parametric linear correlation (Spearman method) and nonlinear correlation (proposed by Ranjan and Najari (2020)), and,

ii. A nonlinear exponential model adapted from (Miller and Thode 2007, Parks et al. 2014) in the following form:

$$GeoCBI = a + b \cdot e^{c \cdot S}$$

(Eqn 3)

Parameters a, b and c are obtained through nonlinear estimation in R using function *nls* from the stats package (R Core Team 2023). S is the severity indicator being assessed (e.g., dNBR).

To account for observer uncertainty and spatial variability in GeoCBI field surveys, the comparison between satellite-based spectral indices and field GeoCBI was performed at three extents: (i) point level (using the exact coordinates of the central point of the plot), (ii) 20 m buffer around the central point and (iii) a 30 m buffer.

Because products are computed at several quarterly sliding windows (up to 3, 6, 9 or 12 months after the fire), and field surveys have distinct times since the fire, we matched the two by selecting the product whose aggregation period contained the particular survey date.

5.4. GeoCBI descriptive statistics

The GeoCBI protocol allows assessing in situ burn severity across multiple strata, providing valuable insights into the impacts of wildfires. The average of stratum A (A_Average; soil and substrates), with a GeoCBI of 1.4 (±std-deviation of 0.7), shows relatively moderate to low burn severity. In contrast, the average for the B stratum (herbs, low shrubs and trees with less than 1 meter) exhibits a moderate GeoCBI of 1.7 (±0.8), indicating a somewhat higher burn severity and impact on living vegetation. The average GeoCBI of stratum C (tall shrubs and trees from 1 to 5 meters) was 2.0 (±0.8), showing a relatively higher burn severity, particularly affecting leaf area index, altered foliage and living vegetation. For the D stratum (intermediate trees with 5 to 20 meters), the GeoCBI averages at 1.5 (±0.8), signifying moderate burn severity with variable impacts on green vegetation and char height. Although the E stratum (tall trees ≥ 20 meters) is limited in data, it has an average GeoCBI of 0.6 (±0.7), indicating relatively low burn severity. Regarding the range (minimum and maximum values) for the average of each descriptor, we found the full scope of conditions found from strata A to D ranging from 0 to 2.6 and 3.0 – i.e., from no damage to complete consumption of these layers—exception for the E stratum showing a range of 0.0 to 1.3.

Overall, GeoCBI values average 1.5 (±0.7), showing moderate burn severity but ranging from moderate-low to moderate-high severities. The range is bounded between 0.0 for unburned sites up to 2.7.

Table 5 – Descriptive statistics for the GeoCBI samples by stratum and total. Nobs – number of observations for each descriptor, Mean – arithmetic average, StDev – standard deviation, Min – Minimum, Median – median, MAD – Median absolute deviation, Max – Maximum value.

Parameter	Nobs	Mean	StDev	Min	Median	MAD	Max
A1_LitterLF	104	1.4	0.8	0.0	1.5	0.7	2.7
A2_Duff	102	1.2	0.7	0.0	1.2	0.7	2.5
A3_MedHeavyF	57	1.7	0.8	0.0	1.8	0.6	3.0
A4_SoilRockCol	103	1.5	0.8	0.0	1.5	0.7	2.8
A_Average	**106**	**1.4**	**0.7**	**0.0**	**1.5**	**0.7**	**2.6**
B1_PercFolAlt	83	2.4	0.9	0.0	2.8	0.3	3.0
B2_FreqLiv	71	1.7	1.0	0.0	2.0	1.2	3.0
B3_NewSpro	96	1.3	0.9	0.0	1.2	1.1	2.9
B_Average	**100**	**1.7**	**0.8**	**0.0**	**1.8**	**0.7**	**3.0**
B_Fcov	**93**	**0.6**	**0.3**	**0.1**	**0.6**	**0.3**	**1.0**
C1_PercFolAlt	76	2.3	0.9	0.0	2.5	0.6	3.0
C2_FreqLiv	59	1.5	0.9	0.0	1.5	1.2	2.9
C3_LAIchange	76	2.0	0.9	0.0	2.3	0.7	3.0
C_Average	**75**	**2.0**	**0.8**	**0.0**	**2.2**	**0.7**	**2.9**
C_Fcov	**69**	**0.5**	**0.3**	**0.1**	**0.5**	**0.3**	**1.0**
D1_PercGreen	61	1.9	1.0	0.0	2.2	1.0	3.0
D2_BlkBrown	58	1.7	0.8	0.0	2.0	0.7	3.0
D3_FreqLiv	57	0.8	1.0	0.0	0.3	0.4	3.0
D4_LAIchange	61	1.3	0.9	0.0	1.2	1.3	2.8

D5_CharHeight	60	1.9	0.9	0.0	2.2	1.0	3.0
D_Average	**61**	**1.5**	**0.8**	**0.0**	**1.5**	**0.9**	**3.0**
D_Fcov	**58**	**0.7**	**0.2**	**0.2**	**0.7**	**0.1**	**1.0**
E1_PercGreen	3	0.5	0.5	0.0	0.5	0.7	1.0
E2_BlkBrown	3	0.3	0.3	0.0	0.5	0.0	0.5
E3_FreqLiv	3	0.5	0.9	0.0	0.0	0.0	1.5
E4_LAIchange	3	0.6	0.7	0.0	0.5	0.7	1.3
E5_CharHeight	3	1.2	1.0	0.0	1.5	0.7	2.0
E_Average	**3**	**0.6**	**0.7**	**0.0**	**0.6**	**0.9**	**1.3**
E_Fcov	**2**	**0.2**	**0.1**	**0.1**	**0.2**	**0.1**	**0.3**
GeoCBI	**111**	**1.5**	**0.7**	**0.0**	**1.6**	**0.6**	**2.7**
TSF_days	**111**	**254.5**	**108.6**	**12.0**	**279.0**	**80.1**	**386.0**

Additionally, the median TSF (time since fire in days) is 279.0 days, suggesting that, on average, the assessments were conducted approximately 279 days (~9 months) after the fires occurred within the initial assessment period of up to twelve months. The median absolute deviation is 80.1 days.

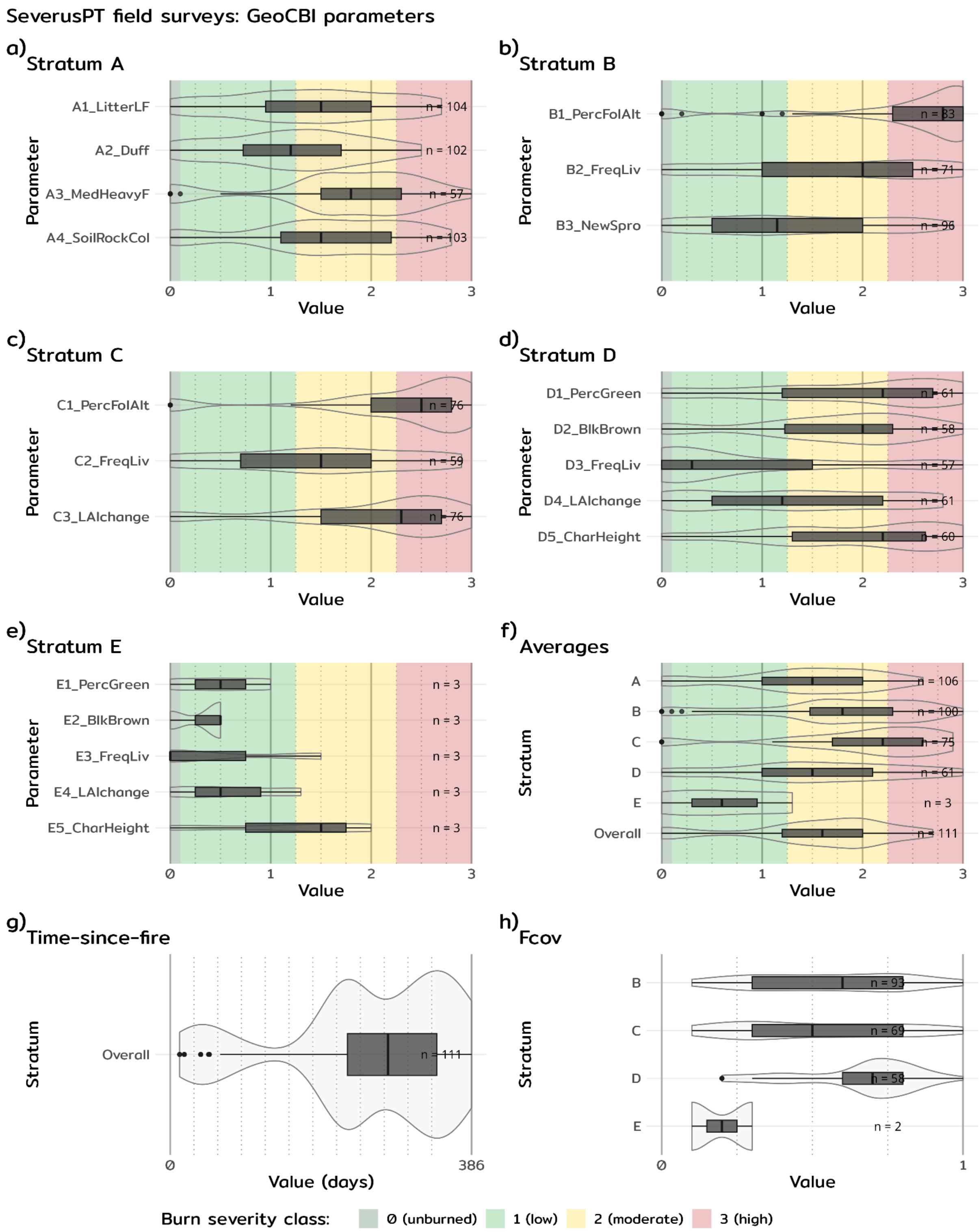


Figure 35 – Box and violin plots with GeoCBI descriptive statistics by stratum and total. n – number of observations by stratum and descriptor. Time-since-fire (difference in days between the fire and the sampling dates) and the Fractional cover (Fcov) are also presented.

5.5. *In situ validation/evaluation results*

Overall (as of October 2023), SeverusPT products agreed well with GeoCBI field measures of burn severity. The best linear correlation results are bounded between 0.64 and 0.71. Sentinel-2 and the NBR spectral index with RBR generally ranked higher when compared to Landsat-8. For nonlinear correlation, results are between 0.65 and 0.76, with best results for Landsat-8 TCTG, closely followed by Sentinel-2 NBR spectral index with RDT or RBR indicator.

The results for the nonlinear model validation were similar, with the best marks attained by the RdNBR, RBR, and dNBR indicators (R^2= 0.64, 0.62, and 0.60, respectively).

5.5.1. *Results for linear and nonlinear correlation*

Table 6 – Results for the (a) linear and (b) nonlinear correlation between satellite burn severity indices and in situ severity estimates given by GeoCBI. RBR – Relative Burn Ratio; RDT – Relativized Delta; DELTA – the difference between pre vs post-fire; NBR - Normalized Burn Ratio; TCTG – Tasseled Caps Transform – "greenness" component. S2MSI – Sentinel-2/MSI; and L8OLI – Landsat-8/OLI satellite mission. Comparison between spectral and field indices was performed at three extents: (i) point level (using the exact coordinates of the central point of the plot), (ii) 20 m buffer around the central point and (iii) a 30 m buffer.

(a) Spearman non-parametric linear correlation

Severity indicator	Spectral index	Satellite	Point	Buffer 20m	Buffer 30m
RBR	NBR	S2MSI	0.68	<u>0.71</u>	<u>0.70</u>
RDT	NBR	S2MSI	<u>0.69</u>	<u>0.71</u>	0.69
DELTA	NBR	S2MSI	0.66	0.69	0.68
RBR	NBR	L8OLI	0.65	0.66	0.65
RDT	NBR	L8OLI	0.65	0.65	0.66
DELTA	NBR	L8OLI	0.64	0.65	0.64
RDT	TCTG	L8OLI	0.61	0.60	0.62
RBR	TCTG	L8OLI	0.55	0.55	0.56
DELTA	TCTG	L8OLI	0.54	0.53	0.54

RDT	TCTG	S2MSI	0.44	0.42	0.43
RBR	TCTG	S2MSI	0.39	0.38	0.40
DELTA	TCTG	S2MSI	0.40	0.38	0.40

(b) Nonlinear correlation (Ranjan and Banerjee, 2019)

Severity indicator	Spectral index	Satellite	Point	Buffer 20m	Buffer 30m
RDT	TCTG	L8OLI	0.76	0.63	0.63
RBR	TCTG	L8OLI	0.74	0.53	0.57
RBR	NBR	L8OLI	0.74	0.67	0.67
RDT	NBR	S2MSI	0.72	0.75	0.73
RBR	NBR	S2MSI	0.71	0.73	0.72
DELTA	NBR	S2MSI	0.68	0.70	0.69
RDT	NBR	L8OLI	0.67	0.67	0.62
DELTA	NBR	L8OLI	0.66	0.66	0.65
DELTA	TCTG	L8OLI	0.51	0.50	0.56
RDT	TCTG	S2MSI	0.37	0.39	0.42
RBR	TCTG	S2MSI	0.30	0.29	0.31
DELTA	TCTG	S2MSI	0.29	0.28	0.30

5.5.2. Results for the nonlinear model at 20-m buffer – Sentinel-2 NBR

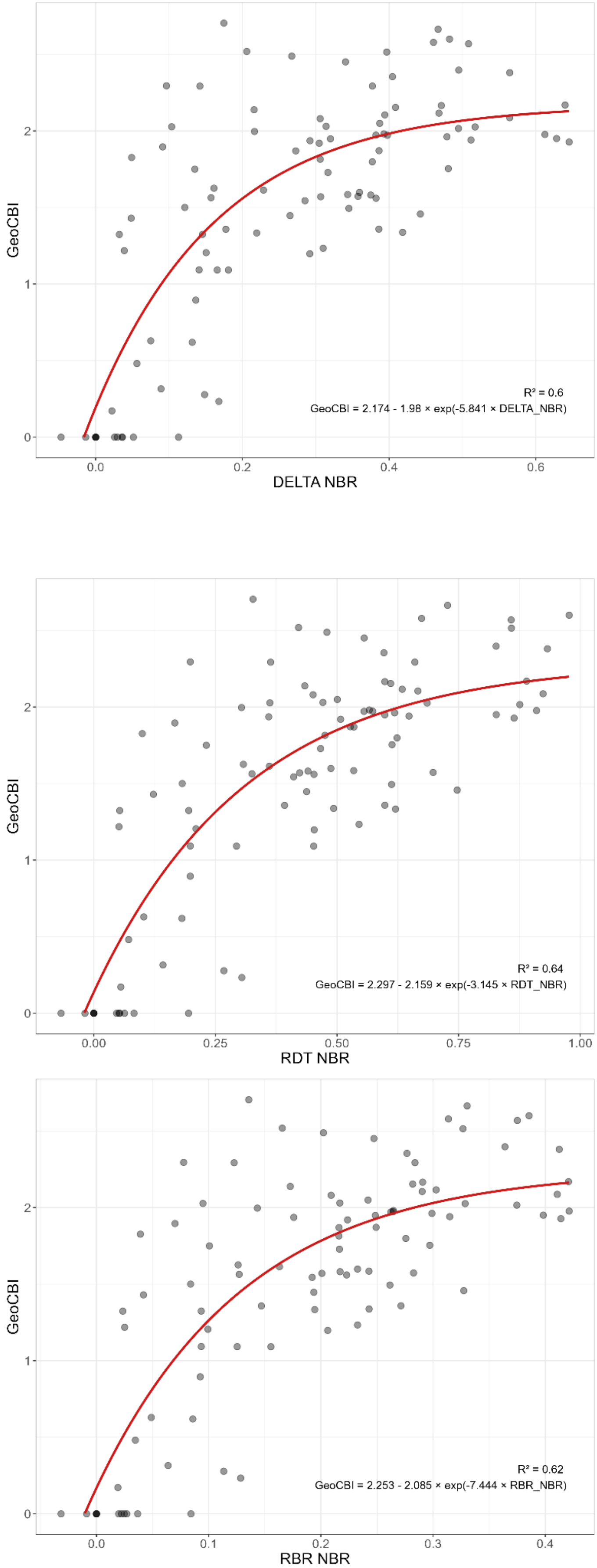
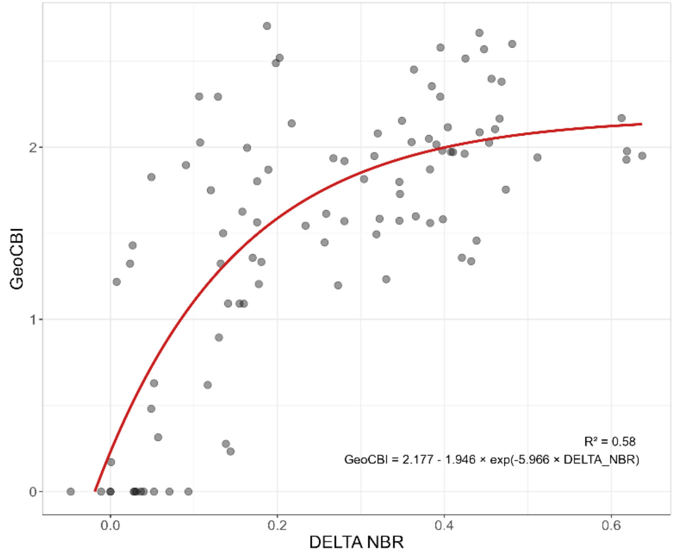
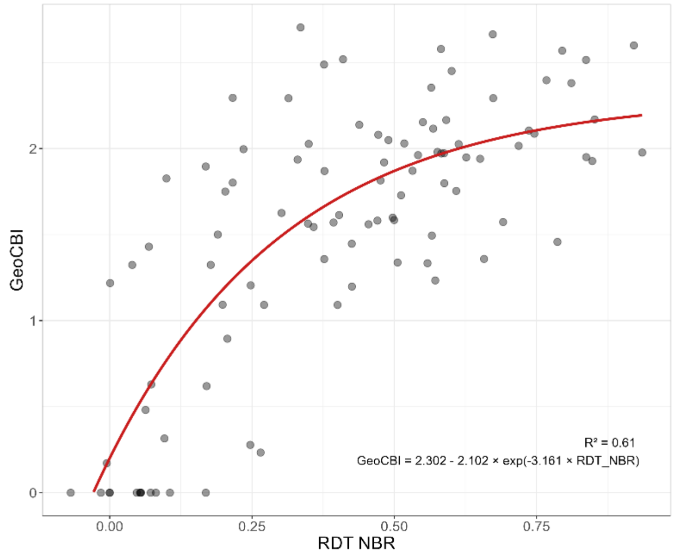


Figure 36 – From top to bottom, non-linear exponential model relating spectral severity of Delta NBR, Relativized NBR and RBR from Sentinel-2 with GeoCBI estimates from the field. Results are for 20 m buffers around the plot central point.

5.5.3. Results for the nonlinear model at 30-m buffers – Sentinel-2 NBR





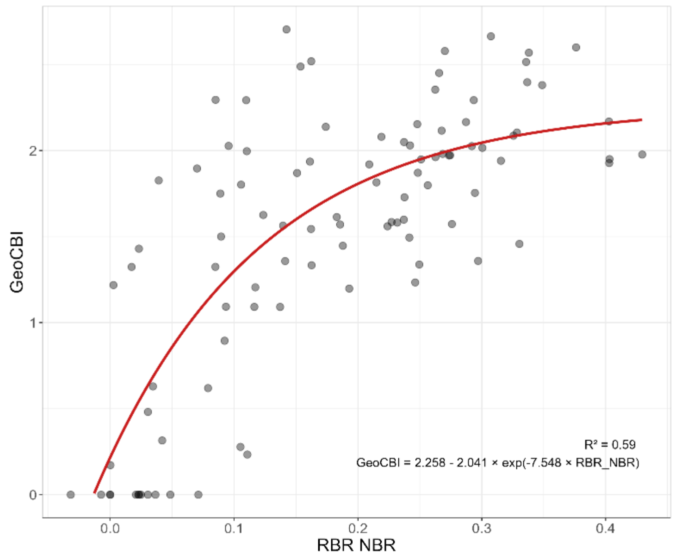


Figure 37 – From top to bottom, non-linear exponential model relating spectral severity of Delta NBR, Relativized NBR and RBR from Sentinel-2 with GeoCBI estimateds from the field. Results are for 30 m buffers around the plot central point.

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