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Linking crown fire likelihood with post-fire spectral variability in Mediterranean fire-prone ecosystems

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ABSTRACT

Background. Fire behaviour assessments of past wildfire events have major implications for anticipating post-fire ecosystem responses and fuel treatments to mitigate extreme fire behaviour of subsequent wildfires. **Aims.** This study evaluates for the first time the potential of remote sensing techniques to provide explicit estimates of fire type (surface fire, intermittent crown fire, and continuous crown fire) in Mediterranean ecosystems. **Methods.** Random Forest classification was used to assess the capability of spectral indices and multiple endmember spectral mixture analysis (MESMA) image fractions (char, photosynthetic vegetation, non-photosynthetic vegetation) retrieved from Sentinel-2 data to predict fire type across four large wildfires **Key results.** MESMA fraction images procured more accurate fire type estimates in broadleaf and conifer forests than spectral indices, without remarkable confusion among fire types. High crown fire likelihood in conifer and broadleaf forests was linked to a post-fire MESMA char fractional cover of about 0.8, providing a direct physical interpretation. **Conclusions.** Intrinsic biophysical characteristics such as the fractional cover of char retrieved from sub-pixel techniques with physical basis are accurate to assess fire type given the direct physical interpretation. **Implications.** MESMA may be leveraged by land managers to determine fire type across large areas, but further validation with field data is advised.

Keywords: canopy fraction burned, crown fire, fire type, MESMA, Sentinel-2, spectral indices, spectral variability, surface fire.

Introduction

Wildfires are a frequent disturbance in terrestrial ecosystems of Mediterranean-type climate regions around the world (Catry *et al.* 2013; Xofis *et al.* 2020). In the western Mediterranean Basin, the abandonment of traditional extensive agricultural practises and forestry uses in past decades. Together with proliferation of unmanaged forest plantations and fire suppression policies, this has led to an extensive and continuous accumulation of dense and flammable fuels (Moreira *et al.* 2011; Fernandes 2013). In addition, anthropogenic climate change has increased the occurrence of prolonged droughts and heat waves (Tripathy *et al.* 2023), leading to dryness conditions of fuel conducive to extreme fire behaviour and intense crown fires (Dimitrakopoulos *et al.* 2007; Pickering *et al.* 2023). These events may have unprecedented ecological consequences (Lasslop *et al.* 2019) and associated losses of human lives, infrastructure and properties (Mansoor *et al.* 2022).

Extreme wildfire events involving crown fires usually occur under severe fire weather conditions, resulting in hazardous and erratic fire behaviour (Mitsopoulos and Dimitrakopoulos 2007) over a wide variety of forest ecosystems throughout the western Mediterranean Basin (Fernández-Guisuraga *et al.* 2019, 2023*a*). A crown fire in forest spreads much faster (up to two to four times) than a surface fire burning in the same conditions (Fernandes *et al.* 2004; Perrakis *et al.* 2023), and its control efforts by direct attack are ineffective (Erni *et al.* 2020; Frost *et al.* 2022). These characteristics, together with increased fire intensity and frequent long-range spotting (Albini *et al.* 2012), may entail a serious threat to property and life in the wildland–urban interface (Fiorini *et al.* 2023). Long-lasting effects of high-intensity crown fires may include near total tree mortality (Woolley *et al.* 2012), abrupt shifts in species composition and structure leading to alternative stable states threatening ecosystem resilience (Allen *et al.* 2002; Knox and Clarke 2012) and biogeochemical cycles (Varner *et al.* 2021). Such fire impacts reflect the type and extent of heat transfer processes to which vegetation and soils were exposed (Fernández-Guisuraga *et al.* 2023*b*). Altogether, predicting the occurrence of crown fire behaviour is of utmost importance for planning pre-fire fuel treatments and fire suppression strategies (Scott and Reinhardt 2001).

Wildfires rarely behave only as crown fires due to changing fuel, topography or fire weather and thus, the spatial variability in the fire type entails major implications for the structure, successional dynamics and functioning of fire-prone ecosystems (Erni *et al.* 2020; Pérez-Izquierdo *et al.* 2021; Taylor *et al.* 2021). Therefore, it is not only important to assess the likelihood of crown fire behaviour, but also the spatial variability of the fire type (e.g. surface, crown) after wildfire extinction. Such knowledge would be of value, for example, in (1) testing the accuracy of fire behaviour models (Alexander and Cruz 2012), (2) providing insights on pre-fire fuel conditions conducive to extreme fire behaviour and severe ecological impacts (Dimitrakopoulos *et al.* 2007), (3) evaluating fuel treatment effectiveness (Cruz *et al.* 2004; Hu *et al.* 2019), and (4) estimating post-fire ecosystem responses including delayed tree mortality (Shearman *et al.* 2023). Indeed, several authors suggested that physically meaningful variables of actual fire effects that can be used as a proxy for fire type, such as crown fraction burned (CFB), can be more readily translated into management applications (Woolley *et al.* 2012; Hood *et al.* 2018), as opposed to integrative fire severity indices (e.g. the Composite Burn Index; Key and Benson 2005) (Morgan *et al.* 2014; Fernández-Guisuraga *et al.* 2023*c*).

Field methods enable assessing the type of fire based on both direct observation of fire behaviour (Cruz *et al.* 2003) and crown scorch and consumption (e.g. Pollet and Omi 2002; Morgan *et al.* 2014), but are labour-intensive and unable to thoroughly cover extensively burned landscapes. In this sense, the synoptic nature of remote sensing earth observations may be more appropriate for wall-to-wall estimation of fire type in post-fire landscapes (Fernández-Guisuraga *et al.* 2023*a*). Most remote sensing-based research to date have been focused on assessing fire severity drivers (e.g. Parks *et al.* 2018; Fernández-Guisuraga *et al.* 2021, 2023*d*; Fernández-García *et al.* 2022) or on developing accurate wall-to-wall fire severity estimates (e.g. De Santis and Chuvieco 2007; Miller *et al.* 2009; Quintano *et al.* 2013; Fernández-Guisuraga *et al.* 2023*a*). Conventionally, multispectral remote sensing data acquired from broadband sensors have been used to compute spectral indices, such as the differenced Normalised Burn Ratio (dNBR; Key 2006) or its relativised variants (Miller *et al.* 2009; Parks *et al.* 2014), as a proxy for the spectral signal of fire effects through empirical models. In this context, many previous studies (e.g. Roy *et al.* 2006; Fernández-Manso *et al.* 2016; Delcourt *et al.* 2021) and operational programs such as the Monitoring Trends in Burn Severity (MTBS; Picotte *et al.* 2020) in the United States or the Rapid Damage Assessment (RDA) module of the European Forest Fire Information System (EFFIS), have extensively used spectral indices computed from Landsat and Sentinel-2 imagery to obtain wall-to-wall fire severity estimates. Physical-based models applied to broadband or narrowband multispectral data, such as multiple endmember spectral mixture analysis (MESMA; Roberts *et al.* 1998), have also been considered in previous research (e.g. Quintano *et al.* 2013, 2023; Meng *et al.* 2017) to decompose sub-pixel reflectance signal and retrieve the fractional cover at pixel level of post-fire ground components (e.g. char or green vegetation) representative of wildfire ecological effects (i.e. fire severity) on vegetation and soils. This advanced pixel unmixing technique is considered to be more robust, scalable and generalisable than spectral indices due to its physical basis (Quintano *et al.* 2013).

Previous studies have seldom considered the potential of post-fire spectral variability to provide fire type estimates, particularly in Mediterranean fire-prone ecosystems (Mitri and Gitas 2006; Collins *et al.* 2018). These studies leveraged either pixel-based or object-based classification schemes and spectral indices computed from multispectral satellite data for mapping fire type or predicting fire severity categories as proxies for fire type. Other authors used a change detection framework for identifying fire type from airborne laser scanning (ALS) data in Sierra Nevada, California (Hu *et al.* 2019). As a bi-temporal change-detection framework, this method requires the acquisition of pre- and post-fire ALS datasets, which is a constraint because of the limited ALS data availability (Fernández-Guisuraga *et al.* 2022), contrary to multispectral satellite data.

To the best of our knowledge, physical-based and generalisable remote sensing approximations applied to broadband multispectral data, together with extensive field assessments, have not been used to detect crown fire in post-fire environments. Accordingly, we explore for the first time in the literature the potential of multispectral satellite data and advanced pixel unmixing models to provide meaningful and generalisable fire type estimates in Mediterranean ecosystems. Specifically, we examined how the post-fire spectral signal variability of MESMA fraction images computed from Sentinel-2 multispectral data reflects the likelihood of distinct fire types (surface, intermittent crown, continuous crown fire; Forestry Canada Fire Danger Group 1992) based on CFB, using spectral indices as a benchmark. See Scott and Reinhardt (2001) and National Wildfire Coordinating Group (2023) for fire type definitions. We selected four wildfires for this purpose that burned different types of broadleaf and conifer forests across the western part of the Mediterranean Basin. We hypothesise that MESMA fraction images, specifically the char fraction, would outperform spectral indices due to their higher physical sense and the intrinsic relationship between CFB and char signal in post-fire landscapes.

Material and methods

Study sites

We selected four wildfires that affected forests, shrublands and grasslands in the western Mediterranean Basin (northwestern and central Spain) under extreme fire weather conditions in the summer seasons between 2017 and 2022 (Fig. 1), with unprecedented prolonged droughts and heat waves in the months prior to the wildfires. The sites encompass wide environmental gradients are in Table 1. We chose as target conifer and broadleaf forests within the wildfires. Maritime pine (*Pinus pinaster* Ait.) dominated conifer forests in lowlands, whereas Scots pine (*Pinus sylvestris* L.) dominated in highlands. Broadleaf forests were mainly dominated by Pyrenean oak (*Quercus pyrenaica* Willd.) and holm oak (*Quercus ilex* L.). Wildfires were selected on the basis of available canopy fraction burned (CFB) data acquired by the same observers.

Field data

Plots of 20 m × 20 m were randomly established in burned areas (ensuring a minimum distance between plots of 100 m) within 2 months after fire, being homogeneous in terms of the dominant species (maritime pine, Scots pine, holm oak, and Pyrenean oak) (Table 1). The plots were located using a high-accuracy GPS receiver ($RMSE_{X,Y} < 1$ m). In each plot ($n = 129$; Table 1), we measured the CFB as the proportion of burned crown (charred or consumed foliage, twigs and branches; Varner *et al.* 2021) with respect to all tree crowns in the plot (Cruz and Alexander 2017), which is indicative of the most probable fire type for crowning-susceptible vegetation (Cruz *et al.* 2003). To validate a measurement, the consensus of two observers was required (Fernández-Guisuraga *et al.* 2023*a*). Fire type in each field plot was classified according to three CFB thresholds: (1) surface fire ($CFB < 0.1$); (2) intermittent crown fire ($0.1 \le CFB \le 0.89$); and (3) continuous crown fire ($CFB > 0.89$) (Forestry Canada Fire Danger Group 1992).

Remote sensing data

Multispectral data acquired from the multispectral instrument (MSI) onboard Sentinel-2 satellite of the (European Space Agency; ESA) Copernicus program were used to compute spectral indices and MESMA fraction images. Sentinel-2 provides multiresolution data (10, 20, 60 m) across visible (VIS; 4 bands), red edge (RE; 3 bands), near infrared (NIR; 3 bands) and short-wave infrared (SWIR; 3 bands) regions. Pre-fire and post-fire Sentinel-2 Level-2A scenes (orthorectified, surface reflectance product) covering the wildfires were downloaded from the Copernicus Open Access Hub (https://scihub.copernicus.eu) for dates as close as possible to the start and end date of the wildfires based on the availability of cloud-free imagery (Table 1). The 10-m bands were downsampled to a spatial resolution of 20 m through nearest neighbour interpolation. The bands at 60 m were discarded for the MESMA procedure because of their susceptibility to atmospheric effects and thus the absence of interpretable surface reflectance data (Jia *et al.* 2016).

Remote sensing data processing

Spectral indices

We calculated the most commonly used bi-temporal, absolute spectral index in the literature; i.e. the dNBR (Eqns 1 and 2), from using bands 8a (NIR) and 12 (SWIR) of pre- and post-fire Sentinel-2 scenes. We also calculated a relativised spectral index; i.e. the Relativised Burn Ratio (RBR; Parks *et al.* 2014) (Eqn 3), for the higher potential it can offer in burned landscapes with heterogeneous vegetation composition, and in areas with sparse vegetation (Miller and Thode 2007). We discarded the commonly-used Relative dNBR index (RdNBR; Miller *et al.* 2009) because of potentially anomalous values as a consequence of the numerical instability of the index when pre-fire NBR displays zero or negative values (Parks *et al.* 2014).

$$NBR_{Sentinel-2} = (\text{Band 8a} - \text{Band 12}) / (\text{Band 8a} + \text{Band 12}) \quad (1)$$

$$dNBR = 1000(NBR_{pre} - NBR_{post}) \quad (2)$$

$$RBR = dNBR/(NBR_{pre} + 1.001) \quad (3)$$

Sentinel-2 dNBR and RBR values were extracted for each plot of 20 m × 20 m by averaging the values of a systematically sampled grid of 20 points with 2-m spacing within each plot in order to account for the mismatch between the Sentinel-2 grid and the plot extent (Fernández-Guisuraga *et al.* 2022).

MESMA procedure

The MESMA algorithm was implemented using VIPER tools ver. 2.1 software (Roberts *et al.* 2019). The initial phase of the procedure involved the identification of candidate endmember (i.e. basic ground components) spectra to build a spectral library and execute the spectral unmixing process on the post-fire Sentinel-2 scenes. This phase is critical, as the precise selection of endmember spectral signatures has a high impact on the accuracy of the MESMA algorithm output (Tompkins *et al.* 1997).

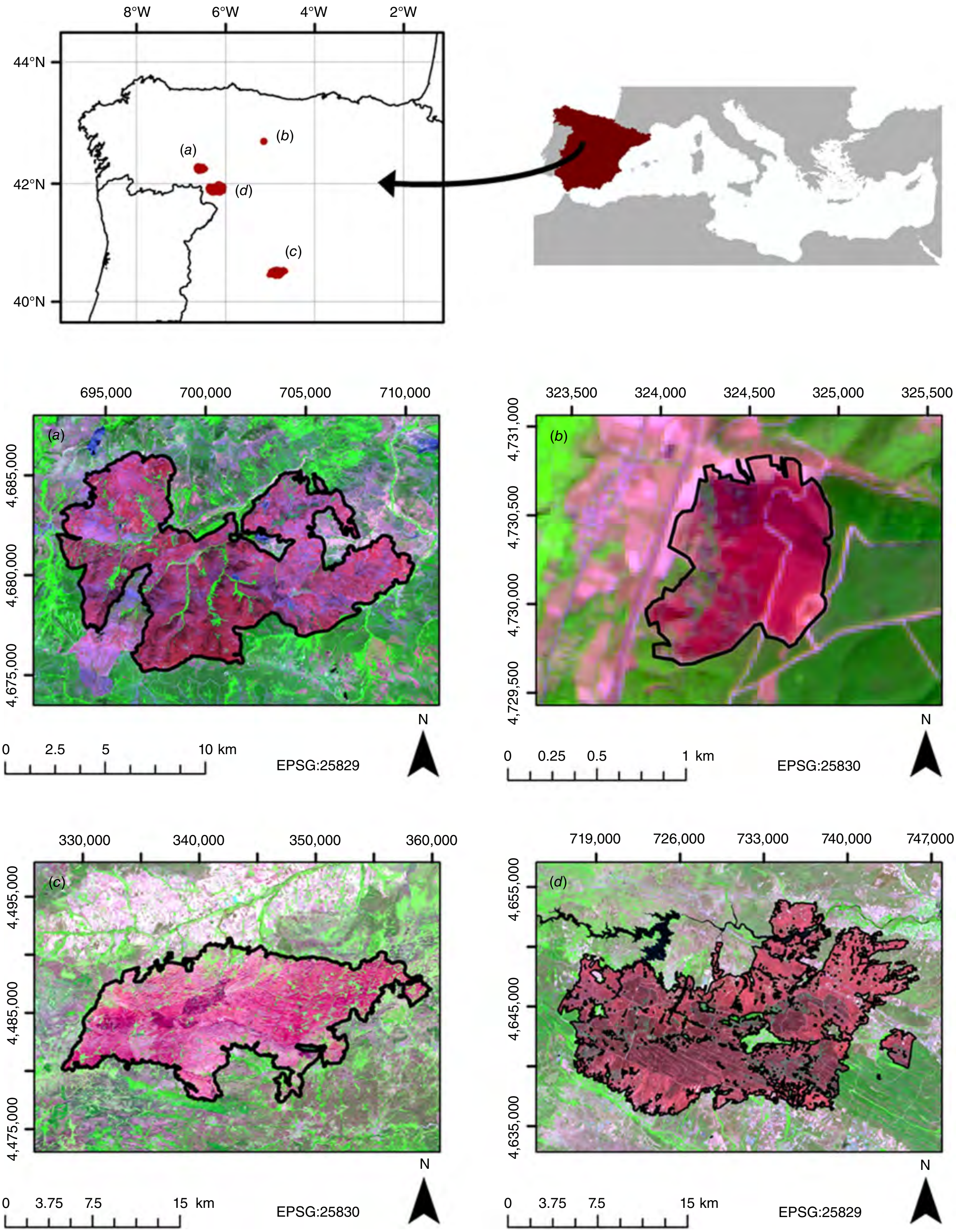

Fig. 1. Location of Sierra de Cabrera (*a*), Villapadierna (*b*), Navalacruz (*c*), and Sierra de la Culebra (*d*) wildfires in the western part of the Mediterranean Basin (north-western and central Spain). A Sentinel-2 false colour composite (R = band 12; G = band 8A; B = band 4) is displayed at the background.

Table 1. Location and characteristics of the four studied wildfires. We provide the number of field plots established within each ecosystem type in the wildfires (**Qp**, *Quercus pyrenaica*; **Qi**, *Quercus ilex*, **Pp**: *Pinus pinaster*; **Ps**, *Pinus sylvestris*).

Wildfire	Sierra de Cabrera	Villapadierna	Navalacruz	Sierra de la Culebra
Location	NW Spain	NW Spain	C Spain	W Spain
Wildfire size (ha)	9940	82	24,444	28,046
Wildfire date	21 August 2017	22 August 2019	14 August 2021	11 June 2022
Elevation range (m)	836–1938	922–1027	939–2157	747–1205
Slope range (%)	0–149	6–27	0–649	0–155
Average annual precipitation (mm)	850	761	758	750
Average annual temperature (°C)	9.0	10.7	9.6	11Confusion matrix and accuracy metrics
Plant communities (# plots)	**Qp** (21)	**Qp** (15) **Pp** (5) **Ps** (5)	**Qi** (8) **Ps** (18)	**Qp** (9) **Qi** (14) **Ps** (21) **Pp** (13)
Pre-fire Sentinel-2 image date	13 August 2017	15 August 2019	9 August 2021	26 May 2022
Post-fire Sentinel-2 image date	2 September 2017	30 August 2019	8 ctober 2021	15 July 2022

To build the spectral library, we first extracted candidate endmembers from Sentinel-2 scenes, including several land cover classes representative of the study site, and second, we identified the optimum endmembers to build the definitive spectral library. We chose photosynthetic vegetation (PV), non-photosynthetic vegetation and soil (NPVS), and char as endmembers to unmix Sentinel-2 scenes following previous post-fire assessments (e.g. Quintano *et al.* 2013, 2023; Fernández-Manso *et al.* 2019). The candidate endmembers were manually delineated inside regions of interest for each class (Quintano *et al.* 2023). Polygon delineation outside the fire scar was assisted using as reference orthophotos from Spanish Aerial Ortho-photography National Plan (PNOA) at a spatial resolution of 50 cm, the Spanish Forest Map, and true (4-3-2) and false (12-8A-4) colour composites of post-fire Sentinel-2 scenes. Spectral signatures were checked to verify that they had the expected shape for the ground covers of interest. Char spectral signatures were extracted from homogeneous polygons within the fire scar using Sentinel-2 colour composites and reviewing the expected char spectral signature (Fernández-Manso *et al.* 2019). We then built the definitive spectral library by a semi-automatic process. We first implemented the Iterative Endmember Selection (IES; Schaaf *et al.* 2011; Roth *et al.* 2012) algorithm to identify the most relevant endmembers of the different land cover classes of interest based on the maximisation of the Kappa index. Following this, we manually included endmembers not selected by the automatic IES algorithm, but where (1) Minimum Average Spectral Angle (MASA; Dennison *et al.* 2004), (2) Count-based Endmember Selection Index (CoB; Roberts *et al.* 2003), and (3) Endmember Average RMSE (EAR; Dennison and Roberts 2003) indices reflected a high endmember representativeness (Quintano *et al.* 2013). An additional endmember per class was included in the definitive spectral library if it jointly exhibits the lowest MASA index value, the highest CoB index value, and the lowest EAR index value.

Once the definitive spectral library was established, the endmembers were hierarchically organised using a multilevel fusion procedure and thus at different levels of complexity (Roberts *et al.* 2003). The process of spectral unmixing executed on Sentinel-2 post-fire scenes was then iterative because it is necessary to adjust the maximum number of endmembers considered in each model, and their optimum spectral signatures, until the imposed restrictions (i.e. fraction values between −0.10 and 1.10, shade fraction values between 0.00 and 1.00, maximum allowed RMSE equal to 0.025 and maximum 5% of unclassified pixels) were fulfilled, following previous research (Quintano *et al.* 2013, 2023; Fernández-Manso *et al.* 2019). Finally, the fraction images (i.e. char, PV and NPVS) were shade-normalised to remove the shade endmember influence (Roberts *et al.* 2019). For more detailed information on the whole MESMA procedure see Quintano *et al.* (2023).

Fractional cover by shade-normalised image fractions was then extracted for each 20 m × 20 m plot following the same procedure as for spectral indices.

Data analyses

First, we assessed the differences in CFB, spectral index values (i.e. dNBR and RBR), and fractional cover by MESMA image fractions (i.e. char, PV and NPVS) between conifer and broadleaf forest ecosystems using Mann–Whitney *U* tests after evidencing non-compliance with parametric test assumptions. The statistical significance of the differences was determined at the 0.05 level. The Kruskal–Wallis test was used to assess statistical differences in spectral indices and image fractions between fire types (surface, intermittent, crown), followed by a pairwise Wilcoxon test.

Second, a Random Forest (RF; Breiman 2001) classification algorithm was used to assess the capability of spectral indices (univariate model) and MESMA image fractions (multivariate model) to predict fire type and link crown fire likelihood with post-fire spectral variability in conifer and broadleaf forests separately. RF classification algorithm was selected due to the absence of assumptions about the distribution of the response variable and its capacity to unravel complex, non-linear relationships between the dependent variable and predictors (Rodriguez-Galiano *et al.* 2012; Wang *et al.* 2019). The *ntree* RF hyperparameter was set to 2000 for ensuring prediction stability (Probst and Boulesteix 2018). The optimum value of the *mtry* RF hyperparameter was found through tuning experiments consisting of repeated 10-fold cross-validation. RF classification performance was assessed through the confusion matrix averaged across 10-fold cross validation resamples. The following accuracy metrics were computed: overall accuracy (OA; %), Kappa index, user's accuracy (UA; %), and producer's accuracy (PA; %) for each fire type category. Variable importance in multivariate RF models (i.e. those calibrated with MESMA fraction images) was calculated using the mean decrease in accuracy (MDA; %) metric. We also computed partial dependence plots depicting continuous crown fire likelihood in a centred logit scale. Finally, we fitted a RF model using global data (conifer and broadleaf forests pooled together) to test the generalisation ability of MESMA image fractions and the best-performing spectral index. RF model objects were used to generate wall-to-wall predictions (i.e. fire type maps) for the broadleaf and conifer forests within the Sierra de la Culebra wildfire scar (Fig. 1), selected because it is one of the largest wildfires ever recorded in Spain and has a large area occupied by conifer and broadleaf forests. The Spanish Forest Map derived from the fourth Spanish National Forest Inventory was used to delimit the broadleaf and conifer stands.

All analyses were conducted in R (R Core Team 2021).

Results

The CFB of conifer forests was significantly larger than that of broadleaf forests (Mann–Whitney P-value < 0.01) in the study sites (Fig. 2). Char fractional cover estimated from MESMA was significantly higher in conifer than in broadleaf forests (P-value < 0.01), with NPVS fraction exhibiting the opposite behaviour (Fig. 2). Both spectral indices (i.e. dNBR and RBR) and the GV MESMA fraction did not significantly differ (P-value > 0.05) between forest types (Fig. 2).

All spectral indices and MESMA fractions differed significantly between fire types ($\chi > 46.96$; P-value < 0.001), with a significant increase from surface to crown fires in the case of spectral indices and the char MESMA fraction, and the opposite behaviour in the case of the GV and NPVS fractions (Fig. 3). The strongest relationship with fire type corresponded to the char MESMA fraction.

In broadleaf forests, the highest performance in fire type classification was obtained by the multivariate RF model calibrated from MESMA fractions (OA = 82.09% and Kappa index = 0.71). The Producer's and User's accuracy of the model were balanced and no remarkable confusion was observed among all classes (Table 2). Classification accuracy was notably lower for the spectral indices (OA < 71.96% and Kappa index < 0.55), particularly for the dNBR (Table 2). The greatest confusion was observed for both indices between surface and intermittent crown fires, and between intermittent and continuous crown fires. Continuous crowning was never misclassified as a surface fire for all remote sensing products (Table 2).

In conifer forests, the overall accuracy provided by spectral indices and MESMA fractions in the RF fire type classification, as well as the Producer's and User's accuracy of the models (Table 3), followed the same pattern as in broadleaf forests (MESMA accuracy > RBR > dNBR). The very low confusion rate in the MESMA-based classification is worth noting (Table 3).

All remote sensing products performed better in conifer (OA = 76.88% ± 8.11% and Kappa = 0.62 ± 0.13) than in broadleaf (OA = 72.71% ± 8.99% and Kappa = 0.56 ± 0.15) forests.

The likelihood of continuous crowning relative to the spectral variability of burned areas captured by the MESMA fractions was very similar in conifer and broadleaf forests (Fig. 4). Occurrence of continuous crowning is linked in both ecosystems to post-fire char fractions greater than 0.5, the maximum likelihood being reached when char fraction is equal to 0.8. When GV and NPVS fractions are greater than 0.25–0.30, the likelihood of continuous crowning is very low. The MESMA char fraction was the most important variable to explain fire-type likelihood in broadleaf and conifer forests (Fig. 4). Consistency of continuous crowning likelihood between spectral indices and ecosystem types was lower than in the case of MESMA fractions (Fig. 4). dNBR values above 500 seem to be associated with maximum crowning probability in conifer forests, while in broadleaf forests the probability continues to increase progressively above such dNBR threshold. The same behaviour in both forest types was observed with RBR values above 300.

When pooling data from conifer and broadleaf forests, the RBR index shows poor generalisation in fire type estimates (OA = 62.88% and Kappa index = 0.42) (Table 4) when comparing results with RF classification models by single ecosystems (OA = 73.84% ± 2.79% and Kappa = 0.58 ± 0.04) (Tables 2 and 3), with even greater underestimation of continuous crowning and higher confusion between surface and intermittent crown fires. Conversely, the performance loss of the global RF model was negligible (OA = 82.95% and Kappa index = 0.73 vs OA = 83.79% ± 2.40% and

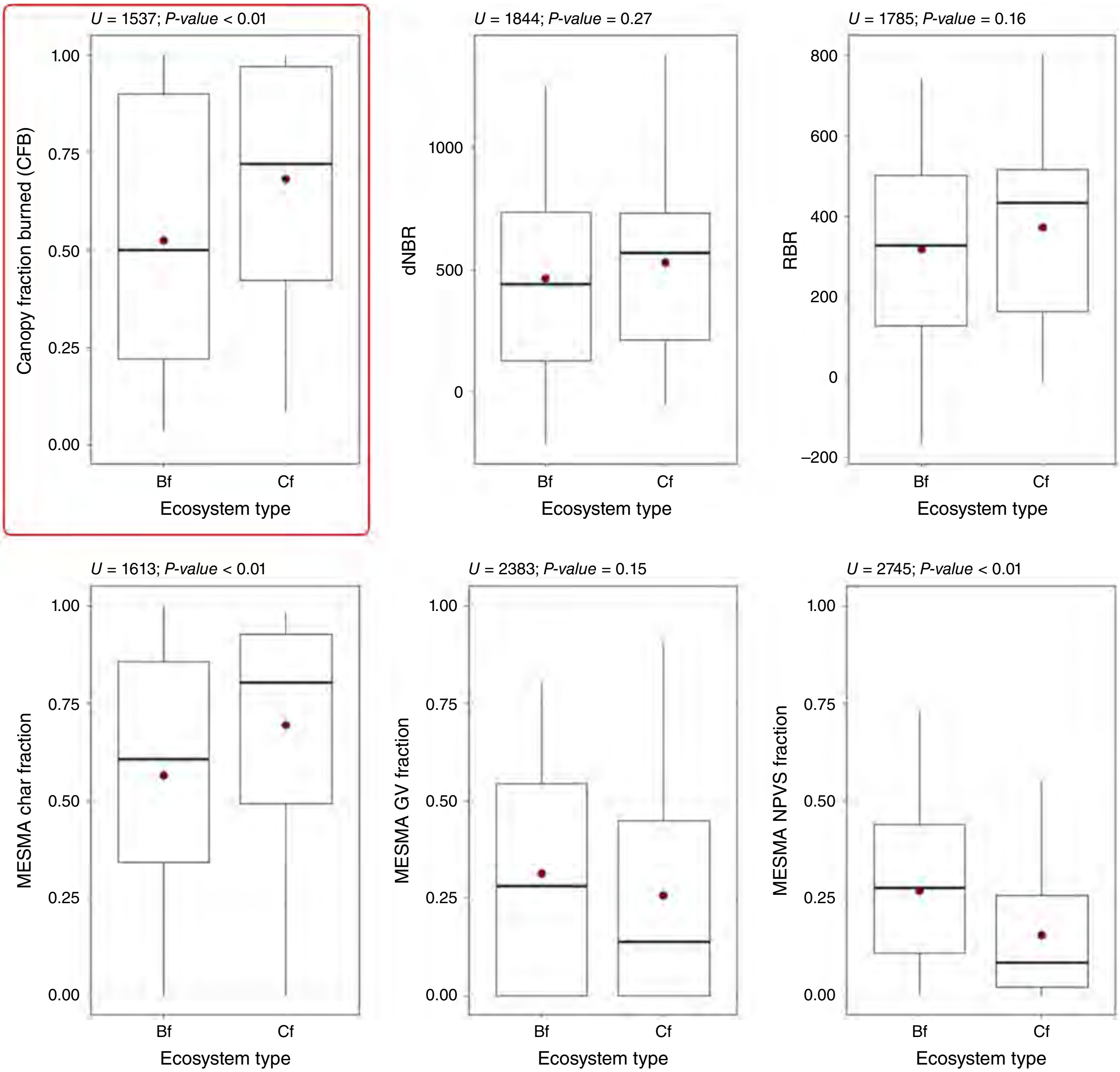

Fig. 2. Boxplots depicting the relationship of canopy fraction burned (CFB), spectral indices (dNBR and RBR) and MESMA image fractions (char; GV, green vegetation; NPVS, non-photosynthetic vegetation and soil) with ecosystem type (BF, broadleaf forests; Cf, conifer forests). Mann–Whitney *U* test results are shown in the upper part of the plots.

Kappa = 0.74 ± 0.04) when calibrated with MESMA fractions (Table 4).

These results are consistent with wall-to-wall fire type maps computed from RF model objects at landscape scale in broadleaf and conifer forests within the Sierra de la Culebra wildfire (Fig. 5). The area of continuous crowning is much smaller in RBR than in MESMA estimates due to the high confusion between intermittent and continuous crown fire types in the former product. Wall-to-wall estimates of the RF models calibrated in conifer and broadleaf forests separately are quite consistent with those of the RF model calibrated from global data in the case of MESMA fractions. In contrast, wall-to-wall estimates of RBR-based models are much less consistent between the two model calibration strategies.

Discussion

Despite the extensive literature on fire severity assessments through remote sensing techniques using integrative field measurements (e.g. Fernández-Guisuraga *et al.* 2023*a*; Miller *et al.* 2023) or physically meaningful variables such as crown scorch height or crown consumption (e.g. Lentile *et al.* 2009; Lydersen *et al.* 2016; Arkin *et al.* 2023), the

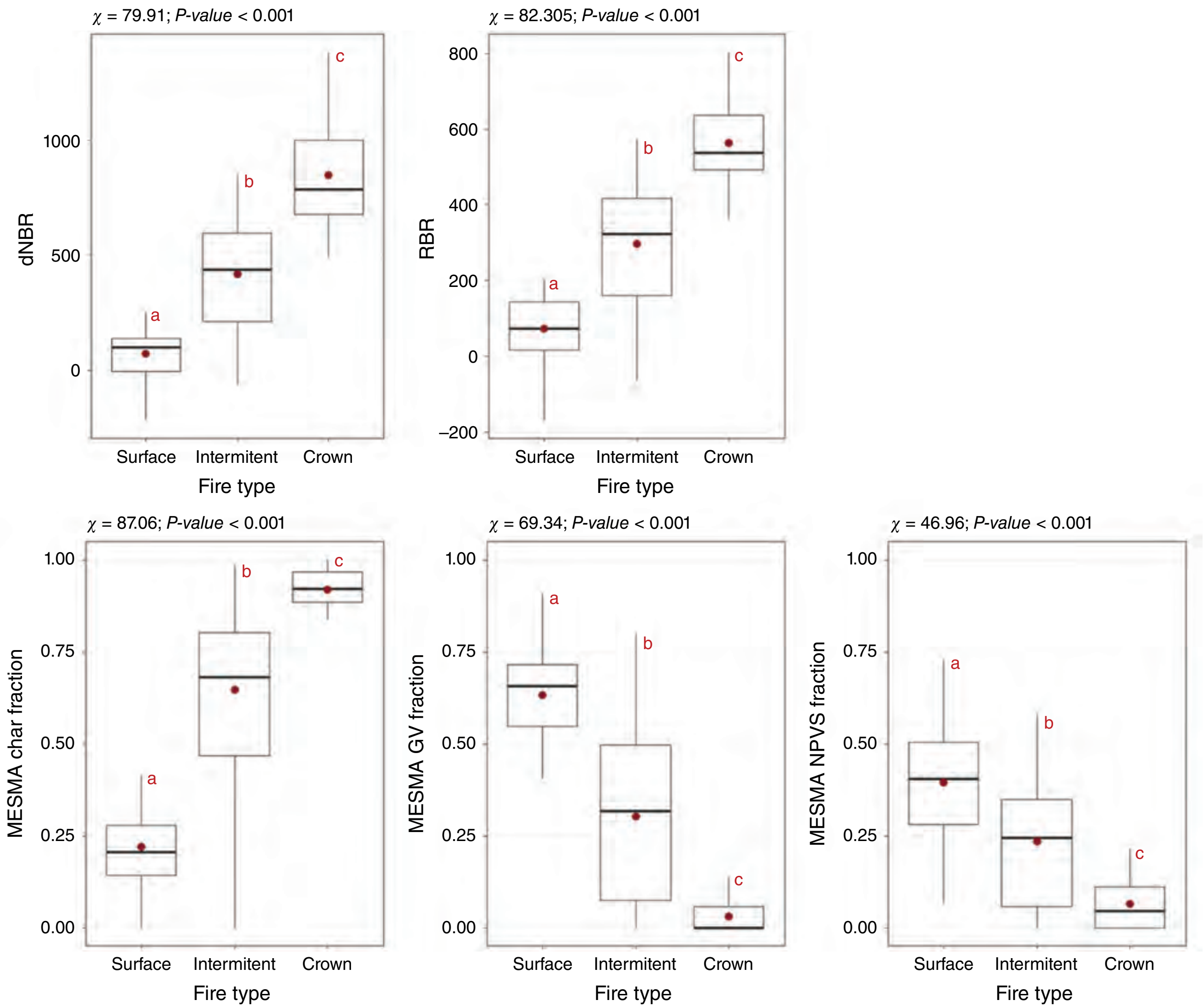

Fig. 3. Boxplots depicting the relationship of spectral indices (dNBR and RBR) and MESMA image fractions (char; GV, green vegetation; NPVS, non-photosynthetic vegetation and soil) with fire type. We show Kruskal–Wallis test results in the upper part of the plots. Lowercase red letters denote significant differences between fire types at $P = 0.05$.

potential of physically-based and generalisable remote sensing approximations to provide wall-to-wall fire type estimates representative of wildfire behaviour is examined for the first time in this study. Our results showed the importance of generalisable remote sensing techniques to procure accurate crown fire likelihood estimates that align with post-fire land management needs in Mediterranean burned landscapes (Keeley 2009). This is particularly relevant because, although fire severity is closely related to fire behaviour (Finney 2005), the latter is what really determines the effectiveness of fire suppression efforts and size-dependent fire impacts (Fernandes *et al.* 2010).

Typically, remote sensing techniques with a physical basis, including MESMA, perform better than empirical methods based on spectral indices for retrieving biophysical properties of burned landscapes (e.g. De Santis and Chuvieco 2007; Fernández-Guisuraga *et al.* 2021, 2023*a*; Quintano *et al.* 2023). Accordingly, MESMA image fractions also procured here a remarkably higher performance than spectral indices in the fire type RF classifier, particularly when pooling field data from several ecosystems. Mitri and Gitas (2006) used an object-based classification relying on spectral indices computed from a post-fire IKONOS scene, together with object contextual information, for mapping fire type within a single, small wildfire that affected a Mediterranean pine forest in Greece. The authors reported a classification accuracy (overall accuracy and Kappa index) comparable to that obtained here with MESMA fractions. However, they did not consider intermittent crown fire in the fire type classification, which may be responsible for high patchiness of fire effects over the landscape (Scott and Reinhardt 2001) and thus for mixed spectral responses. In

Table 2. Confusion matrix and accuracy metrics of Random Forest (RF) fire type classification using spectral indices (dNBR and RBR) and MESMA image fractions in broadleaf forests.

Fire type		Ground truth		
		Surface	Intermittent	Crown
Predicted (dNBR)	Surface	9	6	0
	Intermittent	7	22	6
	Crown	0	5	12
	PA (%)	56.25	66.67	66.67
	UA (%)	60.00	62.86	70.59
	OA (%)	**Kappa**		
	64.18	0.42		
Predicted (RBR)	Surface	10	5	0
	Intermittent	6	24	5
	Crown	0	4	13
	PA (%)	62.50	76.67	72.22
	UA (%)	71.43	67.65	81.25
	OA (%)	**Kappa**		
	71.86	0.55		
Predicted (MESMA fractions)	Surface	12	2	0
	Intermittent	4	27	2
	Crown	0	4	16
	PA (%)	75.00	81.82	88.89
	UA (%)	85.71	81.82	80.00
	OA (%)	**Kappa**		
	82.09	0.71		

Table 3. Confusion matrix and accuracy metrics of Random Forest (RF) fire type classification using spectral indices (dNBR and RBR) and MESMA image fractions in conifer forests.

Fire type		Ground truth		
		Surface	Intermittent	Crown
Predicted (dNBR)	Surface	5	5	0
	Intermittent	3	21	8
	Crown	0	3	17
	PA (%)	62.50	72.41	68.00
	UA (%)	50.00	65.63	85.00
	OA (%)	**Kappa**		
	69.36	0.50		
Predicted (RBR)	Surface	6	5	0
	Intermittent	2	22	6
	Crown	0	2	19
	PA (%)	75.00	75.86	76.00
	UA (%)	54.55	73.33	90.47
	OA (%)	**Kappa**		
	75.81	0.61		
Predicted (MESMA fractions)	Surface	6	0	0
	Intermittent	2	25	3
	Crown	0	4	22
	PA (%)	75.00	86.21	88.00
	UA (%)	100.00	83.33	84.62
	OA (%)	**Kappa**		
	85.48	0.76		

contrast to our study, only one ecosystem type within a single wildfire was examined, and it has been previously reported that spectral indices (1) suffer from generalisation issues between different vegetation types and environmental conditions due to the lack of physics in the retrieval of fire effects (e.g. De Santis and Chuvieco 2007; Lentile *et al.* 2009; Fernández-Guisuraga *et al.* 2023*a*), and (2) have sub-optimal sensitivity to complex spectral responses (e.g. Roy *et al.* 2006; Mallinis *et al.* 2018).

Despite this, the higher accuracy of MESMA image fractions versus spectral indices used as benchmark within the same experimental design for estimating fire-type spatial variability may be related to the sound physical meaning of sub-pixel image analysis techniques in post-fire environments (Quintano *et al.* 2013). In this context, capturing the variability in the fire type spectral signal can be a subpixel matter when using moderate spatial resolution multispectral imagery (Quintano *et al.* 2013; Fernández-Manso *et al.* 2019), such as Sentinel-2. Specifically, the high spatial variability in surface and canopy fuels expected in Mediterranean fire-prone ecosystems (Fernández-Guisuraga *et al.* 2023*a*), together with fine-scale variations in terrain and fire weather, may result in fire behaviour alternation between different fire types at small spatial scales (Scott and Reinhardt 2001). MESMA image fractions also represent intrinsic biophysical characteristics of burned landscapes (i.e. char or photosynthetic vegetation), not only a secondary proxy for these constituents. Indeed, the SWIR region of broadband remote sensing data involved in dNBR and thus RBR calculation is not as sensitive to the spectral variability of char, ash and soil, nor to their complex mixture in post-fire scenarios as traditionally assumed (see Lentile *et al.* 2009), unlike the NIR region to vegetation vigour or amount (Hudak *et al.* 2007). Several authors also stated that spectral indices such as dNBR were originally conceived to map burned areas, and not to estimate the variability in their biophysical properties (Roy *et al.* 2006).

The ability of MESMA to resolve complex and mixed spectral responses of scorched and burned canopies due to the use of full available spectra (Quintano *et al.* 2023), rather than a limited number of bands and thus spectral information as in the case of spectral indices (Mallinis *et al.*

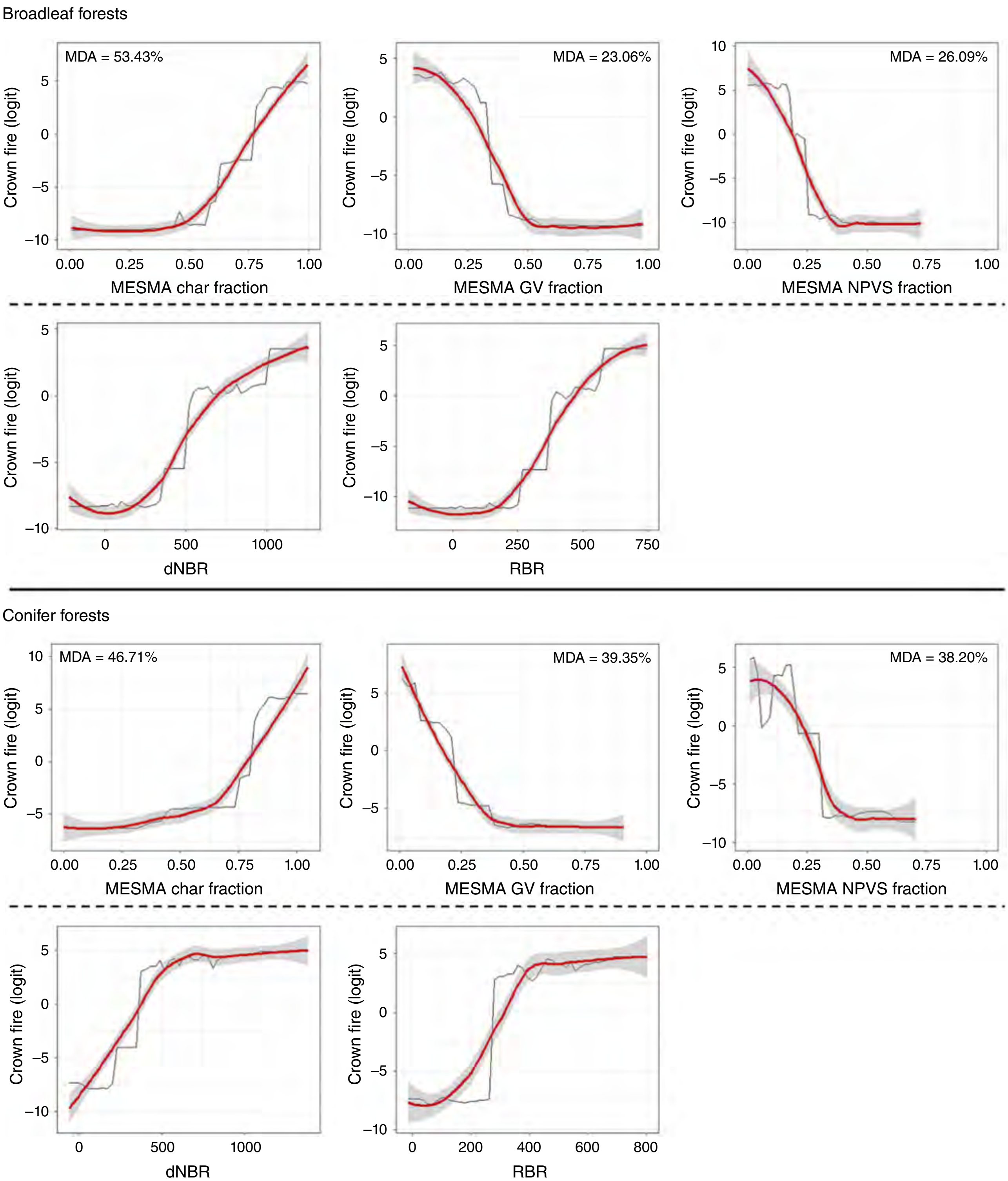

Fig. 4. Partial dependence plots depicting the relationship in broadleaf and conifer forests between crown fire likelihood and the variability of MESMA image fractions and spectral indices in the Random Forests (RF) classification algorithm. The red line is a LOESS smooth curve. Mean decrease in accuracy (MDA;%) metric is shown for each MESMA image fraction (multivariate RF models).

2018), may have prevented the high confusion between fire types and the underestimation of continuous crowning. This effect, evident in dNBR and RBR estimates and highly dependent on vegetation type (Lentile *et al.* 2009), was probably also attributable to the SWIR reflectance saturation and steady NIR reflectance decrease at high char and

Table 4. Confusion matrix and accuracy metrics of Random Forest (RF) fire type classification using spectral indices (dNBR and RBR) and MESMA image fractions for global data (conifer and broadleaf forests pooled together).

Fire type		Ground truth		
		Surface	**Intermittent**	**Crown**
Predicted (RBR)	Surface	13	13	0
	Intermittent	8	40	15
	Crown	3	9	28
	PA (%)	55.56	64.52	65.12
	UA (%)	53.57	62.50	70.00
	OA (%)	**Kappa**		
	62.88	0.42		
Predicted (MESMA fractions)	Surface	18	3	0
	Intermittent	6	51	5
	Crown	0	8	38
	PA (%)	75.00	82.26	88.37
	UA (%)	85.71	82.26	82.61
	OA (%)	**Kappa**		
	82.95	0.73		

ash cover (Soverel *et al.* 2010). Indeed, high crown fire likelihood in conifer and broadleaf forests is linked to a post-fire MESMA char fractional cover of about 0.8 (Fig. 4), close to the CFB defining a continuous crown fire (CFB > 0.89). Consistent with previous fire severity research (Tane *et al.* 2018; Fernández-Manso *et al.* 2019), the char fraction was the most important ground constituent to retrieve fire type likelihood in broadleaf and conifer forests.

The better performance of MESMA-based models (and spectral indices) in conifer than in broadleaf forests may be associated with the typical lower canopy closure in Mediterranean conifer forests than in broadleaf forests (e.g. García *et al.* 2010; Sheffer *et al.* 2015), which may cause the char spectral signal from the lower canopy strata to be better captured by the sensor. This behaviour has been previously reported by Gibson *et al.* (2020) in Mediterranean, semi-arid and subtropical burned areas of eastern Australia. The authors evidenced that high canopy closure may result in the underestimation of the fire severity spectral signal sensed by moderate spatial resolution satellites. Conifer forests were more prone to elevated CFB and thus to high-intensity crown fires than broadleaf forests according to fire hazard generic expectations and previous reports of crowning potential in the Mediterranean Basin (Fernandes 2009; Fernandes *et al.* 2010; Fernández-Guisuraga *et al.* 2023*c*), and in other biomes elsewhere (e.g. Scott and Reinhardt 2001; Epting and Verbyla 2005). This may be linked to higher accumulation of flammable litter and fuel loading of fine-fuel rich species in the understory of unmanaged Mediterranean conifer forests than in those dominated by broadleaf species, coupled with increased vertical fuel continuity and ladder fuels (Safford *et al.* 2012; Fernández-Guisuraga *et al.* 2021).

MESMA fraction images provided not only more accurate fire type estimates than spectral indices in broadleaf and conifer forests, but also featured greater generalisation ability. This could be related to the analogy between the variation in crown scorch and consumption estimated through MESMA fraction images and the fire type definition (CFB) used in the field. In addition, the variability of the background reflectance signal corresponding to bare soil can affect the discrimination of ecological fire effects and generalisation ability when relying on spectral indices (Meng *et al.* 2017; Fernández-Guisuraga *et al.* 2023*a*). Conversely, the endmember collection of all representative ground constituents at each site to build the definitive spectral library in the MESMA algorithm could be accounted for the minimisation of the background influence in the estimation of fire effects (Quintano *et al.* 2023).

Overall, the results of this study could be leveraged by land managers to reliably infer tree damage, mortality and ecosystem responses in Mediterranean post-fire landscapes, and develop accordingly appropriate post-fire management plans and restoration strategies. In particular, the potential implementation of physical-based algorithms such as advanced spectral mixture models in consolidated geospatial processing platforms in the cloud; e.g. Google Earth Engine (GEE; Gorelick *et al.* 2017), could emerge as a valuable resource for minimising data acquisition and processing efforts in wildfire management (Costa-Saura *et al.* 2022). Moreover, future research could leverage the potential of recently-available spectroscopic spaceborne data together with advanced image analysis techniques like MESMA (Quintano *et al.* 2023) to determine whether wall-to-wall fire behaviour estimates reported here can be further refined. Recently, the use of unmanned aerial vehicles (UAVs) has enabled accurate predictions of physically meaningful variables as proxies for fire effects at the level of individual trees (Moran *et al.* 2022; Arkin *et al.* 2023), and can therefore be a reliable tool in future research to characterise the fire type particularly when fire effects vary greatly at fine spatial scales.

Conclusions

We examined for the first time the potential of broadband satellite data to provide meaningful fire type estimates representative of wildfire behaviour in Mediterranean ecosystems. A key result of this study is that intrinsic biophysical characteristics of burned landscapes, such as the fractional cover of char or photosynthetic vegetation, retrieved from sub-pixel image analysis techniques with a physical basis,

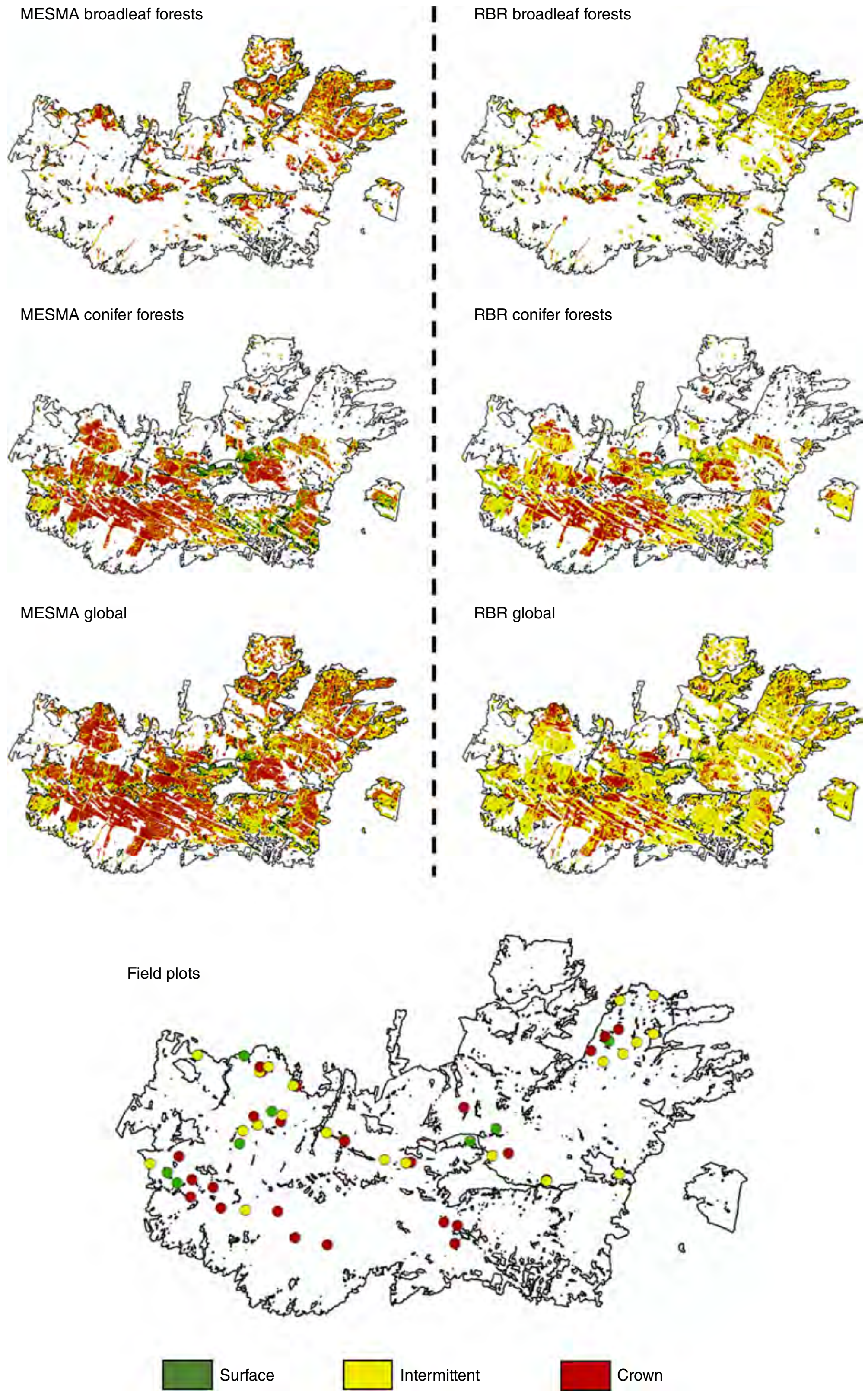

Fig. 5. Location of the field plots and wall-to-wall fire type predictions in broadleaf and conifer forests within the Sierra de la Culebra wildfire (RF model in conifer and broadleaf forests separately). We also present the map for the RF model calibrated from global data (conifer and broadleaf forests pooled together).

are more accurate at assessing fire type (e.g. surface or crown fire), given the direct physical interpretation, than commonly-used spectral indices. For example, post-fire char fraction estimates computed by MESMA can be used by forest managers directly to estimate the CFB and thus determine fire type in distinct ecosystems; i.e. without the need for calibration with field data, unlike spectral indices. Such estimates would enable evaluating both the performance of fire behaviour models and pre-fire treatments as moderators of extreme fire behaviour.

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Data availability. The data that support this study will be shared upon reasonable request to the corresponding author.

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