General comments:

We thank the reviewers for the positive comments to our manuscript. We followed the suggestions and modified some parts of the manuscript to improve it.

In response to the reviewer's suggestions, we harmonized some terms with respect to the analyzed data and included the abbreviations (i.e. RSD: remote-sensing datasets; GBD: ground-based dataset) in the manuscript. In order to clarify the novelty and application of our work, we included some new sentences in the manuscript and we have rewritten others to improve the readability.

We included the Supplementary material as part of the manuscript in Appendix A (Fig. A1 and A2). In this sense, complementary information can be easily accessed by the reader and may support the understanding of the applied methodology. Finally, we also increased the graphical resolution (300 dpi) of all Figures of the manuscript to improve visualization.

Detailed changes in the revised version of the manuscript:

L12-14: Here, we compared three state-of-the-art remote-sensing datasets (RSD; Fire Atlas, FRY and GlobFire) with a harmonized ground-based dataset (GBD) compiled by fire agencies monitoring systems across the Southwestern Mediterranean basin (2005-2015).

L14-15: We assessed the agreement between RSD and GBD with respect to both burned area (BA) and number of fires (NF).

L18-20: The agreement between RSD and GBD was strongly dependent on individual fire size and strengthened when increasing the fire size threshold, with fires > 100 ha denoting higher correlation and much lower error (BA 10%; NF 35%).

L26-28: Vegetation fires are a common and destructive hazard in the Southwestern Mediterranean basin. Over the past four decades, there were, on average, 47,766 fires and 413,209 ha burned annually in this region (San-Miguel-Ayanz et al., 2017) causing extensive economic and ecological losses, and even human casualties (Keeley et al., 2011; Molina-Terrén et al., 2019).

L35-36: Projecting future changes to fire activity requires modeling efforts across broad geographical scales to better understand processes and mechanisms conductive to fire ignition and spread.

L66-68: In this work, we compared for the first time the three most recent remote-sensing datasets of individual fires (Fire Atlas, FRY and GlobFire) with quality-controlled fire databases compiled by regional agencies across the most active fire region in Europe (i.e. Southwestern Mediterranean basin) during the common period of observations (2005 to 2015).

L68-71: While most previous studies have evaluated remote-sensing data on a fire-by-fire basis, this study aggregates individual fires across months and pixels (0.25°) and seeks to estimate to what extent the temporal variability in both fire frequency and burned area are captured by remote-sensing datasets.

L73-74: To answer these questions, we examined the agreement between remotely-sensed and ground-based fire datasets aggregated at monthly and 0.25° resolutions across a range of individual fire size thresholds (1 to 500 ha).

L74-75: This study may inform end-users about remote-sensing datasets' ability to proxy actual fire activity but also on their limitations.

L78-79: The ground-based dataset (GBD) was built from multiple fire agencies sources, including fire records from Portugal, Spain, France and Sardinia in Italy (Table 1).

L84: Table 1. Fire agencies and reference links to the data used to build the harmonized ground-based dataset (GBD) across the Southwest Mediterranean basin.

Agency	**Country**	**Coverage**	**Reference link**
DECIF	Portugal	National	http://www2.icnf.pt/portal/florestas/dfci/relat/rel-if (last access: 10 January 2020)
EGIF	Spain	National	https://www.mapa.gob.es/va/desarrollo-rural/estadisticas/Incendios_default.aspx (last access: 18 December 2019)
Prométhée	France	Regional	https://www.promethee.com/ (last access: 16 December 2019)
Regione Sardegna	Italy	Regional	http://webgis2.regione.sardegna.it/download/ (last access: 22 January 2020)

L92:

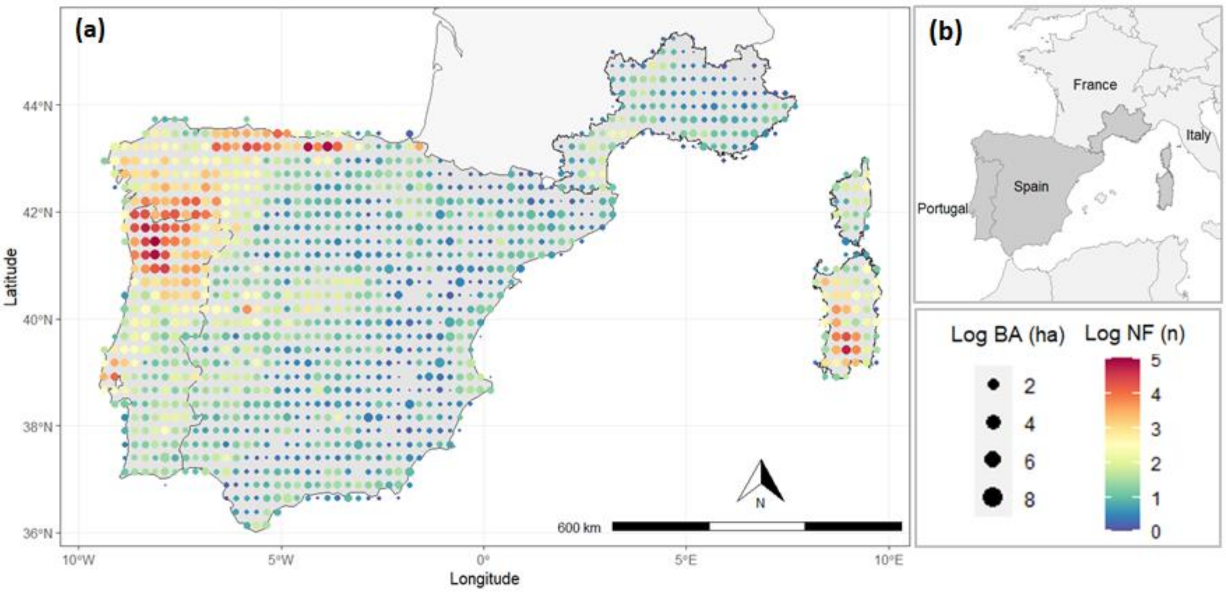


Figure 1. (a) Mean annual burned area (BA, depicted by circle size) and mean annual number of fires (NF, depicted by color) at 0.25° resolution over the study period (2005-2015). (b) Spatial extent of the study area.

L96-97: We used the most recent remote-sensing datasets (RSD) of individual fires: Fire Atlas (Andela et al., 2019a, 2019b), FRY (Laurent et al., 2018a, 2018b) and GlobFire (Artés et al., 2019; Artés Vivancos and San-Miguel-Ayanz, 2018).

L100-102: Fires were individualized from different algorithms such as a progression-based algorithm (Andela et al., 2019), a flood-fill algorithm (Laurent et al., 2018), and data mining (Artés et al., 2019) that share a common objective: assemble burned pixels that were adjacent in both space and time to identify and outline individual fire events.

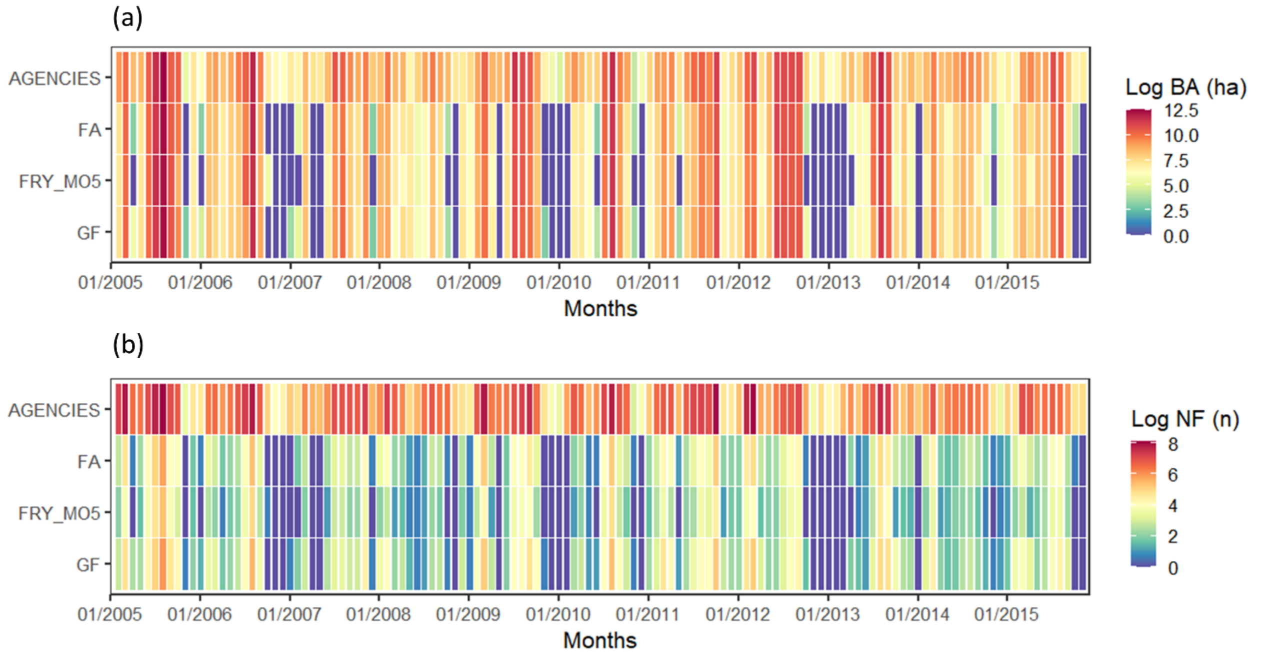
L112-113: The comparison with all FRY cut-off values is available in the Appendix A (Fig A1).

L119: We compared burned area (BA) and number of fires (NF) estimated by RSD, with the ground-based reference GBD (Fig. 2).

L131-133: To account for the land cover changes over the study period, we used CLC 2006 as a reference to filter RSD from the 2005-2009 period and CLC 2012 from 2010-2015. Sensitivity analysis to the land-cover filter is shown in the Appendix A (Fig. A2).

L134-135: As RSD are prone to omit smaller fires (<25 ha) due to the coarse spatial resolution of MODIS product MCD64A1 (500 m) and other limitations, we investigated different fire size thresholds increasing from 1 to 500 ha.

L148: We then sought to examine how the agreement between RSD and GBD datasets varies across space.



L163:

Figure 3. (a) Monthly burned area and (b) number of fires (>1 ha) in each fire dataset across the Southwest Mediterranean basin over 2005-2015.

L 166:

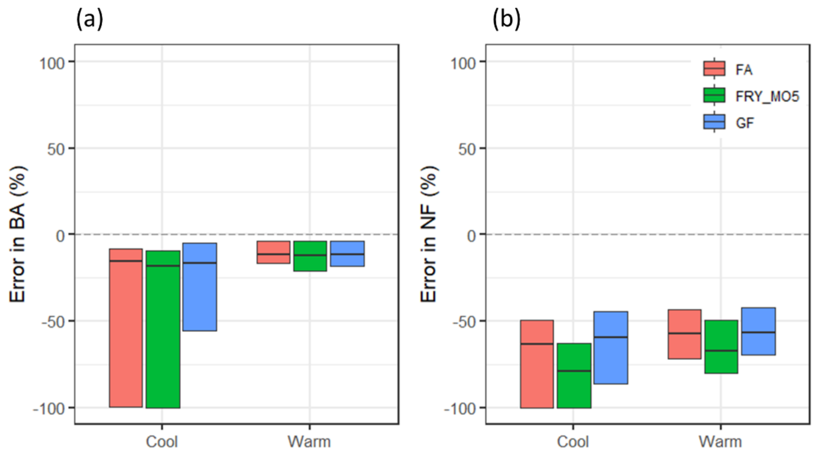


Figure 4. (a) Median and inter-quartile range of the seasonal error (ε) observed each year for burned area and (b) number of fires estimates of each RSD for all fires >1 ha in the studied area. Cool season from November to April and warm season from May to October. Dashed lines represent the perfect agreement between the datasets.

L170-171: Table 3 presents the total BA and NF as well as monthly (i.e. including the seasonal cycle) and annual correlation (i.e. excluding the seasonal cycle) between RSD and GBD for all fires (>1 ha).

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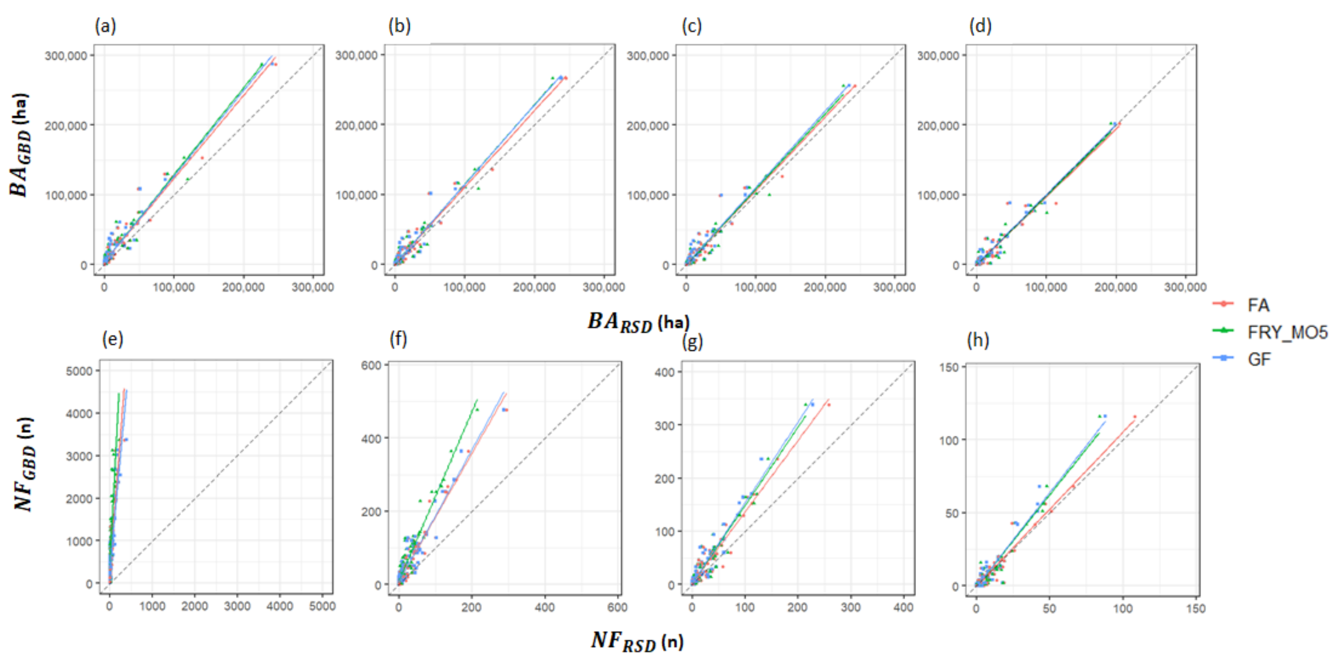

Figure 5. Comparison of GBD and RSD in respect to monthly burned area (top) and the number of fires (bottom) when considering a) all fires (> 1 ha), b) fires >50 ha, fires >100 ha and d) fires >500 ha. (e-h) Same as a-d) but for the number of fires. The 1:1 dashed lines represent the perfect fit between the datasets.

L222-223: Although RSD may miss a substantial number of fires, the temporal variations in both NF and BA match very well with ground-based observations.

L223-224: Our results also demonstrate that agreement between RSD and GBD is strongly dependent on individual fire size.

L242-244: Environmental conditions (e.g. topography, cloud/smoke cover) may influence the sensor detection power, resulting in a break in BA continuity thereby increasing the risk of artificially splitting single fires into different fire events.

L270-271: Further studies are still needed to examine RSD spatio-temporal variability at the fire patch level (i.e. assign individual fires from RSD to GBD) in order to more precisely quantify the dataset accuracy at the fire scale.

L279-280: Overall, RSD contain only a small fraction of the total number of fires documented by GBD.

L280-281: However, they capture reasonably well the temporal variability of fire activity across monthly and annual scales.

L294-296: Our findings suggested that global RSD of individual fires can be used to proxy variations in fire activity on monthly or annual timescales, however caution is advised when drawing from smaller fires (< 100 ha) across the Mediterranean region.

L296-297: Fire agencies may also benefit from the spatial and temporal consistency of remote-sensing data to support their operational fire mapping system at regional/national level.

Assessing the accuracy of remotely-sensed fire datasets across the Southwestern Mediterranean basin

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Abstract. Recently, many remote-sensing datasets ~~remote-sensing (RS) based datasets~~ providing features of individual fire events from gridded global burned area products have been released. Although very promising, these datasets still lack a quantitative estimate of their accuracy with respect to historical ground-based fire datasets~~bases~~. Here, we compared three state-of-the-art remote-sensing ~~RS~~ datasets (RSD; Fire Atlas, FRY and GlobFire) with a harmonized ground-based dataset (GBD) compiled by fire agencies monitoring systems across the Southwestern Mediterranean basin (2005-2015). ~~with high-quality ground databases compiled by regional fire agencies (AG) across the Southwestern Mediterranean basin (2005-2015).~~ We assessed the ~~spatial and temporal accuracy in estimated~~agreement between RSD and ~~AGD~~GBD with respect to both~~RS~~ burned area (BA) and number of fires (NF). RSD and GBD were aggregated at monthly and 0.25° resolutions, considering different individual fire size thresholds ranging from 1 to 500 ha. Our results show that ~~both~~~~RS~~all datasets were highly correlated ~~with AG~~ in terms of monthly BA and NF but RSD severely underestimated both (by 38% and 96%, respectively) when considering all fires > 1 ha. The agreement between RSD and GBD wa~~i~~s strongly dependent on individual fire size and strengthen~~ed~~s when increasing the fire size threshold~~Stronger agreement was found when increasing the fire size threshold~~, with fires > 100 ha denoting higher correlation and much lower error (BA 10%; NF 35%). The agreement ~~between RS and AG~~~~the datasets~~ was also ~~the highest~~ higher during the warm season (May to October) in particular across the regions with greater fire activity such as the Northern Iberian Peninsula. ~~-~~The Fire Atlas displayed a slightly better performance, with a lower relative error, although uncertainty in gridded BA product largely outpaced uncertainties across the RSD~~ datasets~~. Overall, our findings suggest a reasonable agreement between RSD and ~~ground-based datasets~~GBD for fires larger than 100 ha, but care is needed when examining smaller fires at regional scales.

1 Introduction

Vegetation fires are a common and destructive hazard in the Southwestern Mediterranean basin. Over the past ~~last~~ four decades, there were, o~~a~~n average, ~~of~~ ~~about~~ 47,766 fires ~~annually and~~ ~~an average of~~ ~~were responsible every year for~~ 413,209 ha burned annually in this region (San-Miguel-Ayanz et al., 2017) causing extensive economic and ecological losses, and even human casualties (Keeley et al., 2011; Molina-Terrén et al., 2019). Fire is a complex phenomenon due to the confluence of several factors including climate, weather, human activities and vegetation (Bowman et al., 2009). The Mediterranean fire regime is dominated by human-caused ignitions (Ganteaume et al., 2013) with most of the total burned area (BA) linked to a limited ~~small~~ number of large fires during the summer (Turco et al., 2016). These large fire events are facilitated by dry conditions and high temperatures, which are both expected to increase in the future under ~~the ongoing~~ climate change (Dupuy et al., 2020; Ruffault et al., 2020; Turco et al., 2018a). Additional factors such as landscape changes as well as changes in forest and fire management may also shape future fire activity (Moreira et al., 2020; Pausas and Fernández-Muñoz, 2012). Projecting future changes to fire activity requires modeling efforts across broad geographical scales to better understand processes and mechanisms conductive to fire ignition and spread. However, ~~However, there is still much uncertainty in the projected change of fire activity, and modeling efforts across broad geographical scales are needed to better understand processes and mechanisms conductive to fire ignition and spread.~~

o~~O~~ne of the main limitations in fire modeling lies in the lack of reliable and homogeneous~~armonized~~ information on fire activity across space (Hantson et al., 2016; Williams and Abatzoglou, 2016). This is particularly true in Europe where the lack of data sharing as well as the lack of consistent quality-control procedures of national ground-based fire datasets has hampered analysis of fire regimes across broader regional or continental scales (Mouillot and Field, 2005; Turco et al., 2016). To overcome this challenge, the European Forest Fire Information System (EFFIS; San-Miguel-Ayanz et al., 2015) is increasingly ~~relying on~~using remote-sensing ~~(RS)~~ techniques for monitoring fire ~~incidence~~ activity across Europe.

In the last decade, remote-sensing~~RS~~ has contributed to ~~'fill the gap of knowledge' fostering~~foster fire-related products with spatial and temporal consistency, and global coverage (Chuvieco et al., 2019; Mouillot et al., 2014). The MODIS sensor outstands as one of the best data provider for most burned area products~~applications~~ such as MCD64A1 (Giglio et al., 2018) and FireCCI50 (Chuvieco et al., 2018). In particular, the latest generation of BA ~~mapping~~ products, the MCD64A1v006, sets the basis for an exhaustive global estimation of fire-related carbon emissions, compiled in the GFED4 database (Giglio et al., 2013; Randerson et al., 2015; van der Werf et al., 2017). Although BA products typically offer information about the pixels that burned in a given day, they do not provide information such as starting/ending dates or final extent of individual fire events (Mouillot et al., 2014). This limitation has hampered distinguishing fire regimes dominated by different fire sizes as both small but frequent fires and large but rare fires may contribute equally to total burned area.

In this sense, global datasets of individual fires derived from pixel-level BA information have recently emerged as an important resource for the fire community, improving our understanding of fire regime (Andela et al., 2019b; Artés et al., 2019; Laurent et al., 2018a). Unlike raw BA products, remote-sensing ~~RS~~ datasets of individual fires provide information beyond the BA, such as~~like~~ fire shape, rate of spread and the number of fires (NF). The Fire Atlas (Andela et al., 2019a, 2019b), FRY (Laurent et al., 2018b, 2018a) and GlobFire (Artés et al., 2019; Artés Vivancos and San-Miguel-Ayanz, 2018) represent the most recent ~~RS~~ individualized fire datasets. These datasets were built from specific algorithms to reconstruct fire patches from MCD64A1 pixel-based BA. In spite of using different methodologies and different assumptions, these datasets shared a common objective: aggregate neighbouring burned pixels with sequential burn dates into individual fire patches.

Alt~~T~~hough very promising, remote-sensing ~~RS~~ datasets of individual fires have been sparingly compared to historical ground-based fire databases, that are generally thought to be- the most reliable source of data regarding fire occurrence and fire extent (Moreira et al., 2011; Mouillot et al., 2014). Previous studies indicated that rigorous evaluation of satellite ~~estimates~~ data with ground-based data is needed ~~to assess the reliability of the RS information at regional scale~~ (Turco et al., 2019). Most validation procedures of these remote-sensing ~~RS~~ datasets were based on comparisons between different satellite products (Andela et al., 2019b; Laurent et al., 2018a), with however scarce attention to independent ground-based observations (Artés et al., 2019). In this work, we compared for the first time the three most recent remote-sensing ~~RS~~ datasets of individual fires (Fire Atlas, FRY and GlobFire) with ~~high-quality~~quality-controlled fire databases compiled by regional agencies across the most active fire region in Europe (i.e. Southwestern Mediterranean basin) during the common period of observations (2005 to 2015). While most previous studies have evaluated remote-sensing data on a fire-by-fire basis, this study aggregates individual fires across months and pixels (0.25°) and seeks to estimate ~~how much~~to what extent the temporal variability in both fire frequency and burned area are captured by remote-sensing datasets. We sought to provide a solid answer to the following questions. (i) Are remote-sensing ~~RS~~ datasets capturing the actual pattern of fire occurrence and burned area? (ii) To what extent is their accuracy dependent on fire size? ~~(iii) Can we rely on~~ remote-sensing ~~RS datasets to analyze fire regimes?~~ To answer these questions, we ~~assessed both the spatial and temporal uncertainty~~ies ~~in respect to BA and NF of estimated~~ remote-sensing examined the agreement between remote-sensing and ground-based datasets~~RS~~ ~~BA and NF~~ aggregated at monthly and 0.25° resolutions across a range of individual fire size thresholds (1 to 500 ha). This study may inform end-users about remote-sensing datasets~~RS~~ ability to proxy actual fire activity but also on their limitations.~~, and provide guidance on the correct usage of global fire datasets~~~~RS information at regional scale.~~

2 Data and Methods

2.1 Ground-based fire data

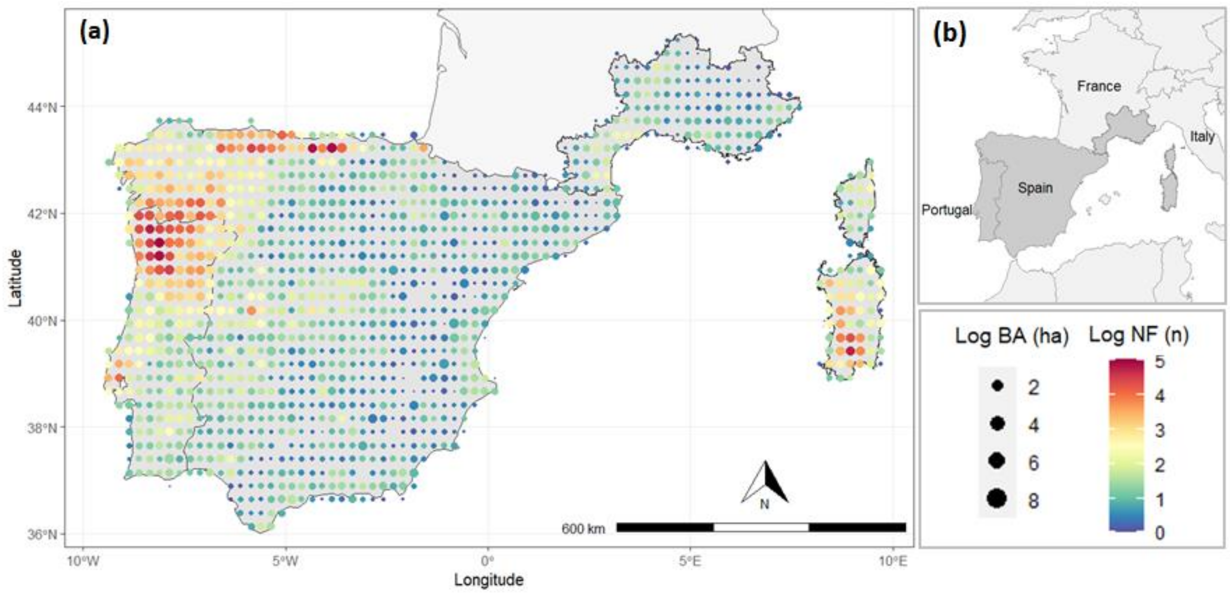
The ground-based dataset (GBD) was built from multiple fire agencies sources~~The ground-based dataset was built from multiple regional/national sources~~, including fire records from Portugal, Spain, France and Sardinia in Italy (Table 1). All these ground monitoring systems provide high-quality datasets that have been extensively used in previous studies across France (Curt et al., 2014), Portugal (Pereira et al., 2011), Sardinia (Salis et al., 2013) and the Mediterranean basin (Rodrigues et al., 2020; Turco et al., 2016). Although not free of errors, these datasets constitute the most accurate source of historical information about fires available across~~in~~ ~~Europe~~the region.

Table 1. ~~Description of~~ F~~regional f~~ire agencies and reference link to the data used to build the harmonized ground-based ~~database~~ dataset (GBD) across the Southwest Mediterranean basin.

Agency	Country	Coverage	Reference link

DECIF	Portugal	National	http://www2.icnf.pt/portal/florestas/dfci/relat/rel-if ~~http://www2.icnf.pt/portal/florestas/dfci/inc/estat-sgif~~ (last access: 10 January 2020)
EGIF	Spain	National	https://www.mapa.gob.es/va/desarrollo-rural/estadisticas/Incendios_default.aspx (last access: 18 December 2019)
Prométhée	France	Regional	https://www.promethee.com/ (last access: 16 December 2019)
Regione Sardegna	Italy	Regional	http://webgis2.regione.sardegna.it/download/ (last access: 22 January 2020)

~~A harmonized database was constructed from the aforementioned fire agencies (AG) datasets.~~ We extracted the following information from each regional datasets: the day of ignition, the fire size, and location of ~~the fire event~~each fire. To ensure consistency across regions and scales, we analyzed the overlapping recording period among the datasets, i.e., 2005–2015. Small fires (<1 ha) were discarded to ensure the coherence of the analysis since these were not reported systematically by agencies over the studied period. The harmonized dataset~~base~~ contained 95,561 fire records, including only events that required a firefighting response (i.e., disregarding agricultural and prescribed fires) (see Fig. 1).



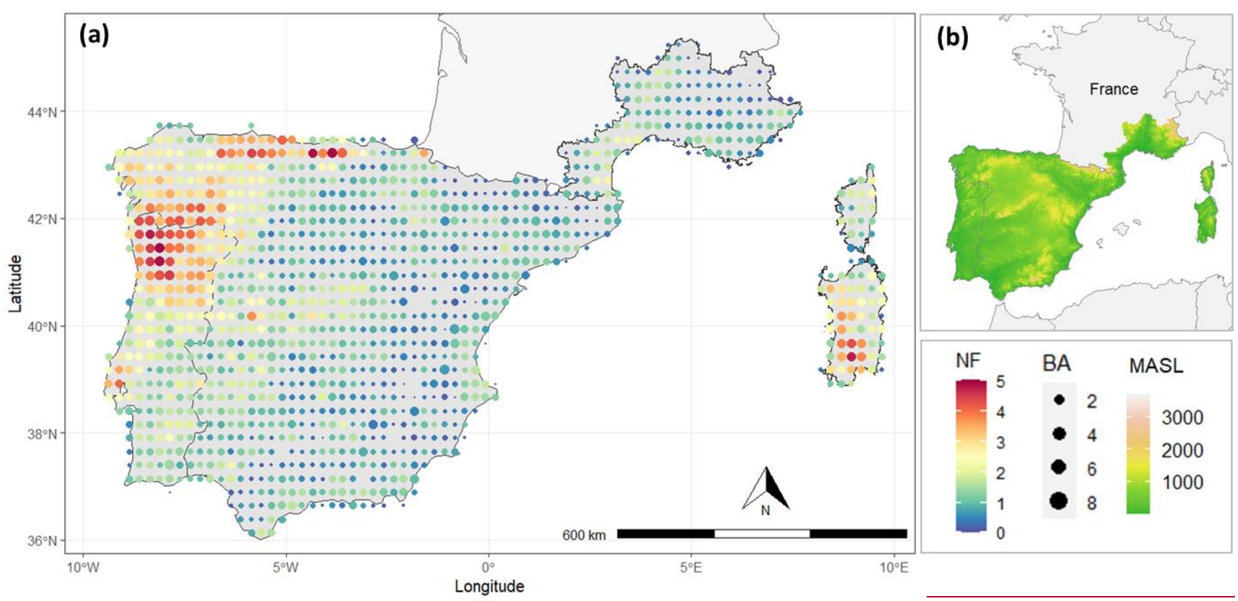


Figure 2. (a) Mean annual burned area (BA, depicted by circle size) and mean annual number of fires (NF, depicted by color) at 0.25° resolution over the study period (2005-2015). ~~Note the logarithmic scale.~~ (b) Spatial extent of the study area.~~Orography (in meters).~~

2.2 Remotely-sensed fire data

We used the most recent remote-sensing datasets (RSD) ~~datasets~~ of individual fires: Fire Atlas (Andela et al., 2019a, 2019b), FRY (Laurent et al., 2018a, 2018b) and GlobFire (Artés et al., 2019; Artés Vivancos and San-Miguel-Ayanz, 2018). These datasets provide the date and the spatial extent of individual fires from the pixel-based burned area MODIS product MCD64A1 Collection 6 (Table 2). The Terra and Aqua combined MCD64A1 is derived from the surface reflectance imagery and active fires observation. It provides a global coverage of burned area estimation at a resolution of 500 m (Giglio et al., 2018). Fires were individualized from~~The RS datasets of individual fires were derived using~~ different algorithms such as a progression-based algorithm (Andela et al., 2019), a flood-fill algorithm (Laurent et al., 2018), and data mining (Artés et al., 2019) that share a common objective: assemble burned pixels that were adjacent in both space and time to identify and outline individual fire events. All RSD~~ dataset ~~provide fire starting and ending dates, location and the final burned area for each retrieved fire event.

A key parameter of these algorithms is the cut-off value, which is defined as the maximum burn date difference allowed between two neighbouring pixels to be considered as belonging to the same fire event. This cut-off influences the size, shape and the degree of clumpiness and fragmentation of individual fire events (Laurent et al., 2018a; Oom et al., 2016). Fire Atlas used spatially varying cut-off thresholds (4 to 10 days) depending on the fire frequency (Andela et al., 2019b), while the FRY algorithm processed four different cut-off scenarios (3, 5, 9 and 14 days), used in previous studies (Archibald and Roy, 2009; Hantson et al., 2015; Nogueira et al., 2017). Finally, GlobFire defined a fire event as a set of burned pixels that are connected within a 5-day window and have not been burned over the 16 previous days (Artés et al., 2019). For simplicity, we only reported the FRY cut-off value that performed the best (5 days). The comparison with all FRY cut-off values is available in the Appendix A ~~Supplementary material ~~(Fig A~~S~~1).

Table 2. Description of the remote-sensing datasets ~~remote-sensing ~~(RSD) ~~datasets ~~of individual fires, including the digital object identifier (DOI) and reference of each dataset. FA: Fire Atlas; FRY_M05: FRY MODIS (5 days) and GF: GlobFire.

RSD ~~dataset~~	**Methodology**	**Cut-off values**	**Period**	**Dataset DOI**	**Reference**
FA	Progression-based algorithm	4 to 10 days	2003-2016	https://doi.org/10.3334/ORNLDAAC/1642	(Andela et al., 2019b, 2019a)
FRY_M05	Flood-fill algorithm	5 days	2000-2017	https://doi.org/10.15148/0e999ffc-e220-41ac-ac85-76e92ecd0320	(Laurent et al., 2018a, 2018b)
GF	Data mining	5 and 16 days	2000-2019	https://doi.org/10.1594/PANGAEA.895835	(Artés et al., 2019; Artés Vivancos and San-Miguel-Ayanz, 2018)

2.3 Methodology

We compared burned area (BA) and number of fires (NF) estimated by RSD~~ datasets of individual fires~~, with the ground-based reference GBD ~~reference ground-based dataset ~~(~~AG; ~~Fig. 2). Only the common period between RSD ~~datasets ~~and GBD records (2005–2015) has been considered ~~in the following (2005–2015).~~ We evaluated the ability of RSD~~ estimates~~ to reproduce the ~~observed~~ temporal and spatial patterns of fire activity observed in ~~AG~~GBD by fitting ordinary least squares (OLS) linear regressions and using different metrics (OLS slope, R-squared correlation, and bias) to measure RSD accuracy. We calculated the relative error (ε) as: ~~Only the common period between RS datasets and AG records has been considered in the following (2005–2015).~~

$$\varepsilon = 100 \times \frac{BA_{RSD} - BA_{AGD}}{BA_{AGD}} \qquad (1)$$

where, BA_{RSD} represents the ~~burned area (~~BA~~)~~ detected by remote-sensing datasets (RSD) and BA_{AGD} represents the ~~burned area~~BA registered in the fire agencies datasets (GBD) over the study period. The analysis was repeated for the number of fires (NF).

We applied a land cover filter to the RSD data using CORINE Land Cover (CLC) ~~2006 and 2012~~ to exclude fires located within agricultural or artificial lands that are not always reported by fire agencies. -To account for the land cover changes over the study period, we used CLC 2006 as a reference to filter RSD from the 2005-2009 period and CLC 2012 from 2010-2015. Sensitivity analysis to the land-cover filter is shown in the Appendix A (Fig. A2)~~Supplementary material (Fig S2)~~. As RSD ~~datasets~~ are prone to omit smaller fires (<25 ha) due to the coarse spatial resolution of MODIS product MCD64A1 (500 m) and other limitations, we investigated different fire size thresholds increasing from 1 to 500 ha. Analyses were repeated for each size-filtered sample (i.e. excluding fires smaller than a given threshold).

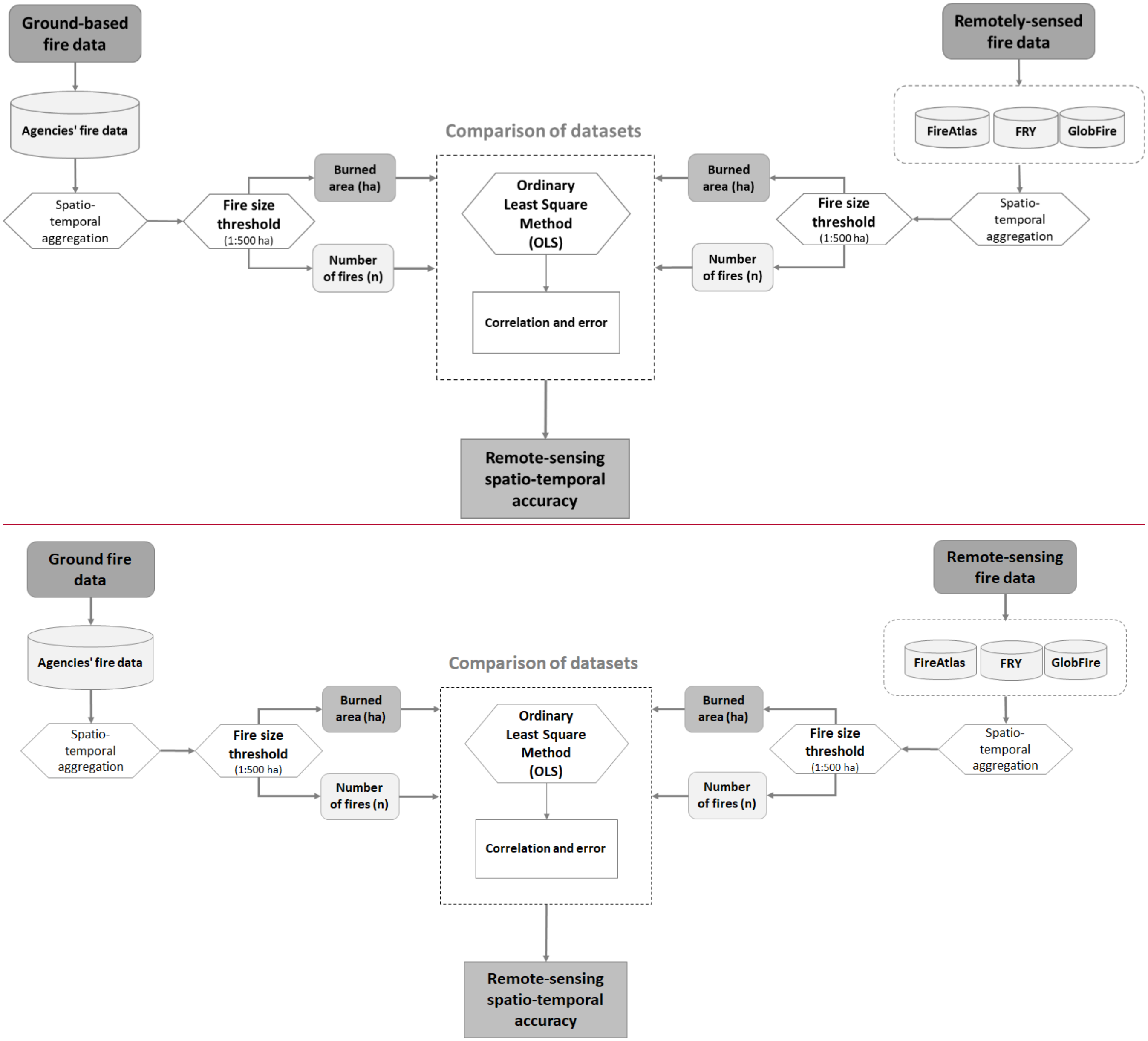


Figure 2. The general framework for comparison of RSD ~~estimated burned area and number of fires~~ with ~~AG~~GBD in terms of burned area (BA) and number of fires (NF) ~~ground-based observations~~ across a range of individual fire size thresholds (1 to 500 ha).

2.3.1 Temporal agreement

All datasets were aggregated to monthly scale over the whole study area. We retrieved the slope coefficient of OLS regressions and the coefficient of determination (R-squared) as a proxy of agreement between RSD and ~~AG~~GBD. Slope values greater than 1 indicated an underestimation of fire activity as seen by ~~AG~~GBD ~~datasets~~ and vice versa. A slope equal to 1 would imply a perfect agreement. ~~We also calculated the relative error (Eq. 1) over the study period. We also calculated the relative error (ε) as:~~

$$\cancel{\varepsilon = 100 \times \frac{RS-AG}{AG} \qquad (1)}$$

~~where, *RS* is the total BA or NF detected by remote-sensing datasets and *AG* is the BA or NF reported by the agencies over the study period.~~

2.3.2 Spatial agreement

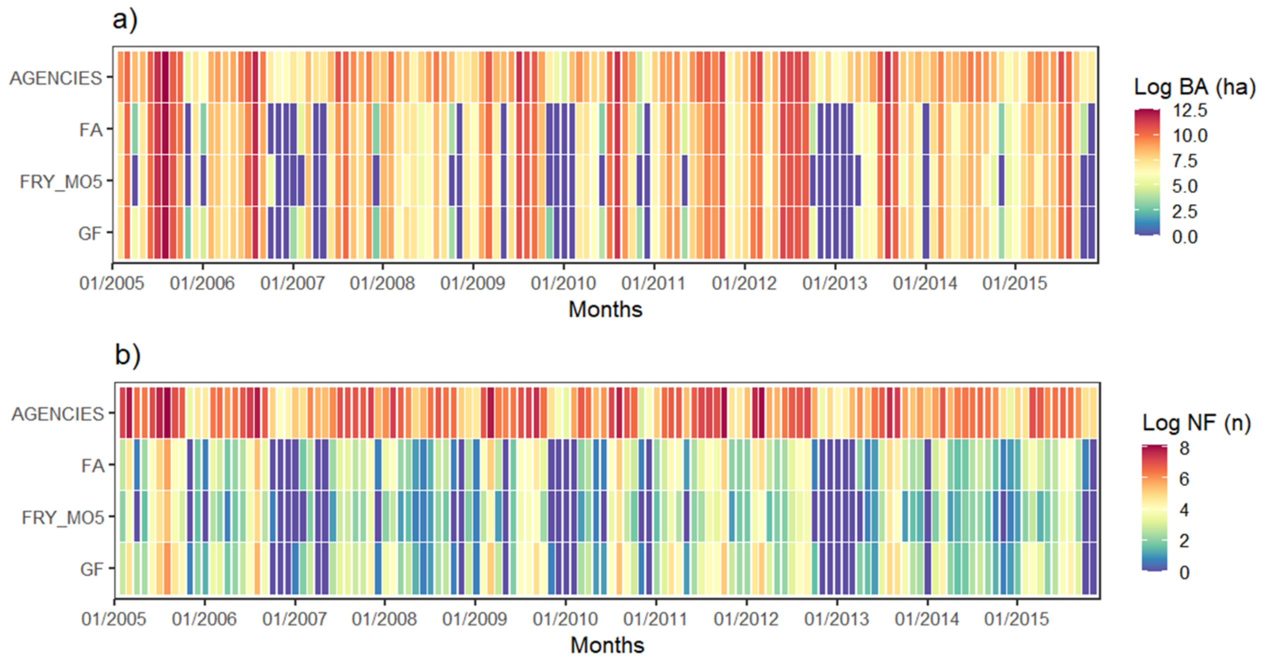
We then sought to examine how the agreement between RSD and GBD datasets varies across space. There is much uncertainty in estimating the ignition point from satellite data, mainly due to the spatial and temporal proximity of fire pixels and the possibility of multiple ignition points in a single fire event (Benali et al., 2016). Likewise, ~~AG~~GBD ~~databases~~ do not provide systematically ignition points. Thus, to overcome this limitation, we aggregated both RSD and ~~AG~~GBD ~~datasets~~ onto a 0.25° grid (≈ 25 km), setting a common ground for both datasets.

To examine the spatial agreement between RSD and ~~AG~~GBD, we calculated the relative error (Eq. 1) for each grid cell. Finally, we estimated the overall spatial error, computed as the ε averaged across all grid cells for each dataset.

3 Results

3.1 Temporal agreement

We first analyzed the monthly distributions of ~~RS and AG~~BA and NF ~~observations~~ for all fires (>1 ha) aggregated across the whole studied area. Fig. 3 shows that RSD ~~estimates~~ follow a similar variability in terms of monthly BA but systematically underestimate BA and~~the~~ NF with respect to ~~AG~~GBD. The best agreement between RSD ~~estimates~~ and ~~AG~~GBD occurs mainly during the warm season (May to October; see Fig. 4). This is usually the period experiencing the largest fires, which account for the bulk of BA in the region (Turco et al., 2016). Conversely, the poorest agreement was found during the cool season (November to April), a period dominated mainly by small fires linked to agricultural activities.



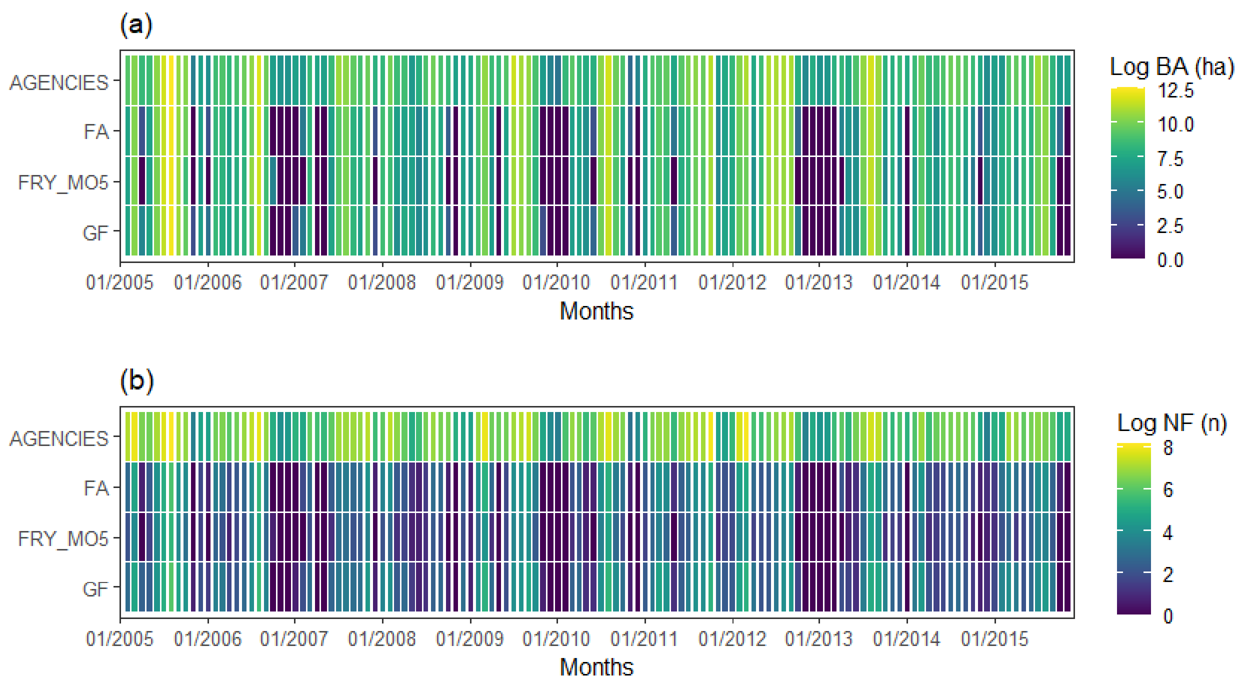
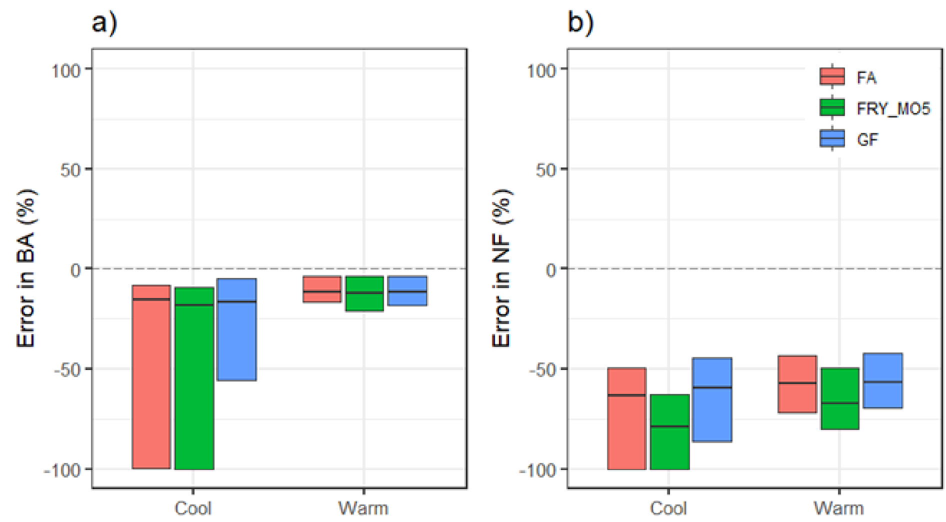


Figure 3. (a) Monthly burned area and (b) number of fires (>1 ha) in each fire dataset across the Southwest Mediterranean basin over 2005-2015.



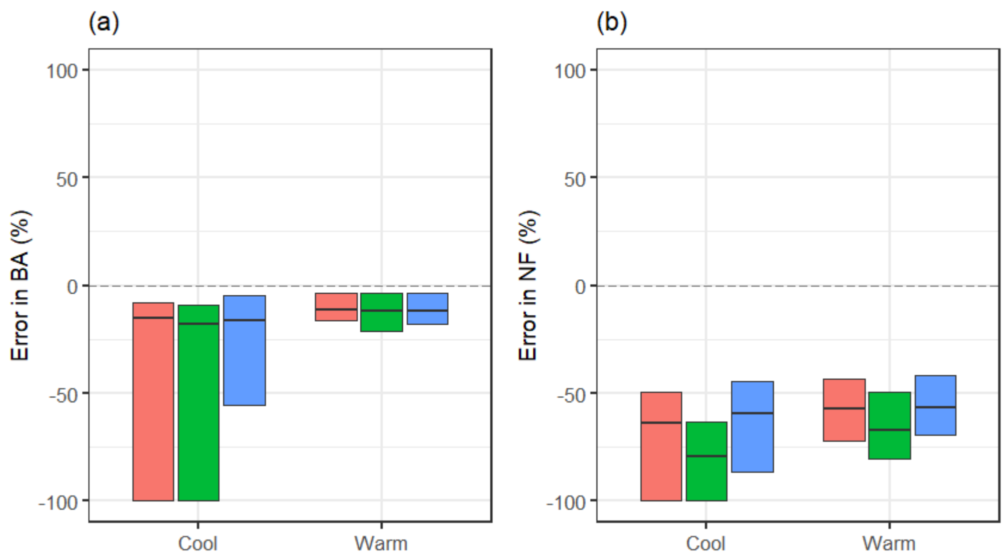


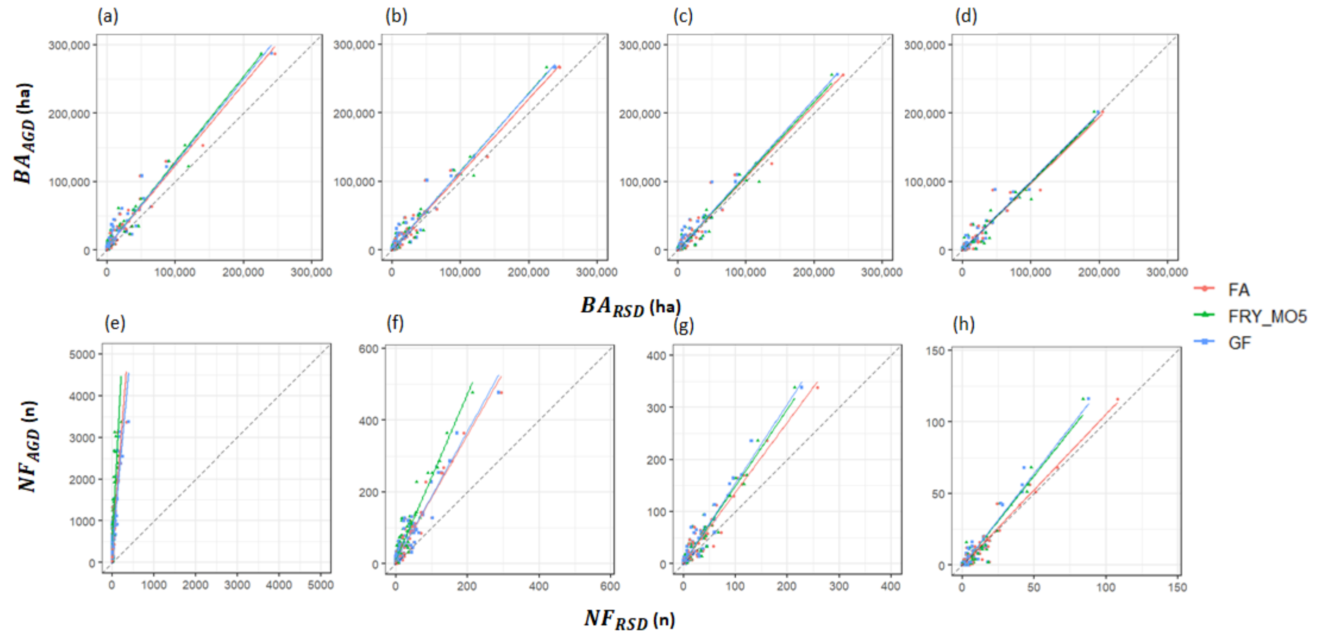
Figure 4. (a) Median and inter-quartile range of the seasonal error (ε) observed each year ~~Seasonal monthly error (ε)~~ for burned area and (b) number of fires estimates of each RSD ~~dataset~~ for all fires >1 ha in the studied area. Cool season from November to April and warm season from May to October. Dashed lines represent the perfect agreement between the datasets.

Table 3 presents the total BA and NF as well as monthly (i.e. including the seasonal cycle) and annual correlation (i.e. excluding the seasonal cycle) between RSD and GBD for all fires (>1 ha). Monthly correlations showed a stronger agreement for BA ($R^2 \approx 0.98$) than for NF ($R^2 \approx 0.89$). Annual correlations, where the effect of the seasonal cycle was removed, also showed very high values ($R^2 \approx 0.99$). Despite the fact that RSD underestimated the total BA by 38% and the NF by 96% for all fires, they reproduced almost perfectly the temporal variability on both monthly and annual basis. The difference in absolute numbers thus relates to undetected small fires in RSD ~~datasets~~.

Table 3. C~~Temporal c~~orrelation between RSD and GBD of monthly and annual burned area and number of fires ~~between RS and AG datasets~~ for all fires (>1 ha) between 2005 and 2015~~ across the study domain~~.

Dataset	**Burned area**			**Number of fires**		
	Total (ha)	Mo. correlation	Yr. correlation	Total (n)	Mo. correlation	Yr. correlation
AGENCIES	2,527,603	-	-	95,561	-	-
FA	1,609,267	0.99	0.99	3,875	0.90	0.99
FRY_M05	1,524,171	0.99	0.99	2,134	0.88	0.99
GF	1,562,001	0.98	0.99	4,637	0.90	0.99

The monthly agreement of BA and NF (Fig. 5) strongly varies with fire size thresholds (1, 50, 100 and 500 ha). The positive slope of the linear trends indicates that RSD generally underestimate both BA and NF when accounting for all fires (> 1 ha). However, they become progressively more accurate as the fire size threshold increases, a feature that is particularly evident in NF estimates (Fig. 5 e-h).



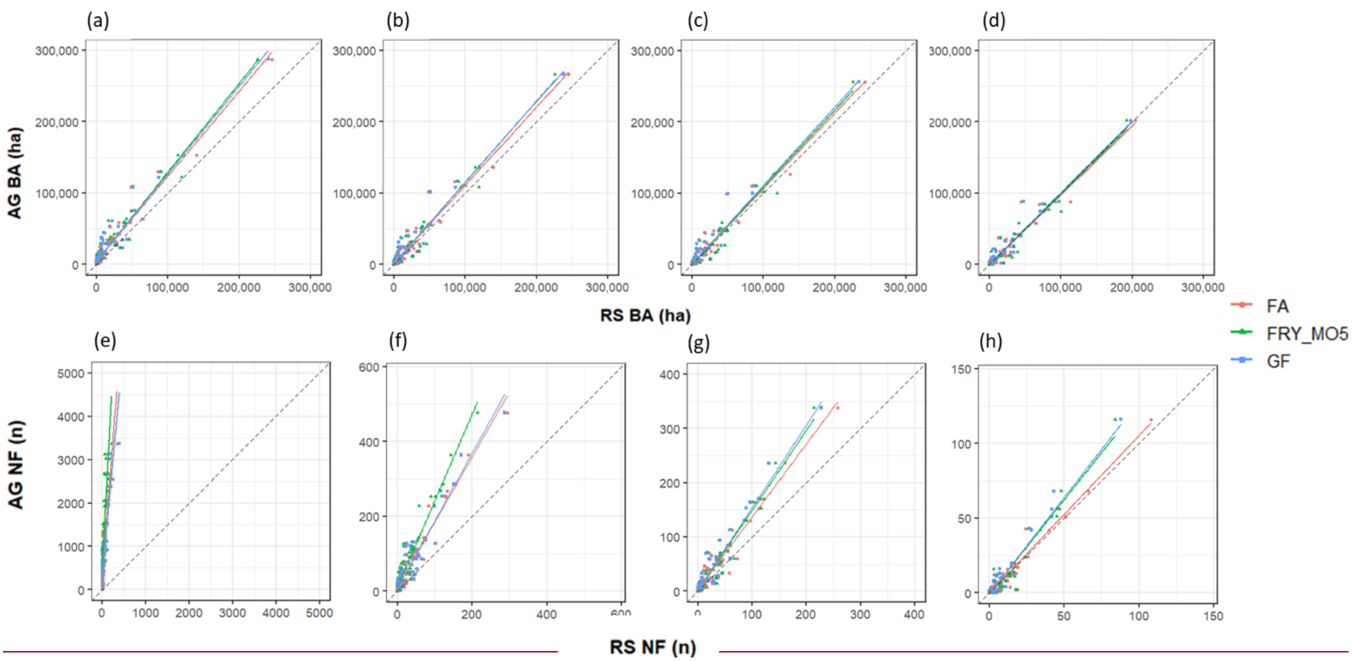
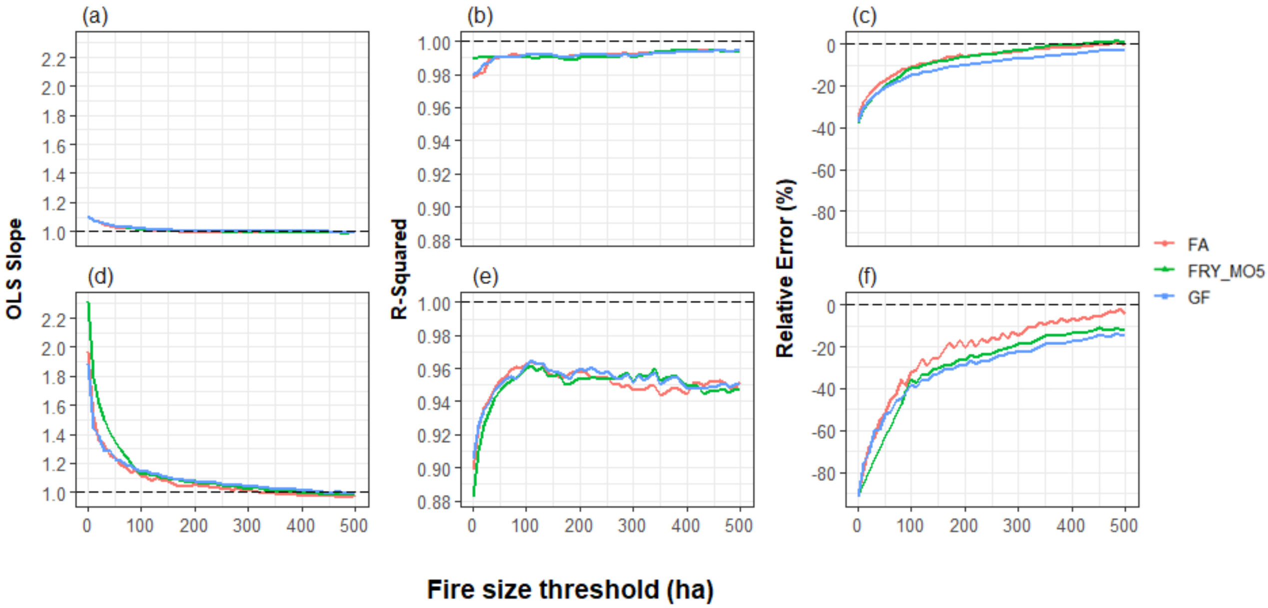


Figure 5. Comparison of ~~AG~~GBD and RSD in respect to monthly burned area (top) and the number of fires (bottom) when considering a) all fires (> 1 ha), b) fires >50 ha, fires >100 ha and d) fires >500 ha. (e-h) Same as a-d) but for the number of fires. The 1:1 dashed lines represent the perfect fit between the datasets.

Fig. 6 shows the evaluation of RSD~~ datasets~~ through different metrics over the continuum of fire size thresholds. Except for the R-Squared (Fig. 6, middle) which saturates for fires >100 ha for NF, all metrics present a similar behavior showing better agreement when increasing the fire size threshold. ~~Generally~~Overall, BA (Fig. 6, top) presented better accuracy than NF (Fig. 6, bottom). Despite the different methodologies used to reconstruct individual fires, all datasets showed~~followed~~ similar scores, albeit FA displayed lower relative error (ε) for NF.



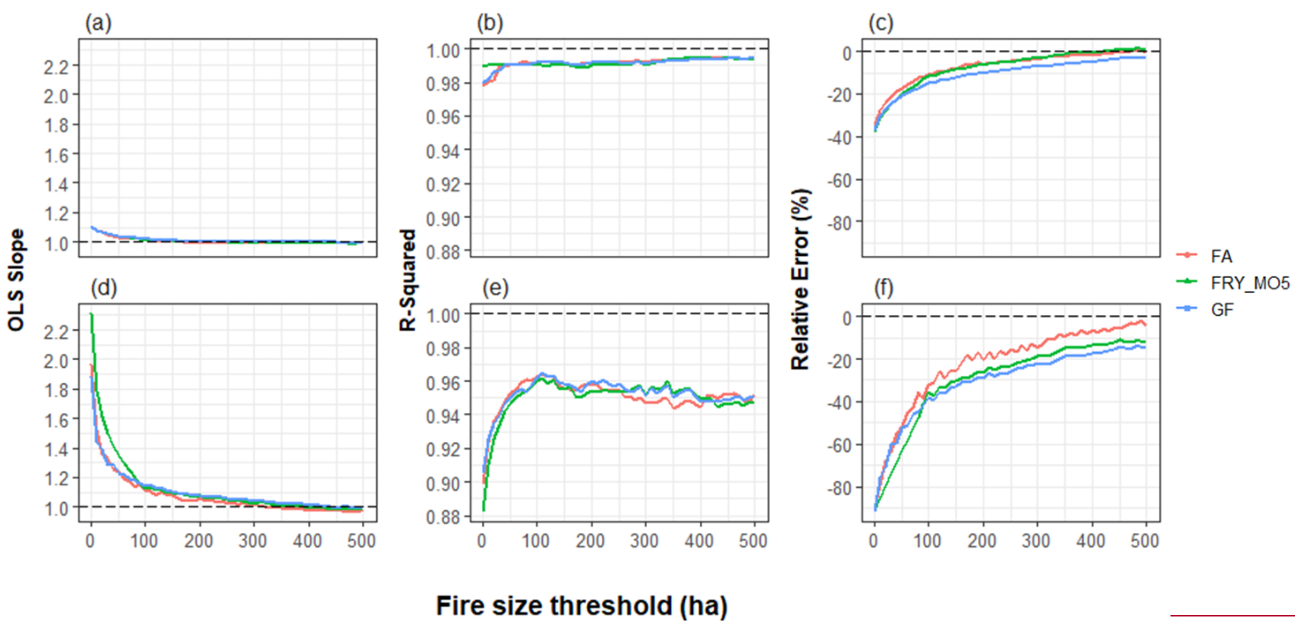
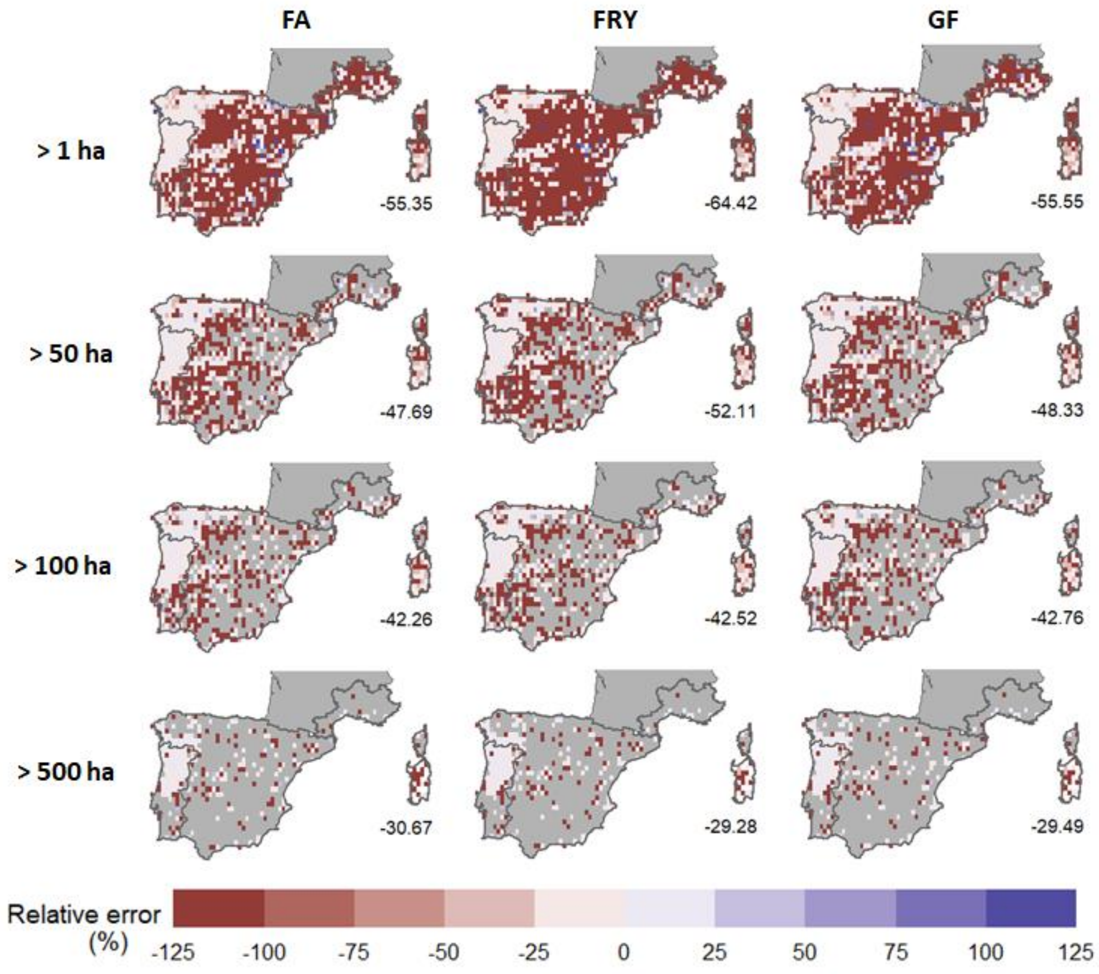


Figure 6. Evaluation of RSD~~ datasets~~ through different metrics including the slope (left), R-squared correlation (middle) and relative error (right) for both burned area (top) and the number of fires (bottom) over a range of individual fire size thresholds (1 to 500 ha). Dashed lines indicate a perfect fit between RS and AG fire data.

3.2 Spatial agreement

Fig. 7 shows the spatial distribution of the relative error (ε) for BA over different individual fire size thresholds (for all fire size thresholds see Supplementary material~~Data~~). As expected from previous results, RSD~~ datasets~~ strongly underestimated BA, especially when including smaller fires. However, a few exceptions are seen for fires < 50 ha mainly over eastern Spain, suggesting that RSD detect in that case more fires than ~~AG~~GBD. This may be related to a few and small prescribed fires that we~~a~~re not reported in ~~AG~~GBD. Also, we found much lower ε ~~relative errors~~ in regions with higher fire activity, such as the Northern Iberian Peninsula. This is rather expected, as an absolute change in regions with high (low) baseline will result into a small (large) percentage change.


FA
FRY
GF
> 1 ha
-55.35
-64.42
-55.55
> 50 ha
-47.69
-52.11
-48.33
> 100 ha
-42.26
-42.52
-42.76
> 500 ha
-30.67
-29.28
-29.49
Relative error (%)
-125
-100
-75
-50
-25
0
25
50
75
100
125

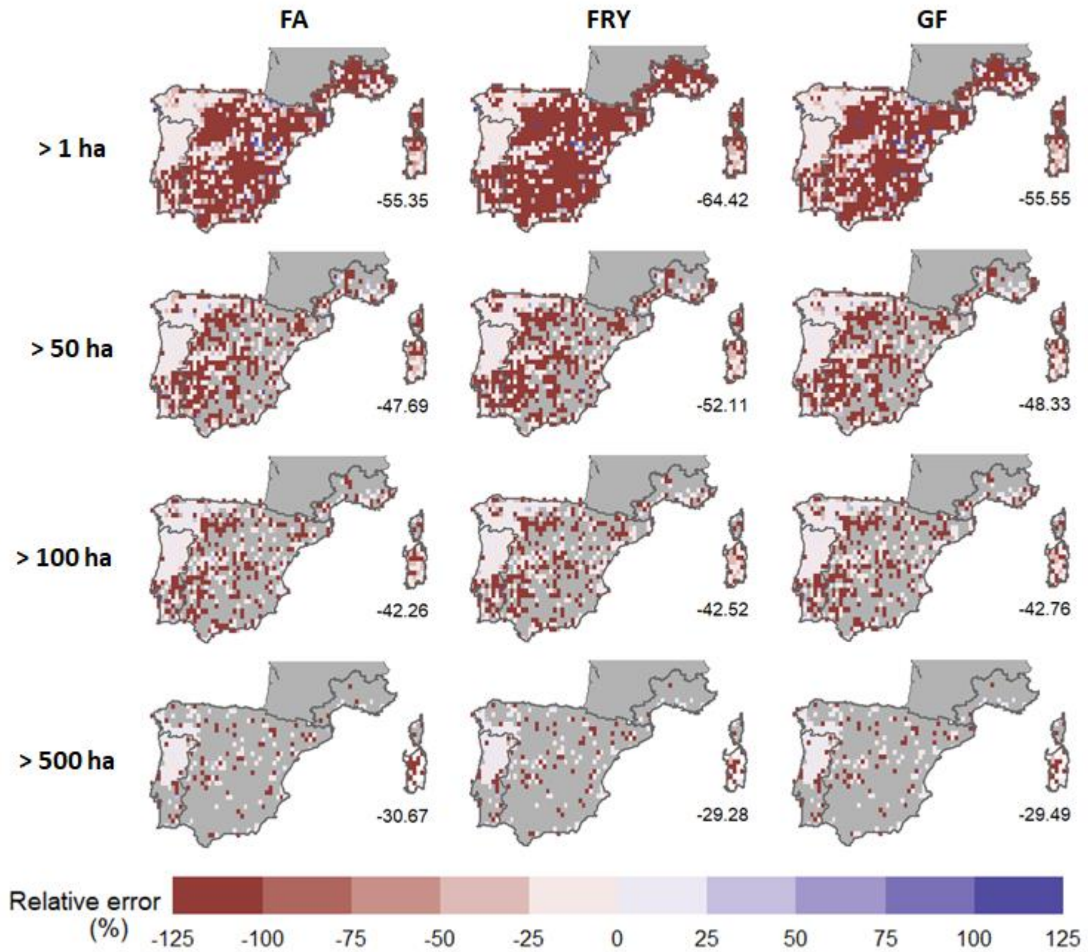
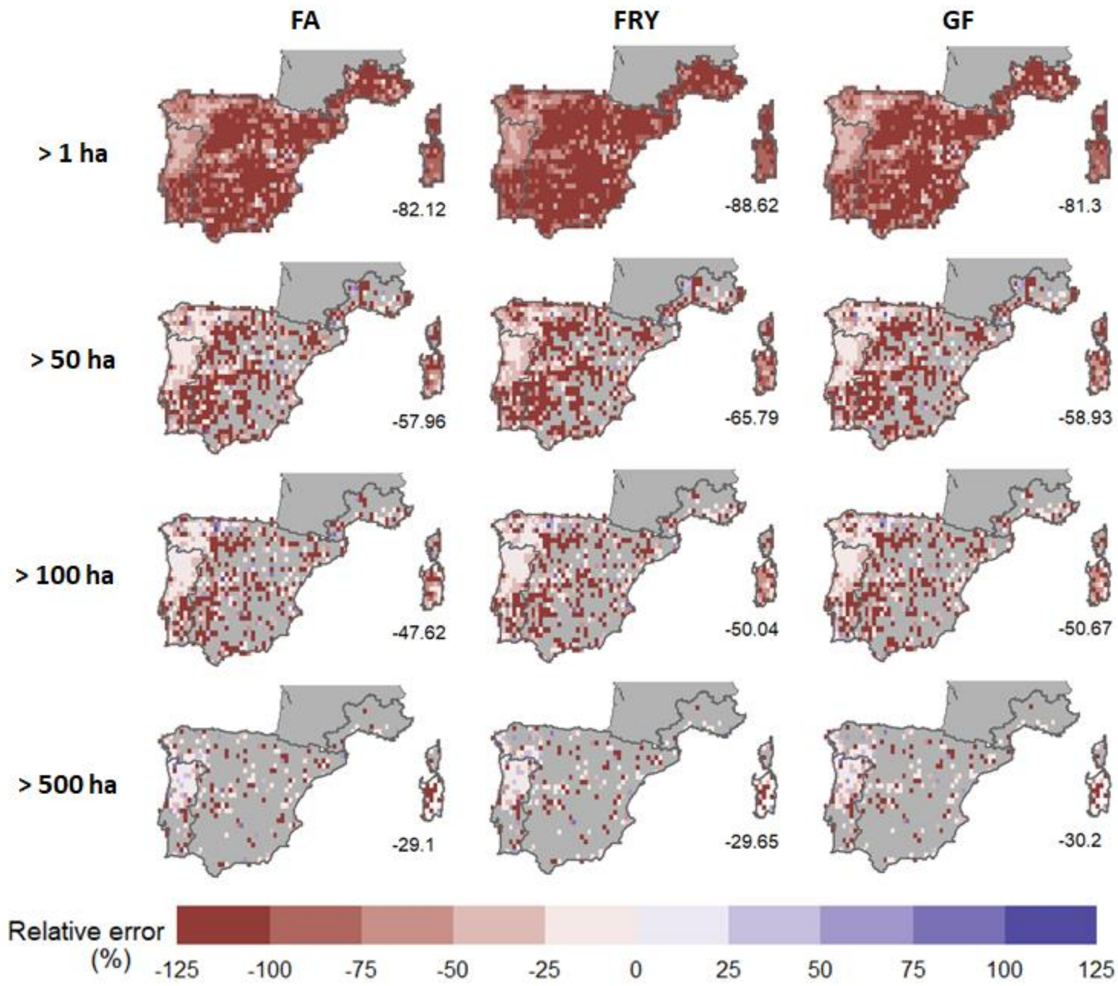


Figure 7. The relative error (ε) of the total burned area computed as the relative difference between RSD and ~~AG~~GBD data over different individual fire size thresholds (1, 50, 100 and 500 ha). The overall ε is indicated on each map.

Likewise, RSD strongly underestimated NF (Fig. 8), likely disregarding those smaller fires not detected by MODIS. Surprisingly, a few areas showed positive differences in NF for fires >100 ha across parts of Spain. This overestimation of large fires may be related to the fact that RSD algorithms are likely to split larger fires into multiple events. Nevertheless, the overall relative error between RSD and ~~AG~~GBD decreases when focussing on larger fires for both NF and BA, highlighting the important role of fire size on RSD accuracy.


FA
FRY
GF
> 1 ha
> 50 ha
> 100 ha
> 500 ha
-82.12
-88.62
-81.3
-57.96
-65.79
-58.93
-47.62
-50.04
-50.67
-29.1
-29.65
-30.2
Relative error (%)
-125
-100
-75
-50
-25
0
25
50
75
100
125

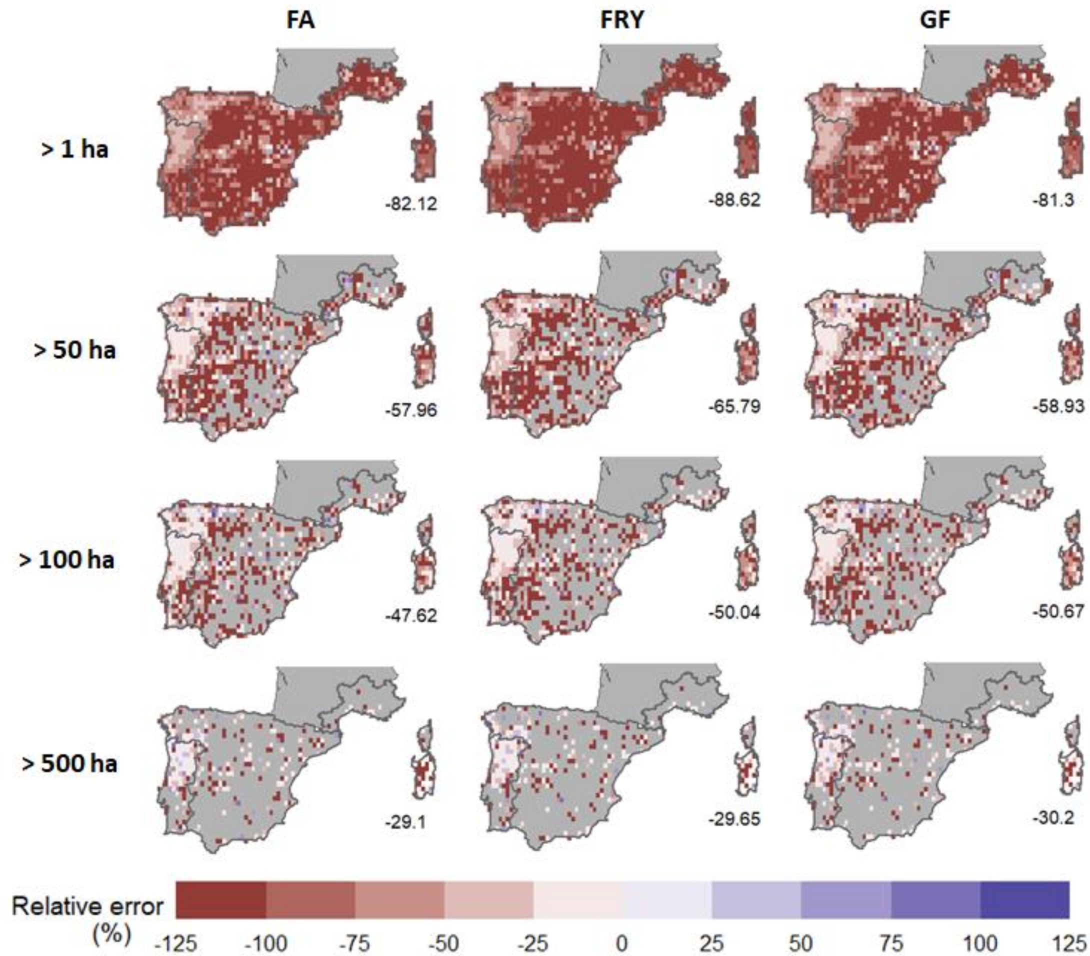


Figure 8. Same as Fig. 7 but for ~~NF~~number of fires.

4 Discussion

U~~The necessity to properly u~~nderstanding global changes in fire activity calls for efficient and harmonized approaches to record fire activity~~incidence~~. Satellite-borne spectral and thermal sensors offer several global fire products, evolving from BA mapping and active fire detection to novel developments post-processing BA products into single fire datasets (Chuvieco et al., 2019). The ongoing challenge lies in determining their reliability and usefulness. Here, we compared RSD with ~~ground-based datasets~~GBD across the Southwestern Mediterranean basin to better understand RSD~~ datasets~~ limitations and guide end-users.

Although RSD may miss a substantial number of fires, the temporal variations in both NF and BA match very well with ground-based observations. Our results also demonstrate that agreement between RSD and GBD is strongly dependent on individual fire size.~~individual fire size plays a major role in the fire detection from RS.~~ Focusing on larger fires (fire typically

> 100 ha), RSD~~ datasets~~ were in~~ a~~ stronger agreement with ~~AG~~GBD regardless of the evaluated metrics. Fires > 100 ha denoted much lower error (BA 10%; NF 35%), especially in regions~~.~~ ~~Likewise, larger fires denoted higher spatial coherence. As expected, the error was lower in areas~~ with higher fire activity such as the northwest of the Iberian Peninsula or the south of Sardinia~~ (Fig.7- Fig.8)~~. Our findings are in agreement with previous studies, which pointed at fire size as the primary limiting factor for remotely-sensed fire data ~~RS estimates~~ (Campagnolo et al., 2021; Rodrigues et al., 2019; Ying et al., 2019; Zhu et al., 2017).

The ability of RSD ~~-datasets~~ to identify individual fires depends mainly on two features: the processing algorithm and the underlying reliability of the BA product. The relatively low capacity of the latter to detect small fires is related to the coarse spatial resolution (500 m) of the MODIS sensor. Several recent studies have shown that MODIS products rather reliably detect fires over 40–120 ha but miss a number of smaller fires (Fusco et al., 2019; Giglio et al., 2018; Rodrigues et al., 2019; Zhu et al., 2017). Although other BA products, such as FireCCI50 (Chuvieco et al., 2018), provide finer spatial resolution (250 m), a substantial number of small and/or highly fragmented fires remain undetected, leading to a considerable underestimation of BA (Roteta et al., 2019). In addition, all space-borne BA products face many other well-documented limitations such as the variability in orbital coverage, satellite overpass time, and satellite view obstruction (Cardoso et al., 2005; Padilla et al., 2014). In this sense, detectability may vary regionally across the globe and without ground-based fire datasets, it may be difficult to properly validate their reliability (Turco et al., 2019). Nonetheless, the limitations of MCD64A1 are inherent to all RSD~~ dataset~~, since all of the analyzed products were built on this basis. Hence, differences among RSD~~ datasets~~ are rather expected to be associated with the underlying algorithm used to identify single fire events.

RSD~~ datasets~~ were found to better ~~simulate~~ estimate BA than NF. This disparity relies on the complexity of extracting individual fires from gridded BA products. Environmental conditions (e.g. topography, cloud/smoke cover) may influence the sensor detection power, resulting in a break in BA continuity thereby increasing the risk of artificially splitting single fires into different fire events.~~, including factors that may influence the sensor detection power, resulting in a break in BA continuity thereby increasing the risk of artificially splitting single fires into different fire events.~~ Likewise, if a fire lasts longer than the defined cut-off window, it will be automatically split into different events (Oom et al., 2016). In addition, if multiple fires occur simultaneously in the same region, the parameterization of the RSD algorithms may merge multiple individual fires (Archibald et al., 2013). Lastly, regional features of the fire regime may constrain RSD accuracy. For instance, the Mediterranean fire regime is known for hosting numerous small fires, which are unlikely to be detected by satellite observations~~RS~~ (Turco et al., 2016). These fires do not contribute very much to the total annual burned area but significantly harm the performance of the RSD~~ datasets~~ in terms of NF~~ (Turco et al., 2016)~~.

The selection of an appropriate fire size threshold depends on the objectives of each analysis. However, in this study~~Even though the selection of an appropriate fire size threshold depends on the objectives of each analysis~~, we can generally recommend a minimum size of 100 ha, which outstands as a change point in multiple statistics (Fig.6 to Fig.8), with the relative error sharply (dowdily) decreasing in both BA and NF above this threshold. Among the analyzed RSD~~ datasets~~, FA displayed a slightly better performance, with a lower relative error. This may arise~~s~~ from the use of a spatially explicit cut-off threshold, taking both fire spread rate and satellite coverage into account to track the extent of individual fires (Andela et al., 2019b). However, uncertainty in MODIS largely outpaces the uncertainties across the RSD~~ datasets~~. The low capacity of gridded BA products to detect small-mid fire events (< 100 ha) can be improved by the generation of products based on higher resolution sensors in the range of 10–30m (Roteta et al., 2019). RSD of individual fires derived from finer gridded BA would provide better accuracy in the fire metrics, specifically for NF. In addition, the MCD64A1 product already incorporates the uncertainty of detection as an auxiliary variable of gridded BA data (Giglio et al., 2018). RSD could benefit from this and report similar information at individual fire level.

The spatio-temporal aggregation applied in our study is expected to increase the signal-to-noise ratio and thus decrease the uncertainty in RSD estimates. According to Turco (2019), the spatial agreement between remotely-sensed and ground based fire data ~~AG and RS~~ increases at lower resolutions, being generally best when aggregating the data onto a 1° grid (approximately 110 km) or beyond. Likewise, aggregating the data over time (either monthly or annually) also increases the signal-to-noise ratio by filtering out the temporal stochastic noise (Spadavecchia and Williams, 2009). Evaluating RSD~~ datasets~~ on shorter timescales and/or finer spatial resolutions would likely deteriorate the agreement with ~~AG~~GBD. Nevertheless, the~~a~~ spatio-temporal aggregation, such as the one employed here, has been extensively used in previous studies analyzing fire regimes at regional (Barbero et al., 2014; Jiménez-Ruano et al., 2020; Parisien et al., 2014) and global scales (Bedia et al., 2015; Di Giuseppe et al., 2016; Turco et al., 2018b).

Further studies are still needed to examine RSD spatio-temporal variability~~estimates~~ at the fire patch level (i.e. assign individual fires from RSD to ~~AG~~GBD) in order to more precisely quantify ~~RS~~ the dataset accuracy at the fire scale.

5 Data availability

The above described fire datasets, their characteristics and reference to access the data can be found in Tables 1 and 2. All these fire datasets are open access except one of the ground-based datasets (EGIF) that is available upon request. The different data producers host the data in different ways, typically using websites or data repositories. The harmonized ~~AG~~GBD~~ database~~ used here as ground-based reference is available at https://doi.org/10.5281/zenodo.3905040 (Galizia et al., 2020).

6 Conclusion

In this work, we built upon previous research and investigated the reliability of three RSD~~ datasets~~ of individual fires over a range of fire size thresholds across the Southwestern Mediterranean basin. Overall, RSD contain only a small fraction of the total number of fires documented by GBD. However, they ~~RS datasets were able to~~ capture reasonably well the temporal variability of ~~and spatial patterns of~~ fire activity across monthly and annual scales. ~~, with however limited ability to outline small-to-mid fire events.~~ Despite the different methodologies used to reconstruct fire patches, all ~~datasets~~ RSD ~~(FA, FRY and~~

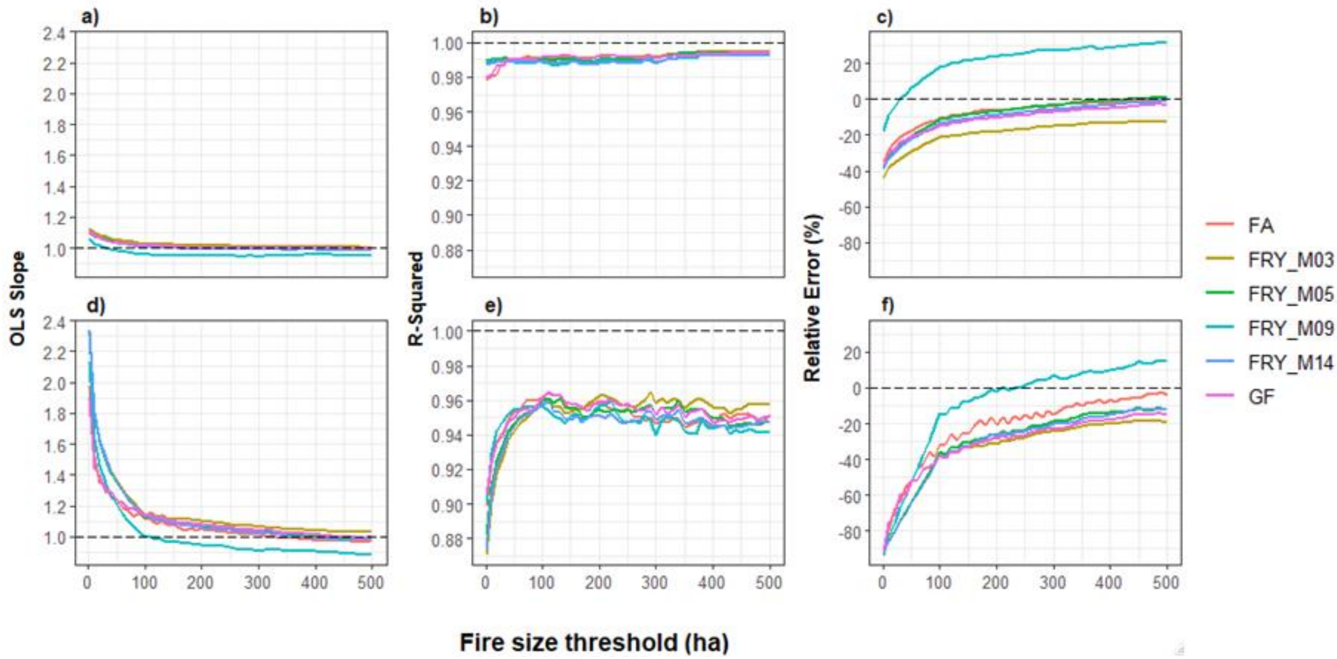
~~GlobFire)~~ performed similarly and were increasingly accurate when focusing on larger fires. Specifically, when considering fires > 100 ha, RSD denoted reasonable agreement with ~~observed~~ ~~AG~~GBD ~~data~~.

Generally, the RSD underestimation of BA and NF for smaller fires is related to the coarse spatial resolution (500 m) of the pixel-based BA product and other observation limitations, preventing the detection of small fires. ~~Fire size distribution presented as a fundamental driver of accuracy, and should be included in the assessment of RSD.~~ Features of fire regime at regional scales may also influence the ~~RS~~ accuracy (e.g. fire ~~size~~duration, density, and spread rate). In this sense, our analysis was framed in the Mediterranean region to capture homogeneous conditions in terms of fire regimes, even though local signals do exist.

We found a better agreement during the warm season (May to October), the main fire season in Southern Europe, especially in regions with higher fire activity (Northern Iberian Peninsula and Southern Sardinia). Also, RSD were found to better estimate BA than NF. This is rather expected as numerous small fires, which are not detected by satellites, do not contribute very much to the total burned area across the study region.

In practical applications, ~~O~~our results may provide guidance for end-users. A quantitative estimate of uncertainty is crucial to the correct interpretation of RSD ~~datasets~~ and users should take into account their limitations~~.~~ Our findings suggested that global RSD ~~datasets~~ of individual fires can be used ~~for fire~~ to proxy variations in fire activity on monthly or annual timescales~~analyze fire regimes~~~~modeling~~, however caution is advised when drawing from smaller fires (< 100 ha) across the Mediterranean region. Fire agencies may also benefit from the spatial and temporal consistency of remotely sensed data to support their operational fire mapping system at regional/national level. Future studies using high-quality ground-based fire data in other regions of the world featuring different fire regimes would provide further insights on RSD uncertainties.

7 Appendix A



460 **Figure A1**. Evaluation of RSD including all FRY cut-off values (3 to 14 days) through different metrics including the slope (left), R-squared correlation (middle) and relative error (right) for both burned area (top) and the number of fires (bottom) over a range of individual fire size thresholds (1 to 500 ha). Dashed lines indicate a perfect fit between RSD and GBD.

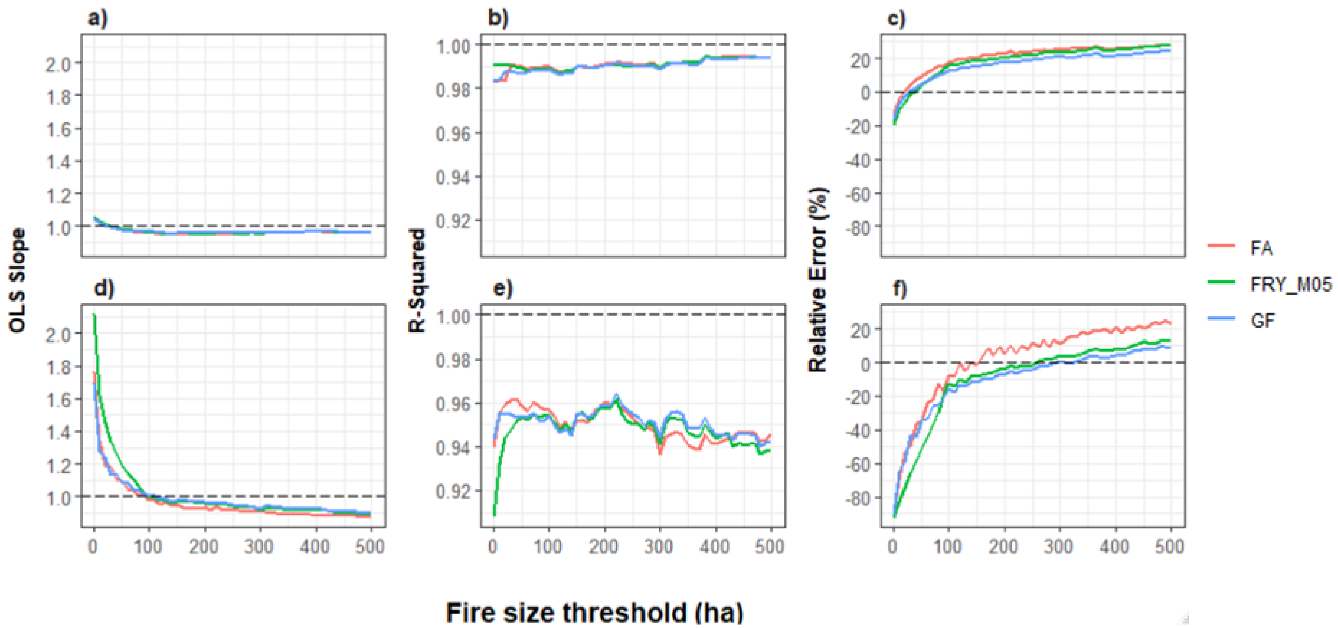


Figure A2. Evaluation of "raw" RSD (i.e. without the land cover filter) through different metrics including the slope (left), R-squared correlation (middle) and relative error (right) for both burned area (top) and the number of fires (bottom) over a range of individual fire size thresholds (1 to 500 ha). Dashed lines indicate a perfect fit between RSD and GBD.

Author contributions. LG carried out the analysis. All authors contributed to the design of the methodology, to discuss the results and to writing the paper.

Competing interests. The authors declare that they have no conflict of interest.

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