Dear Dr Chaparro,
We want to thank you for your thorough proofreading and your relevant comments. We took them into account and believe the manuscript has been substantially improved thanks to your suggestions.
The major modification was the addition of the land covers "shrublands", "croplands", and "natural vegetation mosaic" to our study. The maximum threshold on the seasonal water fraction has also been increased from 10% to 20%. The exclusion of regions subject to seasonal fires and of Australia was better justified. The suggested references have been included. Other minor changes were made according to your suggestions, in order to improve the clarity of the text.
Please find below in blue font a detailed description of how we addressed your comments.
Sincerely,
Emma Bousquet et al.

Review of the manuscript "SMOS L-VOD shows that post-fire recovery of dense vegetation is slower than what is depicted with X- and C-VOD and optical indices"

This paper studies the time evolution of several climate and vegetation variables before (triggering factors) and after (recovery of vegetation) fire occurrences worldwide. The study is divided in two parts. The first part details fire episodes in the Amazon, California and Australia. The second part extends the research to a global scale. The authors confirm the capacity of different Earth observation sensors to capture drought situations leading to fire ignitions, and nicely show how vegetation recovery can be monitored with microwave and optical-infrared data. Importantly, they demonstrate which VOD frequencies are appropriate for monitoring vegetation recovery after fires in different land cover types. The main finding is that L-VOD, which is more related to tropical biomass, shows delayed recovery if compared to higher VOD frequencies and optical-infrared indices in this forest type.

The paper is well written and, as explained above, the findings are sounding. However, I have some major concerns that must be addressed before being accepted for publication. The most important one refers to the completeness of the fires database. Both major and minor comments are detailed hereafter.

Major comments

1. Figure 4 shows the fires studied in this work during a nine-years study period (July 2012– December 2020). The authors explain that "the considered fires are well spread spatially […]." However, the map of fires is certainly omitting a large amount of wildfire episodes worldwide and, most importantly, it scarcely includes fire episodes for all relevant fire-prone regions. Probably the most relevant cases in that sense are the Sahel and the Mediterranean, where a large number of wildfires occur within the land cover types under study (grasslands, savannahs…), according to the monthly maps of the product applied. It is likely that, in part, these regions are not well represented in the study because it does not include shrubland covers. This land cover type should be included as well in this research. Hence, please ensure completeness for all fire-prone regions, especially the Mediterranean and the Sahel, and all land cover types (shrublands are lacking). With this, large and continuous fire occurrence patches (similar to those in the Russian and North American grasslands and forests) should be observed in the northern Mediterranean (especially southern Italy, the Iberian Peninsula and Greece), and in the Sahel.

The reviewer is right, we omitted the land cover class "shrublands" to focus only on five biomes to lighten the observations and not to disperse our efforts. Nevertheless, taking into account the referee's comments, we decided to add this land cover (IGBP labels 6 and 7) to the biome "tropical and subtropical savannas" (IGBP labels 8 and 9). We also added the land covers "croplands" (IGBP label 12) and "natural vegetation mosaic" (IGBP label 14) to the biome "grasslands" (IGBP label 10). Figure 4 of the manuscript was replaced by the resulting Fig. R1 below.
Despite this modification, the number of points is still low in the Sahel, because of the selection method described at lines 280-282 : "*Fires with a number larger than 5 in the MODIS dataset were considered, and only if no other fire occurred on the same area (number lower than 2 apart from the main fire event). This was done to observe only the impact of the major fires, without any other disturbance.*" In the Sahel, these

conditions are not fulfilled because many fires occur each year, and the second threshold is exceeded. An example is shown in Fig. R2.

The above paragraph was replaced by : “*To properly observe the factors and impacts of a fire event without any other disturbance, only 25 km regions showing a unique and heavy fire over the time period were considered. This excluded areas with regular seasonal fires, such as the Sahel region. For that, a minimum threshold of 5 was applied on the maximum number of fires ; and a maximum threshold of 2 was applied outside the main fire event period (i.e. outside the period -6/+6 months around the fire event).*”

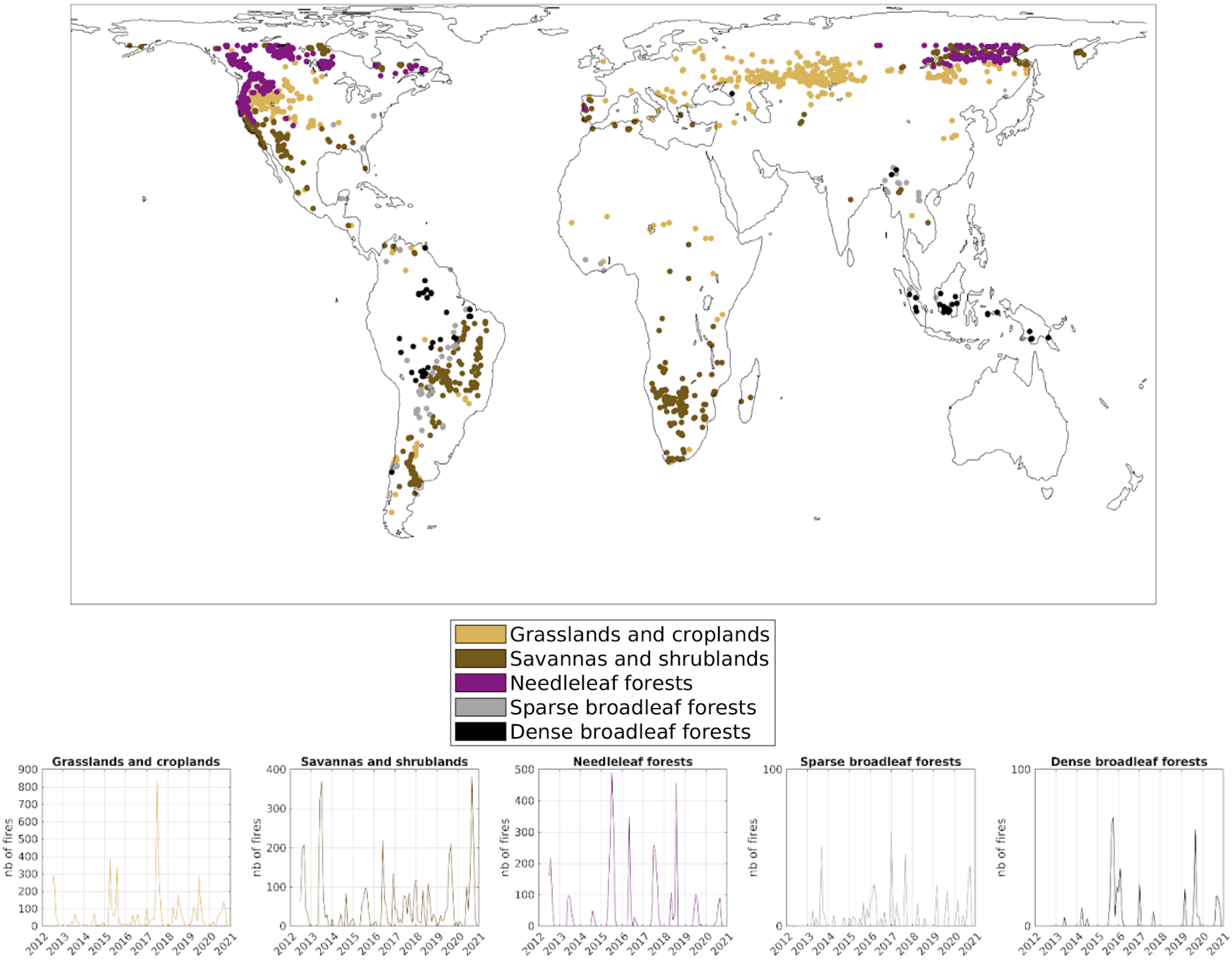


Figure R1 - Location of the selected fires and histograms of the fire dates, for grasslands and croplands (IGBP label 10, 12 and 14), savannas and shrublands (IGBP labels 6, 7, 8 and 9), needleleaf forests (IGBP labels 1 and 3), sparse broadleaf forests (IGBP labels 2 and 4, AGB ≤ 150 Mg ha-1), and dense broadleaf forests (IGBP labels 2 and 4, AGB > 150 Mg ha-1). Australia was excluded as well as areas affected by water, snow, or strong topography.

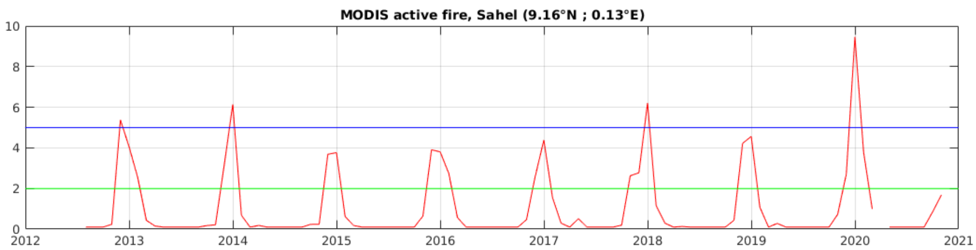
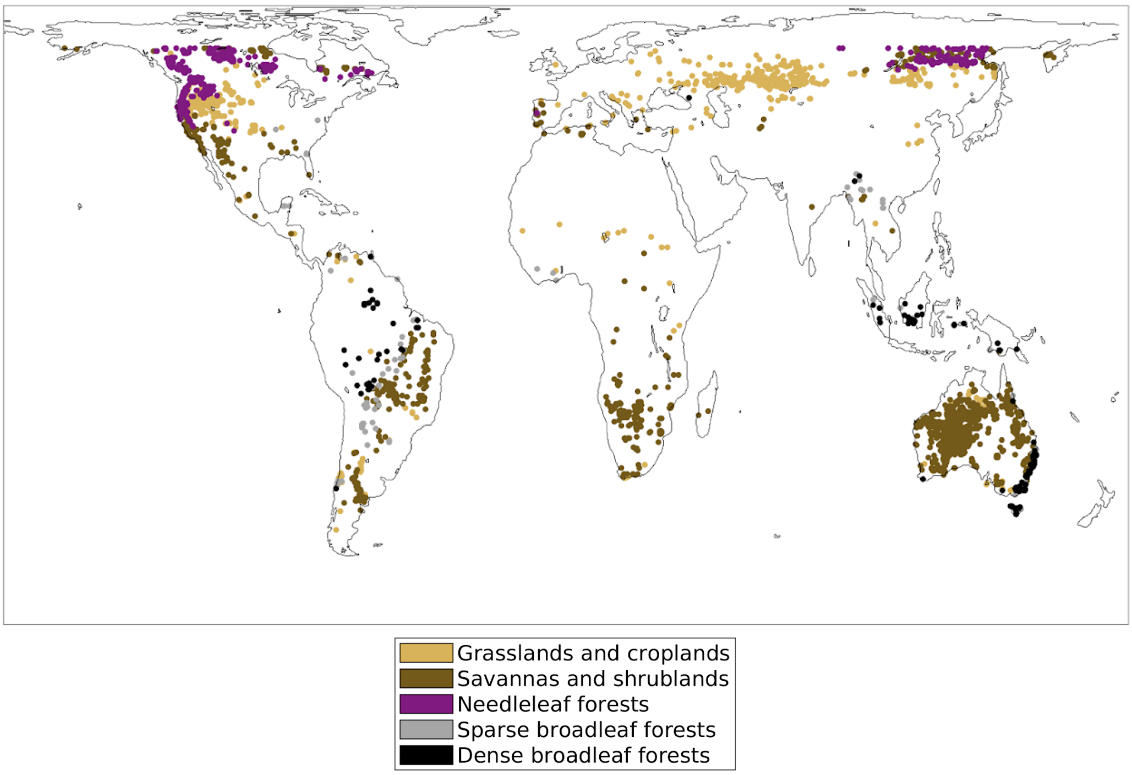


Figure R2 - Time series of the number of fires (MODIS active fire product) over a 25 km pixel in the Sahel (red). The blue line represents the minimum threshold s1 = 5 for the strongest fire event detection; and the green line represents the maximum threshold s2 = 2 for the rest of the period (which is exceeded).

In the case of Australia, the authors appropriately excluded this continent as explained in section 3.2. However, justification for this exclusion is provided for vegetation variables and vegetation recovery. However, the authors should include the region at least for CVs explaining wildfires ignition in the region (i.e., SM, TWS and P).

First, we wanted to be consistent between CVs and VVs analysis, so the same regions were kept for all variables. Second, we fully agree with the reviewer that Australia is a very interesting case, this is also the reason why we included a detailed case study in South-East Australia in the first part (Fig. 3a). However, unfortunately, using the methodology described in Sect. 3.2, the majority of fires in Australia occured in 2012 in the Outback (shrublands) and in 2019/2020 in the South-East (broadleaf forests), at the very beginning (resp. end) of the study period. This prevents a robust pre- and post-fire study, especially since these fires become predominant in the global dataset (Fig. R3): Australia represents respectively 57% and 54% of the total fires for the savannas and shrublands biome and for the dense broadleaf forests biome. This continent is strongly over-represented in the MODIS active fire product due to the large size of the fire events over this continent (Giglio et al., 2016). With Australia, time series are indeed very different from the previous ones (Fig. R4 and R5). In shrublands and savannas (Fig. R4b), C- and X-VOD pre-fire values are higher and L-VOD and EVI anomalies are lower than without Australia (Fig. R4a). VVs, C- and X-VOD in particular, recover slower. Temperature remains high two years after fire. In dense broadleaf forests (Fig. R5b), VVs and CVs started to decrease ~2 years before the fire event, and this phenomenon is specific to Australia's long drought. VVs, VODs in particular, also recover faster than elsewhere.
Thus, we reckon that it is more consistent not to analyse those events in the current study. We will certainly revisit the study in Australia with more hindsight in the future, once the time series after the fire will be long enough to properly analyse the vegetation recovery.
We agree that the exclusion of this continent was not justified enough in the text. This paragraph was modified as follows (changes appear in red): "*Australia was excluded because numerous fires were detected in 2012 in the Outback (shrublands) and in 2019/2020 in the South-East (broadleaf forests), which prevailed over the global dataset (~55% of the points) and prevented to perform a robust pre- and post-fire study.*"



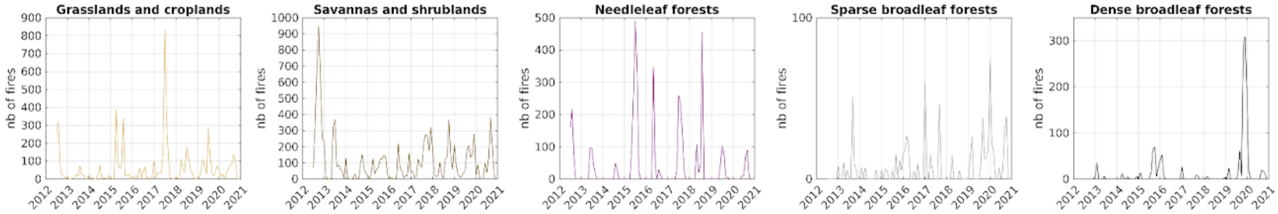


Figure R3 - Same as Fig. R1, without the exclusion of Australia.

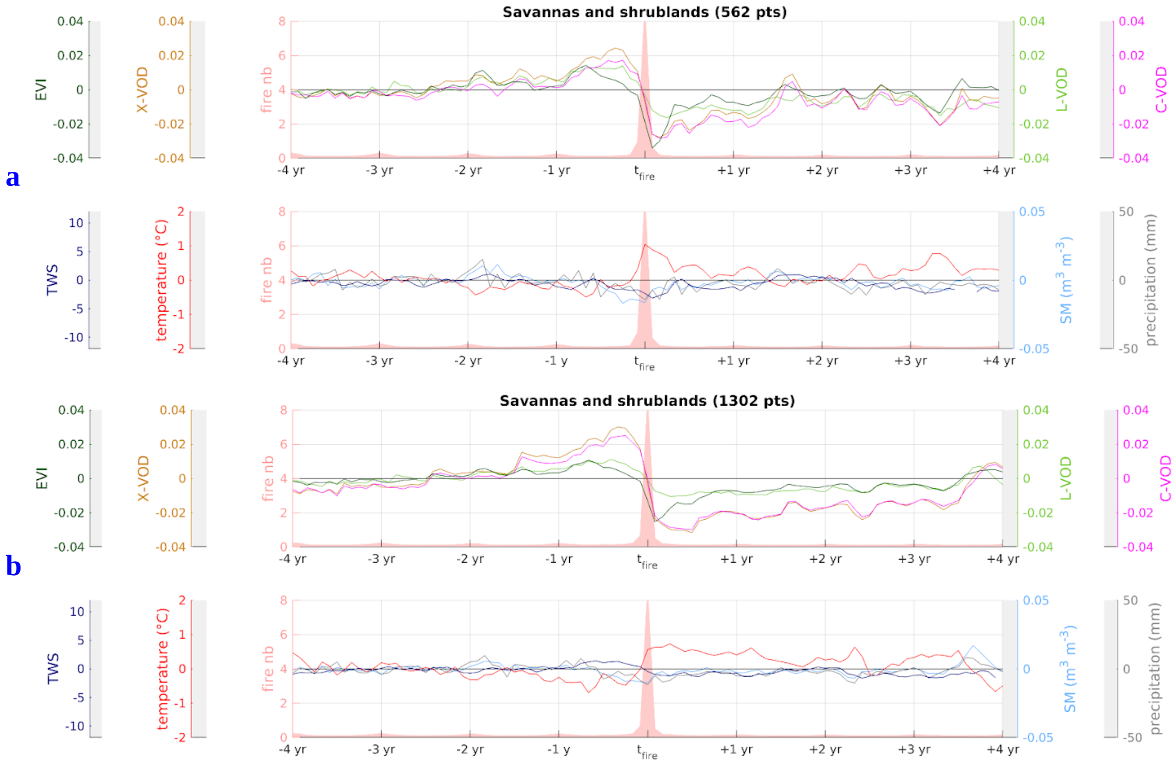
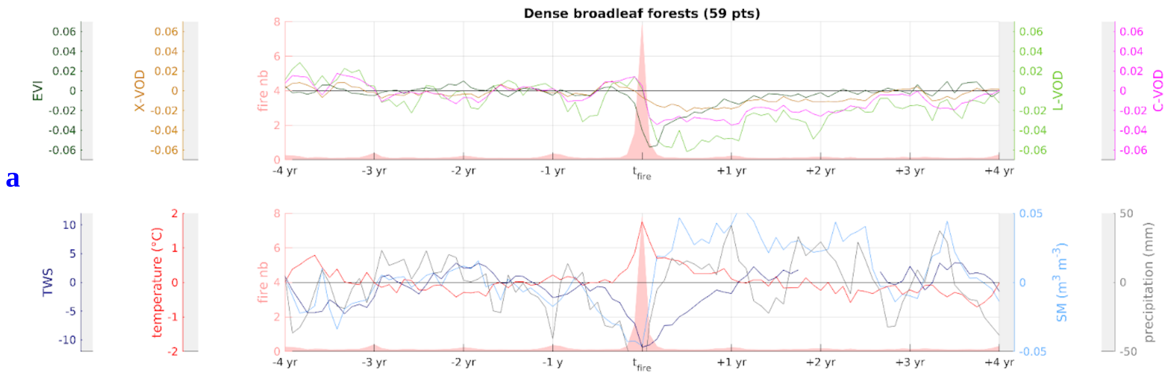


Figure R4 - Time series of all VVs and CVs for the savannas and shrublands biome, a) without and b) with Australia.



b

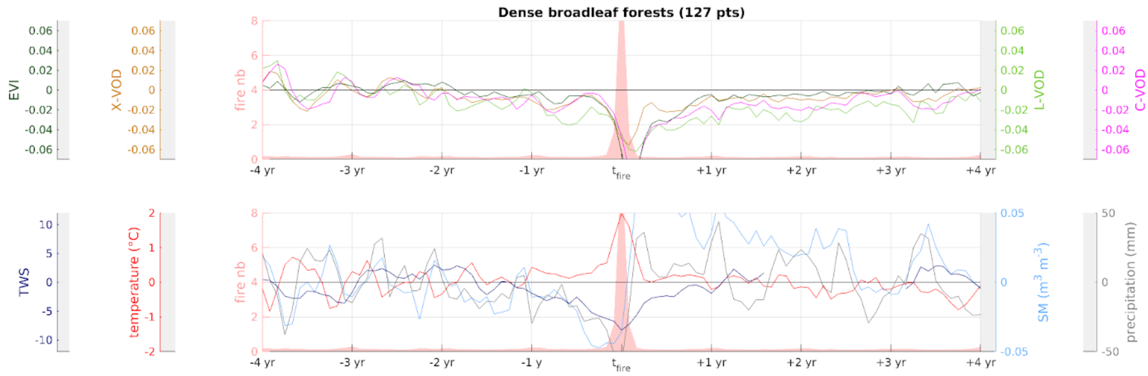


Figure R5 - Time series of all VVs and CVs for the dense broadleaf forests biome, a) without and b) with Australia.

Also, it is quite surprising to me that the number of fires in tropical forests is very low. This is worrying as it can affect the representativeness of the results in tropical forest fires, and consequently the main conclusion of the paper (that L-VOD is the most appropriate for studying fire recovery in the tropics). Can the authors double-check that all fire occurrences in this region have been included?

The number of fires in tropical forests is indeed very low. This is explained in the discussion (line 403): "*We can notice few fires in the densest rainforests (Congo basin, central Amazon) as they are usually too humid to burn (Cochrane, 2003); and because seasonally flooded areas were excluded.*" Seasonally flooded areas were excluded since they were proven to decrease artificially VOD at L-band (Bousquet et al., 2021) and at other microwave frequencies (Jones et al., 2011). They were detected and filtered out using GIEMS-2 database, which shows high values in tropical forests (Fig. R6). In order to keep more points in tropical forests according to your comment, we decided to increase the threshold on the maximum seasonal water fraction from 10% to 20%. The resulting number of points in tropical forests is thus increased from 48 to 59. Their location and date is shown in Fig. R1.
The low number of fires in tropical forests is also due to the significant cloud coverage and the existence of understory fires in this ecosystem, which prevent MODIS active fire detections (Giglio et al., 2020). This additional explanation was added in the discussion: "*We can notice few fires in the densest rainforests (Congo basin, central Amazon) because i) they are usually too humid to burn (Cochrane, 2003); ii) MODIS active fire detections are underestimated under thick cloud coverage or for understory fires (Giglio et al., 2020); and iii) seasonally flooded areas were excluded in order to use only robust VOD estimations (Bousquet et al., 2021).*"

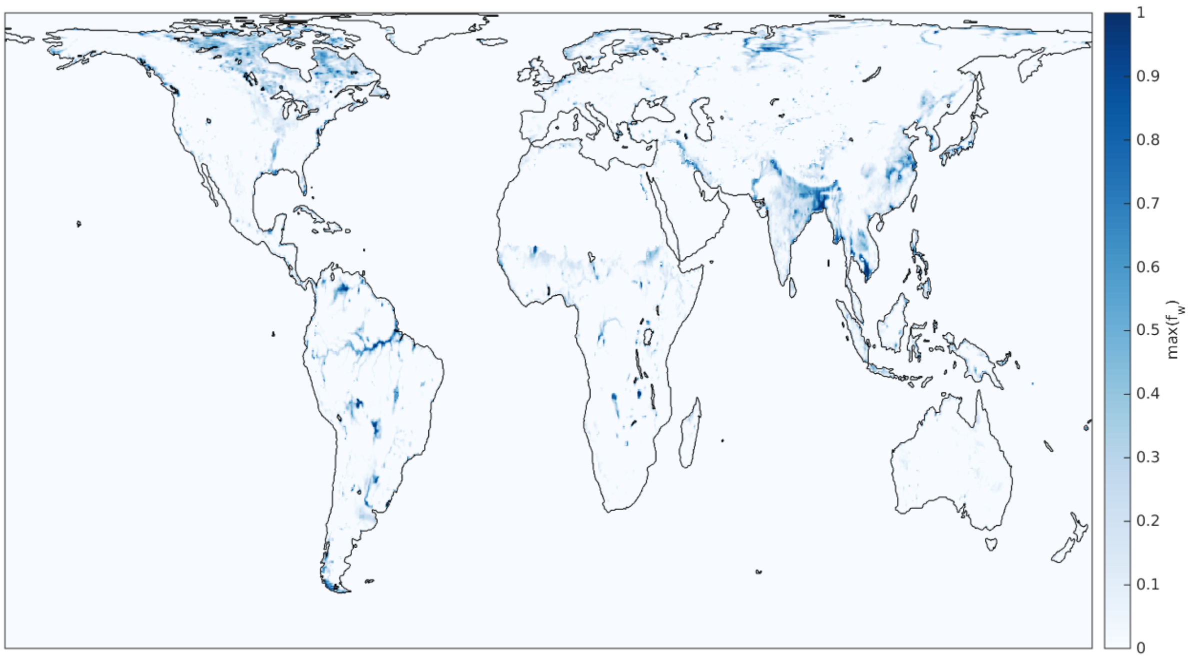


Figure R6 - Maximum water fraction of GIEMS-2 climatology, 2010-2015.

2. Although the main focus of the paper is on vegetation recovery, the work also details which main climate and vegetation variables act as triggers of fire ignition (mainly precipitation, soil moisture, ground water storage, and fuel availability). In that sense, the introduction should be extended to provide further state of the art. On the one hand, GRACE data (groundwater storage) has been previously applied for fire risk assessment in the United States (e.g., Jensen et al., 2018; Farahmand et al., 2020). On the other hand, SMOS soil moisture data has been applied as an alternative source of moisture information in the McArthur Forest Fire Danger Index (FFDI; Holgate et al., 2017). Also, SMOS SM anomalies have been found to explain anomalous fire episodes in the northwestern Iberian Peninsula (Chaparro et al., 2016) and in Canada (Ambadan et al., 2020). Apart from L-band, a nice study of how satellite soil moisture anomalies can be used for fire risk assessment is shown by Forkel et al. (2012; see also my minor comment below).

We agree with the reviewer's comment. We reworked the introductory paragraph regarding the CVs impacts on fire ignition (line 67) in that sense:
"*Naturally, understanding the potential factors triggering large uncontrollable fires is important to anticipate them and thus to reduce their impacts. Mhawej et al. (2015) presented and categorized 28 wildfire likelihood factors into climatic (e.g. precipitation, temperature, air humidity, wind speed), topographic (e.g. slope, altitude), in situ (e.g. fuel type, soil texture, tree diameter), historical, and anthropogenic factors. Drought, i.e. the concomitant increase of air dryness and decrease of fuel moisture, was identified as the most significant fire likelihood factor (Ray et al., 2005). Indirectly, drought also causes leaf shedding and branch losses (Pausas and Bradstock, 2007), which leads to fuel accumulation and direct sunlight reaching the forest floor, and increases forest flammability (Nepstad et al., 2001). Surveying the soil moisture (SM) and the biomass status could then be a good indicator for fire risk detection. The SM deficit monitored with AMSR-E was previously proven to be a major driving factor for the evolution of extreme fire events in Siberia (Forkel et al., 2012). GRACE-assimilated SM was also exploited for fire risk assessment in the United States (Jensen et al., 2018; Farahmand et al., 2020). SMOS SM anomalies have been found to explain singular fire episodes in the northwestern Iberian Peninsula (Chaparro et al., 2016) and in Canada (Ambadan et al., 2020). Finally, SMOS SM has been used as an alternative source of moisture information in the McArthur Forest Fire Danger Index (FFDI; Holgate et al., 2017). ~~Currently, drought is mainly monitored with temperature and precipitation observations. Fuel availability is monitored with optical sensors, but with fast saturation over dense vegetation, and lack of sensitivity for dry biomass (not green), which is the main fuel.~~*"

Minor comments

Line 15 (and through the entire paper): optical vegetation indices → optical-infrared vegetation indices. Or VIS/IR vegetation indices, if you prefer. The point is that EVI includes both visible and infrared bands.
Agreed and done.

L. 30: Amazônia legal → Amazônia Legal
Done.

L. 50: a sentence should be included about the fact that most wildfires are ignited due to human activities. In the Mediterranean regions 95% of fires are due to these causes, and similar percentages are found in other areas (e.g., 90% in South Asia, 85% in South America, 80% in Northern Asia; FAO, 2006).
Agreed and added: "*Nevertheless, most wildfires now are ignited by human activities (95% in the Mediterranean basin, 90% in South Asia, 85% in South America, and 80% in Northern Asia; FAO, 2006).*"

L. 90-91: according to these lines, it seems that soil moisture could be retrieved only from L-band sensors, while this is not true. I suggest explaining the advantage of L-band (more penetration capacity through soils and vegetation) to provide better motivation on the advantage of using L-band for soil moisture retrievals, and to explain why L-band is more linked to dense biomass (this point is important for the interpretation of results in this paper).

These lines were changed as follows:

"*With the arrival of L-band radiometers such as the Soil Moisture and Ocean Salinity (SMOS) satellite, it is possible to infer surface soil moisture, biomass (i.e. fuel) and its water content at deeper sensing depth.*"

The link between L-VOD and AGB is explained at line 98. We added a sentence to provide more information about this point: "*L-VOD is then more sensitive to high AGB values than C- and X-VOD, and is a good proxy for dense vegetation (Rodriguez-Fernandez et al., 2018).*"

L. 94-95: "This study also presents for the first time L-band used in conjunction with other sensors, from optical (EVI) to X- and C-band…": add (specify): "in the study of vegetation recovery after fires."

Agreed and added.

L. 120: from SMOS satellite → from the SMOS satellite.

Done.

L. 136: please specify which months are not included, and how much months does it add up within the entire study period.

This information was added in the text:

"*Data were lacking for 35 dates of the ten-year dataset. One-time gaps were filled by linear interpolation; consecutive missing months were not considered (Sep.−Nov. 2016, Jul. 2017−May 2018, and Aug.−Oct. 2018, 17 months in total).*"

L. 197: watern → water

Done.

L. 216: why are VOD data resampled to 1 km resolution and later averaged to the SMOS grid? This does not make sense because VOD at C- and X-bands have much coarser resolutions than 1 km (as in SMOS). Please, be sure to interpolate directly C- and X-VOD data from their native resolution to the SMOS grid. An intermediate step through 1 km may introduce errors.

SMOS and AMSR-2 are distributed into ~ 25 km grids, but SMOS grid is EASE Grid v2 (irregular grid) while AMSR-2 grid is a regular one (EPSG 4326). Hence, a reprojection is needed and a nearest neighbour interpolation would introduce spatial errors. By adding an intermediate step of oversampling at a finer resolution (1 km here, i.e. 25 times finer), the contributions of each part of the pixel are taken into account and weighted.

However, considering your comment, we conducted a test to compare the approach we used (1 km oversampling) with a direct bilinear interpolation from the native resolution of AMSR-2. We found that the results are very similar, because this method is also based on a weighted average of contributing pixels. Moreover, the bilinear interpolation is more accurate than a nearest neighbour interpolation (Fahmy et al., 2008).

We agree that the proposed method is then not necessary and hence decided to modify the resampling method with a more common bilinear interpolation for the low resolution datasets. For the high resolution datasets, we kept the average method, in order to take into account all contributing pixels in the 25 km grid. The figures will be updated in the revised version of the manuscript, but they are very close to the previous ones, and the conclusions do not change. The text was modified accordingly : "Monthly averages of all datasets were computed and resampled to SMOS EASE-Grid 2.0 (~ 25 km resolution) with a bilinear interpolation for the low resolution datasets (X-VOD, C-VOD, precipitation, TWS, fires, and f_w); and with an average interpolation for the high resolution datasets (EVI, temperature, snow, land cover, and AGB), using GDAL (GDAL/OGR contributors, 2020)".

L. 239: you use "ha" as burned area unit here, but "km 2 " throughout the manuscript. Please be consistent, use only one or the other.

Done.

L. 241: how was burn severity defined and classified in “moderate”, “high”, etc… in this case?
The watershed modeling report of the Mendocino Complex Fire (BLM, 2018) indicated 3% of high severity, 62% of moderate severity, 21% of low severity and 14% of unburned soil.
The corresponding sentence was modified as follows: “*This wildfire caused a 34% vegetation loss in this region (26% in 2018 and 8% in 2019, Fig. 2),* ~~*and caused a burn severity ranging from moderate to high.*~~ *and was predominantly classified as moderate severity (62%; BLM, 2018).*”

L. 303-304: “a strong decrease during the fire event” → Also before it.
Agreed and done.

L. 311-312: it should be noted that the positive T anomalies and the negative TWS and P anomalies reach their maximum and minimum (respectively) at the end of the fire period. Can you provide a possible interpretation for this?
Over Santarem area (Fig. 3c), the MODIS number of fires is 4.4 in Dec. 2015 and 1.9 in Jan. 2016, while the temperature anomaly is 2.5°C in Dec. 2015 and 3.5°C in Jan. 2016.
First, MODIS may not detect all fires in Jan. 2016 in this area, because i) the vegetation cover is dense and Santarem fires mainly affected the understory (Withey et al., 2018); ii) the cloud cover is generally strong in the Amazon in January, and the MODIS active fire product only detects fires unobscured by optically thick clouds (Roy et al., 2008). This explanation would be in line with Hansen et al. tree cover loss product, which detects the forest loss in 2016 (Fig. 2).
Secondly, even if drought predominantly ends at fire extinguishment (rainfall associated with temperature cooling often extinguishes fires, e.g. in South-East Australia), drought conditions may sometimes keep increasing after fire events. This is also visible in the savanna biome (Fig. 5b). Indeed, by removing the vegetation cover and deteriorating the soil, fires maintain a hot and dry climate. Veraverbeke et al. (2010) previously observed the increase of day Land Surface Temperature (LSTd) immediately after the fire event, in the Peloponnese (Greece). Auld and Bradstock (1996) also observed an increase in temperature after fires in Australia, because the removal of the vegetation cover by the fire led to increased levels of solar radiation on the soil surface.

L. 348: please mention that savannahs and grasslands show positive VV anomalies one year before (as you will discuss it later in the discussion).
This was mentioned at line 321. The section of line 348 refers to Fig. 6, which only concerns CVs. This is why we didn’t mention VV anomalies there.

Figure 5: there is an interesting result in Fig. 5 which could be highlighted. Note that, in boreal forests, SM and TWS anomalies are negative also one year before fires. This is interesting as it could be in line with results shown in Forkel et al. (2012). In that case, the authors found that negative SM anomalies in Siberia during summer 2002 led to low amount of water being frozen within permafrost soils during winter 2002-2003. Therefore, a low amount of water was stored (frozen) and then released to the soils during permafrost melting in spring-summer 2003. This led to drier than usual soils in summer 2003, which eased the outbreak of large wildfires. In particular, the Forkel et al. stress in the abstract that “analyses of satellite data for 2002–2009 indicate that previous-summer surface moisture is a better predictor for burned area than precipitation anomalies or fire weather indices for larch forests with continuous permafrost.” Your results are in line with this finding and this could be briefly included in the manuscript.
Thank you for this reference and this relevant advice. We included these observations and explanations in the discussion:
“*We found a strong pre-fire drought in this ecosystem (low SM and high temperature one year pre-fire, Fig. 6), which is well documented for previous fire episodes (Weber and Stocks, 1998). Our results are in line with those of Forkel et al. (2012), who found that previous-summer SM was a good predictor for burned area in Siberian larch forests. Indeed, negative summer anomalies led to low frozen water the following winter, and to less water released during the next spring-summer, which in turn eased the outbreak of large wildfires.*”

L. 340-345: when you comment on TWS and T anomalies, please refer to Figs. 6c and 6d, Respectively.
Agreed and done.

L. 391: the reference to the Australian Bureau of Meteorology should be accompanied by a year and an appropriate reference within the reference list.
We changed that reference by BoM, 2021:
"*BoM: Annual climate statement 2020, available at: http://www.bom.gov.au/climate/current/annual/aus/2020/, accessed 14 December 2021, 2021.*"

L. 401: can you quantify the severity of the fire? Actually, it would be interesting to mention severity indices when discussing the three study cases, if possible.
As previously answered for your comment regarding line 241, the Mendocino complex was classified as moderate severity (BLM, 2018).
Concerning South-East Australia, Ehsani et al. (2020) showed that the severity of the 2019–2020 wildfires was higher than any other event in the past twenty years.
As regards Satarem fire, Berenguer et al. (2018) stated that the region was severely affected by the El Niño drought and by the related extensive wildfires.
Nevertheless, severity indices are difficult to obtain for these areas. We can only quantify this "severity" with the percentage of tree cover loss (Hansen et al., 2013) by SMOS pixel. The sentence at line 401 was modified: "*Even if this type of vegetation is fire-adapted, the strength of the fire seemed to have destroyed most of it (34% vegetation loss, Hansen et al., 2013).*"

L. 428: "which is well documented" → "which is well documented in previous fire episodes in this region."
Agreed and done (see previous comment on Fig. 5).

L. 444 and 449: Argentine → Argentina
Since we refer to the adjective and not the noun of the country, we believe the term "Argentine" is correct (see de Marzo et al., 2021 : "Characterizing forest disturbances across the Argentine Dry Chaco based on Landsat time series").
NB : we have now added this omitted reference to the manuscript.

References

Ambadan, J. T., Oja, M., Gedalof, Z. E., & Berg, A. A. (2020). Satellite-Observed Soil Moisture as an Indicator of Wildfire Risk. Remote Sensing, 12(10), 1543.

Chaparro, D., Piles, M., Vall-Llossera, M., & Camps, A. (2016). Surface moisture and temperature trends anticipate drought conditions linked to wildfire activity in the Iberian Peninsula. European Journal of Remote Sensing, 49(1), 955-971.

FAO, 2006. Fire Management – Global Assessment 2006. A Thematic Study Prepared in the Framework of the Global Forest Resources Assessment 2005. Food and Agriculture Organization, Rome.

Farahmand, A., Stavros, E. N., Reager, J. T., Behrangi, A., Randerson, J. T., & Quayle, B. (2020). Satellite hydrology observations as operational indicators of forecasted fire danger across the contiguous United States. Natural Hazards and Earth System Sciences, 20(4), 1097-1106.

Forkel, M., Thonicke, K., Beer, C., Cramer, W., Bartalev, S., & Schmullius, C. (2012). Extreme fire events are related to previous-year surface moisture conditions in permafrost-underlain larch forests of Siberia. Environmental Research Letters, 7(4), 044021.

Holgate, C. M., van Dijk, A. I., Cary, G. J., & Yebra, M. (2017). Using alternative soil moisture estimates in the McArthur Forest Fire Danger Index. International Journal of Wildland Fire, 26(9), 806-819.

Jensen, D., Reager, J. T., Zajic, B., Rousseau, N., Rodell, M., & Hinkley, E. (2018). The sensitivity of US wildfire occurrence to pre-season soil moisture conditions across ecosystems. Environmental research letters, 13(1), 014021.

References

Auld, T. D., & Bradstock, R. A. (1996). Soil temperatures after the passage of a fire: do they influence the germination of buried seeds? Australian Journal of Ecology, 21(1), 106-109.

Berenguer, E., Malhi, Y., Brando, P., Cardoso Nunes Cordeiro, A., Ferreira, J., França, F., Chesini Rossi, L., Moraes de Seixas, M. M., and Barlow, J.: Tree growth and stem carbon accumulation in human-modified Amazonian forests following drought and fire, Phil. Trans. R. Soc. B., 373, 20170308, https://doi.org/10.1098/rstb.2017.0308, 2018.

BLM: Mendocino Complex Fire, Watershed Modeling Report, available at: https://www.blm.gov/sites/blm.gov/files/uploads/Programs_Fire_California_Watershed_Modeling_Report-Mendocino-Complex-Fire.pdf, accessed 14 December 2021, 2018.

BoM: Annual climate statement 2020, available at: http://www.bom.gov.au/climate/current/annual/aus/2020/, accessed 14 December 2021, 2021.

de Marzo, T., Pflugmacher, D., Baumann, M., Lambin, E. F., Gasparri, I., and Kuemmerle, T.: Characterizing forest disturbances across the Argentine Dry Chaco based on Landsat time series, Int. J. Appl. Earth Obs., 98, 102310, https://doi.org/10.1016/j.jag.2021.102310, 2021.

Ehsani, M. R., Arevalo, J., Risanto, C. B., Javadian, M., Devine, C. J., Arabzadeh, A., Venegas-Quiñones, H. L., Dell'Oro, A. P., and Behrangi, A.: 2019–2020 Australia fire and its relationship to hydroclimatological and vegetation variabilities, Water, 12, 3067, https://doi.org/10.3390/w12113067, 2020.

Fahmy, S. A. (2008, December). Generalised parallel bilinear interpolation architecture for vision systems. In *2008 International Conference on Reconfigurable Computing and FPGAs* (pp. 331-336). IEEE.

Giglio, L., Schroeder, W., & Justice, C. O. (2016). The collection 6 MODIS active fire detection algorithm and fire products. Remote Sensing of Environment, 178, 31-41.

Giglio, L., Schroeder, W., Hall, J. V., and Justice, C. O.: MODIS Collection 6 Active Fire Product User's Guide Revision C, Department of Geographical Sciences, University of Maryland, 2020.

Jones, M.O., Jones, L.A., Kimball, J.S., McDonald, K.C., 2011. Satellite passive microwave remote sensing for monitoring global land surface phenology. Remote Sensing of Environment, vol. 115, no. 4, pp. 1102-1114.

Veraverbeke, S., Van De Kerchove, R., Verstraeten, W., Lhermitte, S., & Goossens, R. (2010). Fire-induced changes in vegetation, albedo and land surface temperature assessed with MODIS. In 30th EARSeL symposium: Remote sensing for science, education, and natural and cultural heritage (pp. 431-438). European Association of Remote Sensing Laboratories (EARSeL).

Withey, K., Berenguer, E., Palmeira, A. F., Espírito-Santo, F. D., Lennox, G. D., Silva, C. V., et al. (2018). Quantifying immediate carbon emissions from El Niño-mediated wildfires in humid tropical forests. Philosophical Transactions of the Royal Society B: Biological Sciences, 373(1760), 20170312.