Modeling post-fire recovery in Mediterranean ecosystems in Spain: influence of fire severity, post-fire climate and site conditions.

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ABSTRACT

Mediterranean ecosystems are greatly adapted to a certain fire regime but climate change and foreseeable increases in droughts and fire severity may alter the rates of recovery following wildfire. Vegetation regrowth after a stand-replacing disturbance as wildfire, is undoubtedly susceptible to several issues like fire severity or post-fire climate among others, although regeneration processes are far from being fully comprehended and there is a clear gap in understanding the impact of those issues on forest recovery ratios.

In this study, we analyze effects of burn severity, topographic factors, and post-fire humidity on vegetation recovery in one of the greatest forest wildfires occurred in Spain in 1994. We examined both short-term (5 years) and mid-term (10 years) vegetation recovery patterns, following the hypothesis that vegetation regrowth varies as burn severity intensities, post-fire climate parameters, species and site ecological conditions.

Recovery processes have been assessed from spectral profiles using annual 30-meter Landsat time series and the LandTrendr model (Landsat-based Detection of Trends in Disturbance and Recovery) (Kennedy, Yang, & Cohen, 2010). Burn severity has been estimated by means of PROSPECT and GeoSAIL radiative transfer models following methodologies described in De Santis and Chuvieco (2009). Modeling is based on the use of geographically weighted regressions including spatial variation coefficients.

Results have shown that vegetation regrowth after stand-replacing wildfire in western Mediterranean basin is linked to wetness availability in the immediate years after fire, favorable topography, burn severity and distance to forest edge. Results contribute to a further understanding of the post-fire processes in Mediterranean forestry areas and to develop effective strategies for sustainable forest management specially in foreseen climate scenarios.

KEYWORDS

wildland fires, GeoCBI, vegetation recovery, burn severity, LandTrendr, Landsat time-series

INTRODUCTION

It is widely known that Mediterranean ecosystems are greatly adapted to a certain fire regime (Moreno, Conedera, Chuvieco, & Pezzatti, 2014; Pausas, 2012; Vannière et al., 2008) but climate change and foreseeable increased intensities in droughts (Price et al., 2013) and burn severity may alter the rates of recovery following wildfire. Vegetation regrowth after a stand-replacing disturbance as wildfire, is undoubtedly vulnerable to several issues like burn severity or post-fire climate among others, although regeneration processes are far from being fully comprehended and there is a clear gap in understanding the impact of those factors on forest recovery ratios.

Large wildfires in Mediterranean area are now more and more related to stand-replacing disturbances with increases in the frequency of crown fires (Pausas, Llovet, Rodrigo, & Vallejo, 2008), so that moderate-high and high burn severities are more frequent with consequences that are not yet fully understand.

The objective of this study was the pilot evaluation of the main factors that contribute to short- and mid-term regeneration after stand-replacing wildfires in western Mediterranean basin (Spain). Our hypothesis is that burn severity should have high relevance in vegetation recovery processes as well as local environmental variables as topography and climatic data. Furthermore, we hypothesis that distance to edge (nearest healthy forested patches) may have a significant relevance in vegetation regrowth specifically in areas with intense crown fires. Geographically weighted regressions were applied to model vegetation regeneration.

METHODS

Study region

The study area is placed in northeastern Spain, an area with a Mediterranean climate that lays in the surroundings of Pyrenees Mountains with altitudes reaching 1.100m. It comprises one Landsat footprint (path/row 200/031). Average temperature is about 14ºC and mean annual precipitation rounds 480mm. Forest land covers essentially correspond to woodlands with different *Quercus* species and monospecific stands of anthropogenic origin mainly dominated by *Pinus halepensis* or *Pinus nigra*. The studied wildfire happened in July 16th 1994, caused by lightning and impacting a surface near to 80 km^2.

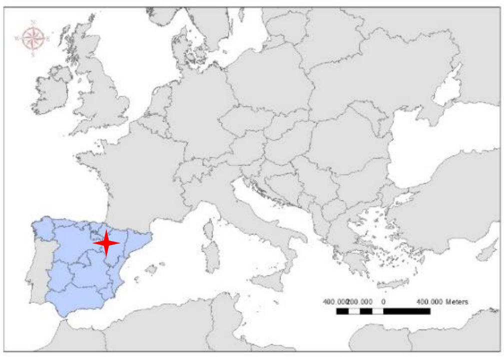

Figure 1. Study area in northeastern Spain

Input data to models

In this study, a collection of 48 remote sensing images (July and August) ranging from 1984 to 2014 were selected which belongs the Landsat series collected by TM and ETM+ sensors. Images were downloaded through the United States Geological Survey (USGS) server (USGS/NASA Earth Explorer: https://espa.cr.usgs.gov/login?next=https%3A%2F%2Fespa.cr.usgs.gov%2F) and the European Space Agency (ESA) server (https://earth.esa.int/web/guest/eoli). Images were acquired in the peak growing season (late June to mid-September). Spatial geometry and radiometry were matched between both image sources to guarantee integrity and coherence. USGS images belong the NASA LEDAPS project (Landsat Ecosystem Disturbance Adaptive Processing System) which transform raw data to surface reflectance using models developed to Terra MODIS (Masek et al., 2006). ESA images were transformed to LEDAPS using the code USGS EROS Center Version 2 (https://github.com/usgs). Afterwards radiometric normalization, all images were transformed into Tasseled Cap (TC) space (Crist & Cicone, 1984). All TC components (wetness TC_W, brightness TC_B, greenness TC_G, and angle TC_A) were processed using *LandsatLinkr* code (https://github.com/jdbcode/LandsatLinkr) to obtain *on-the-fly* mosaics for years with multiple available images. Pixel's spectral values in those composites were taken from the image closest to the median Julian day (1 to 365). Identification of burn pixels was processed using the software Burned Area Algorithm (BAMS) (Bastarrika et al., 2014), by the definition of thresholds on a set of vegetation indices and an approach based on a two-phase supervised classification.

LandTrendr (Landsat-based Detection of Trends in Disturbance and Recovery) algorithm, developed by Kennedy et al. (2010) was used to identify the historical processes of disturbance and regeneration occurred between 1984 and 2014 in the study area at a pixel-by-pixel basis. LandTrendr, following iterative regression and fitting processes, identify vertices in the temporal trajectory of every pixel which represent years of change and define segments corresponding to stable processes between two vertices. Only pixels following a pattern of regeneration (See Figure 2) were filtered and regarded for analyses.

Figure 2. Trajectory filter

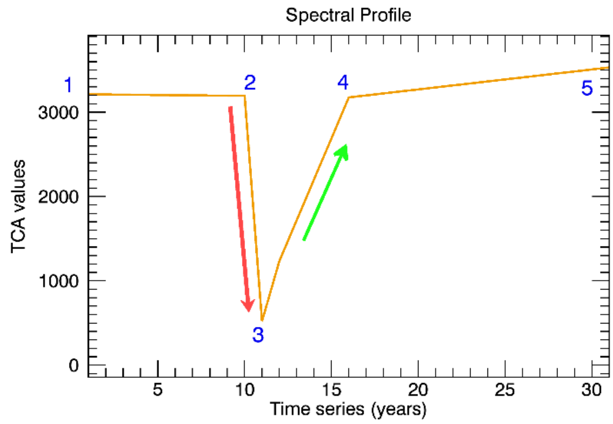

Figure 3. Idealized pixel trajectory to be included in analyses within temporal series 1984-2014. Segment 1-2 (1984-1993): stability process; Segment 2-3 (1993-1994) (1994-point 3: year 11 in temporal series): disturbance caused by wildfire; Segment 3-4 (1994-1999) and segment 4-5 (1999-2014): recovery processes with different slope.

The following environmental variables were considered in this pilot evaluation:

i) TC_A (defined as arctan(TC_G/TC_B)) was used as the indicator of recovery (dependent variable). TC_A was initially defined and successfully tested by Powell at al. (2010) to describe the gradient in the land cover percentage. Pixel TC_A values finally used correspond to year+5 (1999), year+7 (2001) and year+10 (2004) post-fire and were taken from the pixel trajectory after segmentation and fitting processes (fitted value TC_{Af}). Two models were developed as forest species: i) one for areas occupied by *Quercus spp*. (mainly *Quercus faginea*); ii) the second one for areas occupied by *Pinus spp*. (mainly *Pinus nigra*).

ii) Climatic data were derived from MOTEDAS and MOPREDAS databases for Spain (González-Hidalgo, Brunetti, & de Luis, 2011; Gonzalez-Hidalgo, Peña-Angulo, Brunetti, & Cortesi, 2015) which hold monthly temperature and precipitation values respectively, ranging from 1950 to 2010 in a 0,1ºx 0,1º resolution grid. In order to detect anomalies for the series 1950-2010, pixel values were standardize to z-scores using the mean (μ) and standard deviation(σ) for the series ($z= (X-\mu)/\sigma$; being X the raw value and z the anomaly scores). It should be noted that an important disagreement between spatial resolution of climatic variables (1/10 latitude and longitude degree) and Landsat derived variables (30 m) exists, which could affect the relevance of climatic data in explaining dependent variable variability of models. Processed values for five years following 1994 wildfire (1995 to 1999) were: January minimum and July maximum temperature in the year, annual precipitation, and wet season precipitation (from December to May).

iii) TC_W values for 1994 (wildfire year) and the following five years (1995-1999) were included into the analysis representing vegetation and soil wetness within remote sensing pixels (Cohen, Spies, & Fiorella, 1995). Fitted values (TC_{Wf}) were taken from pixel trajectories.

iv) Distance to forest edge (live trees) was calculated to evaluate how is the relevance of biological legacies dispersion in recovery after stand-replacing wildfires (Donato et al., 2009).

v) Burn severity was estimated by GeoCBI values, which were calculated using surface reflectance values of 1994 image. The approach was based on the inversion of PROSPECT and GeoSail models that was developed by De Santis and Chuvieco (2009). Final map assigns to post-fire image pixels a GeoCBI value ranging between 0 to 3.

vi) Slope and aspect variables were processed using a 25 pixel-size digital elevation model (DEM) downloaded from the web site of the geospatial data infrastructure in Spain (http://www.idee.es/). Aspect has been included into models as two continuous variables following Meng et al. (2015): i) N*orthness* (north-south orientation) processed using the cosine of aspect; ii) *Eastness*, processed using the sine of aspect. In this way, for slopes facing north, *Northness* will take values close to 1, while in case of south orientation it will take values around -1. In the case of Eastness, logic is similar.

Regression analysis

Geographically weighted regressions (GWR) were processed to find the set of environmental variables that better and significantly explain the recovery indicator taking successively as dependent variable $TC_{Af\ year\ +5}$, $TC_{Af\ year\ +7}$ and $TC_{Af\ year\ +10}$.

According to preliminary Ordinary Least Square (OLS) tests, stationarity (*Koenker* statistic) and global spatial autocorrelation (global *Moran's I* statistic) criteria were not really accomplished, so regression models considering spatial variation coefficients were advisable in order to avoid violation of statistically critical assumptions (D. Griffith, 2003; D. A. Griffith, Fischer, & LeSage, 2016; Meng et al., 2015). GWR models have been successfully proposed to cope with the occurrence of spatial autocorrelation (D. A. Griffith & Peres-Neto, 2006; Rodrigues, de la Riva, & Fotheringham, 2014).

We have worked out preliminary exploratory analysis and pilot OLS regressions taking successively $TC_{Af\ year\ +5}$ (1999); $TC_{Af\ year\ +7}$ (2001), $TC_{Af\ year\ +10}$ (2010) as dependent variables and the set of predictor variables previously described, which revealed the predictive behavior as well as the accomplishment of statistical assumptions in regression models. Linear relationships between variables, odd-values, stationarity, multicollinearity, spatial autocorrelation, and residuals distribution were taking into account.

RESULTS

Regression analyses

Preliminary exploratory analyses showed that pixel size of climatic data grid, and more precisely the high disagreement between climatic and the resolution of other environmental variables became a limiting factor in GWR models. Furthermore, climatic variables presented high multicollinearity with TC_W. Therefore, climatic data (precipitation and temperature) could not be included in very final processes.

Preliminary OLS tests showed those variables with the best explanatory power in every model for *Quercus spp*. and *Pinus spp.* Figure 4 shows the relative importance for every significant variable, measured as the absolute value of the t-statistic.

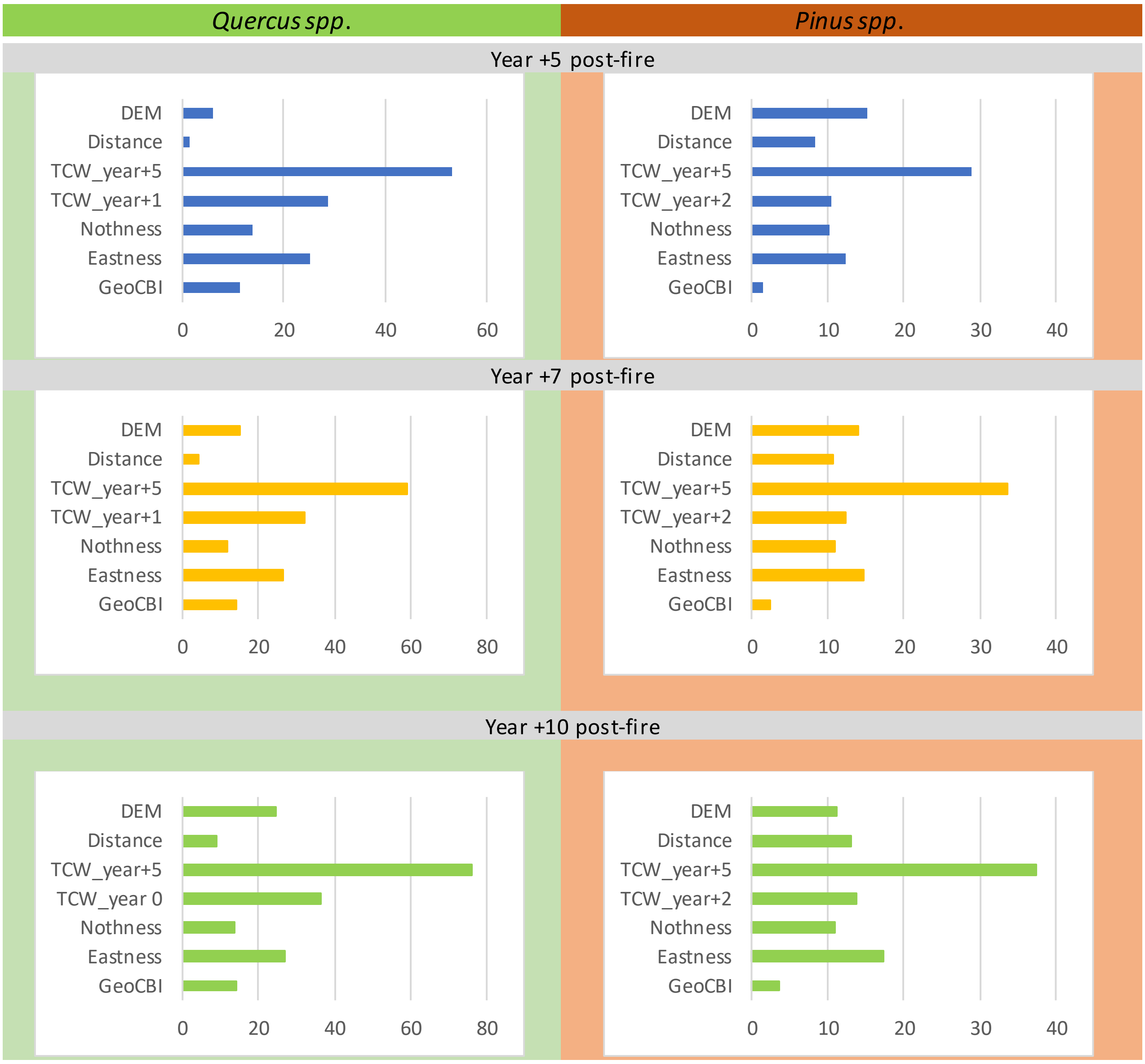

Figure 4: Relative weight of every variable in preliminary OLS regression models (p-values < 0.05)

Table 1 shows the final results of GWR models for *Pinus spp*. and *Quercus spp.*

Table 1. Predictor variables in GWR models and statistics

Quercus spp.			
Year +5	Year +7	Year +10	
$+TC_{wf\ year\ +1}$ $+TC_{wf\ year\ +5}$ +MDE -GeoCBI -Distance -Northness +Eastness	$+TC_{wf\ year\ +1}$ $+TC_{wf\ year\ +5}$ +MDE -GeoCBI -Distance -Northness +Eastness	$+TC_{wf\ year\ +0}$ $+TC_{wf\ year\ +5}$ +MDE -GeoCBI -Distance -Northness +Eastness	
Residuals mapping detail	Residuals mapping detail	Residuals mapping detail	Residuals Standard Deviation
 $R^2_{adj} = 0.62$ Effective number:12.33 Sigma:239.17 AICc: 328.34	 $R^2_{adj} = 0.78$ Effective number:12.33 Sigma:181.28 AICc:316.70	 $R^2_{adj} = 0.82$ Effective number:15.48 Sigma:166.13 AICc:406.45	**StdResid** < -2.5 Std. Dev. -2.5 - -1.5 Std. Dev. - 1.5 - -0.5 Std. Dev. -0.5 - 0.5 Std. Dev. 0.5 - 1.5 Std. Dev. 1.5 - 2.5 Std. Dev. > 2.5 Std. Dev.

Pinus spp.			
Year +5	Year +7	Year +10	
$+TC_{wf\ year\ +2}$ $+TC_{wf\ year\ +5}$ +MDE -GeoCBI -Distance -Northness +Eastness	$+TC_{wf\ year\ +2}$ $+TC_{wf\ year\ +5}$ +MDE -GeoCBI -Distance -Northness +Eastness	$+TC_{wf\ year\ +2}$ $+TC_{wf\ year\ +5}$ +MDE -GeoCBI -Distance -Northness +Eastness	
Residuals mapping detail	Residuals mapping detail	Residuals mapping detail	Residuals Standard Deviation
 $R^2_{adj} = 0.65$ Effective number:12.28 Sigma:270.24 AICc: 702.90	 $R^2_{adj} = 0.66$ Effective number: 3.18 Sigma:101.69 AICc:104.18	 $R^2_{adj} = 0.78$ Effective number:3.18 Sigma:82.52 AICc:101.25	**StdResid** < -2.5 Std. Dev. -2.5 - -1.5 Std. Dev. - 1.5 - -0.5 Std. Dev. -0.5 - 0.5 Std. Dev. 0.5 - 1.5 Std. Dev. 1.5 - 2.5 Std. Dev. > 2.5 Std. Dev.

DISCUSSION AND CONCLUSIONS

GWR resulted a suitable method to study vegetation recovery dynamics in the framework of Mediterranean areas, after stand-replacing wildfires and high spatial resolution variables derived from Landsat data. Near future research will test its application in other large wildfires occurred in Mediterranean basin in Spain during the year 1994. Other methods as OLS with spatial filtering (Meng et al., 2015) could also be tested in near future research to find models with the best performance.

Results have also shown that vegetation regrowth after stand-replacing wildfire in western Mediterranean basin is linked to wetness availability in the immediate years after fire, favorable topography, burn severity and distance to forest edge.

On the whole, variables with highest explanatory power are those related to wetness within the pixel, followed by the influence of topography and pixel orientation. Other studies have also established the relevance of the precipitation factor (water availability) in vegetation recovery after disturbance processes in Boreal (Mansuy, Gauthier, Robitaille, & Bergeron, 2012) or Mediterranean areas (Meng et al., 2015). In contrast, some studies have shown less relevance to this factor in the short-term recovery giving more weight to time since fire (Malak & Pausas, 2006). Topography, and more specifically altitude, showed a positive correlation to recovery which could be connected to the effect of temperature.

Burn severity showed a significant explanatory power in prediction although it is less relevant than topography and wetness. Many factors could explain this aspect, although it seems clear that the wide percentage of moderate-high and high burn severities reported in this area (with GeoCBI values above 2.5 representing more than 98%), could have strongly damaged both *Quercus spp*. and *Pinus spp*. trees forcing both to recover from the same starting point and by using available biological legacies. In that case, individuals could have been required to regrowth by using their own reproductive resources (saplings or seedlings) if present, or turn to legacies from surrounding live trees. In this situation burn severity would have less relevance than other local environment conditions that could boost the establishment of legacies.

Distance to edge (nearest healthy forest patches) revealed relatively high relevance specifically in the case of *Pinus spp*. Donato et al. (2009) found that distance to live trees was the main driver on regeneration in *Pseudotsuga menziesii*. Conifer areas in our study are dominated by *Pinus nigra*, which lacks regeneration ability after crown fire (Pausas et al., 2008). It is also worth noting that *Pinus nigra* seems to have short-distance dispersal capability (Ordoñez, Molowny-Horas, & Retana, 2006). We do not yet know exactly how vegetation ecological succession behaves after stand-replacing wildfire in surfaces dominated by *Quercus spp*. or *Pinus spp*. in the area, but we may expect the ecological succession after stand-replacing fires have probably changed original species distribution in favor of those species prone to recolonize burnt areas such as *Pinus halepensis*.

It will also be crucial to study other potential drivers of regrowth after stand-replacing wildfires as the significance of fire and droughts recurrence.

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REFERENCES

Bastarrika, A., Alvarado, M., Artano, K., Martínez, M. P., Mesanza, A., Torre, L., et al. (2014). BAMS: A Tool for Supervised Burned Area Mapping Using Landsat Data. *Remote Sensing 6*, 12360-12380.

Cohen, W. B., Spies, T. A., & Fiorella, M. (1995). Estimating the age and structure of forests in a multi-ownership landscape of western Oregon, U.S.A. *International Journal of Remote Sensing, 16*(4), 721-746.

Crist, E. P., & Cicone, R. C. (1984). A Physically-Based Transformation of Thematic Mapper Data-The TM Tasseled Cap. *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, 22*(3), 256-263.

De Santis, A., Chuvieco, E., & Vaughan, P. (2009). Short-term assessment of burn severity using the inversion of PROSPECT and GeoSail models. *Remote Sensing of Environment, 113*, 126-136.

Donato, D. C., Fontaine, J. B., Campbell, J. L., Robinson, W. D., Kauffman, J. B., & Law, B. E. (2009). Conifer regeneration in stand-replacement portions of a large mixed-severity wildfire in the Klamathâ€“Siskiyou Mountains. *Canadian Journal of Forest Research, 39*(4), 823-838.

González-Hidalgo, J. C., Brunetti, M., & de Luis, M. (2011). A new tool for monthly precipitation analysis in Spain: MOPREDAS database (monthly precipitation trends December 1945–November 2005). *International Journal of Climatology, 31*(5), 715-731.

Gonzalez-Hidalgo, J. C., Peña-Angulo, D., Brunetti, M., & Cortesi, N. (2015). MOTEDAS: a new monthly temperature database for mainland Spain and the trend in temperature (1951–2010). *International Journal of Climatology, 35*(15), 4444-4463.

Griffith, D. (2003). *Spatial autocorrelation and spatial filtering. Gaining understanding through theory and scientific visualization*: Springer.

Griffith, D. A., Fischer, M. M., & LeSage, J. (2016). The spatial autocorrelation problem in spatial interaction modelling: a comparison of two common solutions (Vol. 10, pp. 75-86).

Griffith, D. A., & Peres-Neto, P. R. (2006). SPATIAL MODELING IN ECOLOGY: THE FLEXIBILITY OF EIGENFUNCTION SPATIAL ANALYSES. *Ecology, 87*(10), 2603-2613.

Kennedy, R. E., Yang, Z., & Cohen, W. B. (2010). Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr — Temporal segmentation algorithms. *Remote Sensing of Environment, 114*, 2897-2910.

Malak, D. A., & Pausas, J. (2006). Fire regime and post-fire Normalized Difference Vegetation Index changes in the eastern Iberian peninsula (Mediterranean basin). *International Journal of Wildland Fire, 15*(3), 407-413.

Mansuy, N., Gauthier, S., Robitaille, A., & Bergeron, Y. (2012). Regional patterns of postfire canopy recovery in the northern boreal forest of Quebec: interactions between surficial deposit, climate, and fire cycle1This article is one of a selection of papers from the 7th International Conference on Disturbance Dynamics in Boreal Forests. *Canadian Journal of Forest Research, 42*(7), 1328-1343.

Masek, J. G., Vermote, E. F., Saleous, N. E., Wolfe, R., Hall, F. G., Huemmrich, K. F., et al. (2006). A Landsat Surface Reflectance Dataset for North America, 1990–2000. *IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, 3(1)*, 68-72.

Meng, J., Dennison, P. E., Huang, C. H., Moritz, M. A., & D'Antonio, C. M. (2015). Effects of fire severity and post-fire climate on short-term vegetation recovery of mixed-conifer and red fir forests in the Sierra Nevada Mountains of California. *Remote Sensing of Environment, 171*, 311-325.

Moreno, M. V., Conedera, M., Chuvieco, E., & Pezzatti, G. B. (2014). Fire regime changes and major driving forces in Spain from 1968 to 2010. *Environmental Science & Policy, 37*, 11-22.

Ordoñez, J. L., Molowny-Horas, R., & Retana, J. (2006). A model of the recruitment of Pinus nigra from unburned edges after large wildfires. *Ecological Modelling, 197*(3), 405-417.

Pausas, J. (2012). *Incendios Forestales. Una visión desde la Ecología*. Madrid: CSIC. Catarata.

Pausas, J., Llovet, J., Rodrigo, A., & Vallejo, R. (2008). Are wildfires a disaster in the Mediterranean basin? A review. *International Journal of Wildland Fire, 17*, 713-723.

Powell, S. L., Cohen, W. B., Healey, S. P., Kennedy, R. E., Moisen, G. G., Pierce, K. B., et al. (2010). Quantification of live aboveground forest biomass dynamics with Landsat time-series and field inventory data: A comparison of empirical modeling approaches. *Remote Sensing of Environment, 114*(5), 1053-1068.

Price, D. T., Alfaro, R. I., Brown, K. J., Flannigan, M. D., Fleming, R. A., Hogg, E. H., et al. (2013). Anticipating the consequences of climate change for Canada's boreal forest ecosystems. *Environmental Reviews, 21*(4), 322-365.

Rodrigues, M., de la Riva, J., & Fotheringham, S. (2014). Modeling the spatial variation of the explanatory factors of human-caused wildfires in Spain using geographically weighted logistic regression. *Applied Geography, 48*, 52-63.

Vannière, B., Colombaroli, D., Chapron, E., Leroux, A., Tinner, W., & Magny, M. (2008). Climate versus human-driven fire regimes in Mediterranean landscapes: the Holocene record of Lago dell'Accesa (Tuscany, Italy). *Quaternary Science Reviews, 27*(11), 1181-1196.