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Assessment of post-fire changes in land surface temperature and surface albedo, and their relation with fire/burn severity using multi-temporal MODIS imagery

Running head: Post-fire changes in land surface temperature and surface albedo, and their relation with fire/burn severity

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Brief summary. This paper assesses post-fire changes in land surface temperature (LST) and surface albedo (α) using remotely sensed time series on the extensive 2007 wildfires in Greece. In addition it evaluates the usefulness of these variables for assessing fire/burn

severity. The study relies on the control pixel selection procedure to mimic the burned pixels' temporal behavior as there would not have been a fire. The type of fire-affected land cover influenced the changes. Lag, i.e. time since fire, and seasonal timing also affected the magnitude of post-fire changes. Moreover, this seasonality constrains the suitability of remotely sensed LST and α layers as indicators of fire/burn severity.

Abstract. Wildfires cause local scale changes that importantly impact species richness, habitats and community composition. This study evaluates the effects of the large 2007 Peloponnese (Greece) wildfires on changes in broadband surface albedo (α), day-time land surface temperature (LST_d) and night-time LST (LST_n) using a two-year post-fire time series of Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data. In addition it assesses the potential of remotely sensed α and LST as indicators for fire/burn. Firstly, a pixel-based control plot selection procedure was initiated based on a pre-fire time series similarity of biophysical variables (α, LST_d, LST_n and Normalized Difference Vegetation Index (NDVI)). Then differences in mean NDVI, α, LST_d and LST_n of the control and burned pixels were compared. Fire severity is defined as the magnitude of change caused by a fire as gauged immediately after the fire event, while burn severity also incorporates vegetation regeneration processes. Fire/burn severity was estimated based on the magnitude of the post-fire NDVI drop. Immediately after the fire event mean α dropped up to 0.039 (standard deviation = 0.012) ($p < 0.001$), mean LST_d increased up to 8.4 (3.0) K ($p < 0.001$), and mean LST_n decreased up to -1.2 (1.5) K ($p < 0.001$) for high severity plots ($p < 0.001$). After this initial alteration, fire-induced changes become clearly smaller and seasonality starts governing the α and LST time series. Compared to the fire-induced changes in α and LST, the post-fire NDVI drop was more persistent in time. This temporal constraint restricts the utility of remotely sensed α and LST as indicators for fire burn severity. For these moments changes in α and LST were significant, the magnitude of changes was related to fire/burn severity elucidating the importance of vegetation as a regulator of land surface energy fluxes. Changes varied also per land cover type: changes in forests were more profound and persistent than those in shrub land. The characteristic phenology of land covers (e.g. coniferous vs. deciduous forest) also resulted in a clearly different post-fire behavior. This research provides insights in the understanding of short-term fire effects on regional climate.

Additional keywords. Land Surface Temperature (LST), albedo, NDVI, MODIS, remote sensing, fire, climate, severity, satellite

Introduction

Biomass burning is a major disturbance in almost all terrestrial ecosystems (Dwyer et al. 1999; Pausas 2004; Riano et al. 2007) partially or completely removing the vegetation layer and affecting post-fire vegetation composition (Epting and Verbyla 2005; Lentile et al. 2005). The fire-induced vegetation depletion causes abrupt changes in carbon, energy and water fluxes at local scale (Bremer and Ham 1999; Amiro et al. 2006*a*; Montes-Helu et al. 2009), thereby influencing species richness, habitats and community composition (Moretti et al. 2002; Capitaino and Carcaillet 2008). Understanding these local scale changes in fluxes, is therefore essential for management practices as they will have a strong impacts on the water and energy balances (Bremer and Ham 1999; Amiro et al. 2006*a*), and may cause changes in circulation and regional heating patterns (Beringer et al. 2002; Wendt et al. 2007).

A key parameter in post-fire management is fire/burn severity. Fire/burn severity relates to the degree of environmental change caused by a fire (Key and Benson 2005). Although the terms fire and burn severity are often interchangeable used (Boer et al. 2008; Keeley 2009), some authors suggest to clearly differentiate between them (Lentile et al. 2006; Veraverbeke et al. 2010a). By doing so, fire severity gauges the fire impact in the pre-recovery phase accounting solely for the direct fire effects. Burn severity, in contrast, combines both the immediate fire impact with ecosystems responses (mainly vegetation regeneration). The main driver for the terminological difference thus relies on the temporal dynamics of the post-fire environment (Key 2006; Veraverbeke et al. 2010a). Remote sensing has proven to be a time-and cost-effective means for mapping wildfire effects (a.o. Viedma et al. 1997; Stroppiana et al. 2002; Lentile et al. 2006; Riano et al. 2007; van Leeuwen 2008). The remote sensing of burned area, fire/burn severity and vegetation regeneration mapping has a long tradition in the use of vegetation indices (VIs) (a.o. Cahoon et al. 1994; Barbosa et al. 1999; Chafer et al. 2004; Chuvieco et al. 2008; French et al. 2008; Clemente et al. 2009). Although the ubiquitous Normalized Difference Vegetation Index relates reasonably well to fire/burn severity (Chafer et al. 2004; Hammill and Bradstock 2006, Veraverbeke et al. 2010b, Lhermitte et al. 2011), the Normalized Burn Ratio (NBR) has become increasingly popular as it consistently outperforms the NDVI for assessing immediate post-fire effects (Epting et al. 2005; French et al. 2008; Veraverbeke et al. 2010b). For monitoring post-fire vegetation recovery, however, the NDVI still is by far the most widely used index (a.o. Viedma et al. 1997, van Leeuwen 2008, Clemente et al. 2009, Lhermitte et al. 2010, van Leeuwen et al. 2010). Hitherto, rather few studies have assessed the potential of remotely sensed bioclimatic variables other than VIs with regards to post-fire effects. A suggestion in this direction originates from Lyons et al. (2008). In their study of the post-fire albedo changes in forested ecotypes in Alaska they saw some potential in the use of bi-temporally differenced metric based on surface albedo as a complementary index to the NBR for estimating fire/burn severity. To date, the majority of the post-fire effects studies has been conducted based on Landsat imagery because of its beneficial spatial resolution for regional-scale studies (French et al. 2008). The use of Landsat imagery, however, can be constrained due to cloud cover (Ju and Roy 2008) and image-to-image normalization problems (Verbyla et al. 2008; Veraverbeke et al. 2010c). Due to the limited image availability, Landsat studies cannot fully account for the temporal dynamics of a post-fire environment. At the expense of spatial detail, low resolution imagery with high temporal frequency pose a solution for this issue (Veraverbeke et al. 2011; Lhermitte et al. 2011).

Several field studies have assessed these effects of fire on bioclimatic variables. In this context, the surface blackening due to charring causes a clear albedo decrease immediately after the fire event (Bremer and Ham 1999; Beringer et al. 2003; Amiro et al. 2006*b*; Wendt et al. 2007; Tsuyuzaki et al. 2009). This decrease is up to half the pre-fire values (Bremer and Ham 1999) and the magnitude of change is dependent on the plot's fire severity (Beringer et al. 2003). This effect, however, is short-lived since albedo quickly recovers to pre-fire values when char materials are removed by weathering and vegetation starts to regenerate (Bremer and Ham 1999; Tsuyuzaki et al. 2009). After the initial short drop, albedo tends to increase during the next post-fire years, especially during the summer season, and the persistency of this increase is function of the rate of vegetation regeneration (Amiro et al. 1999). Albedo values are subject to seasonality and as consequence dissimilarities between evergreen and deciduous ecotypes are evident. Summertime albedo is higher for deciduous ecosystems, while in winter differences are minor (Amiro et al. 2006b), although in winter snow cover often importantly impacts the surface albedo (Betts and Ball 1997). Another typical post-fire change is an increase in Bowen ratio, which is defined as the ratio between sensible and latent heat fluxes (Bowen 1926; Beringer et al. 2003; Amiro et al. 2006*b*; Wendt et al. 2007). This is due to the decrease in latent heat flux and the consequent decrease in cooling by evapotranspiration (Wendt et al. 2007). The energy partitioning is, however, also subject to seasonal changes; the evaporative fraction for example will be higher during the subsequent wet season after the fire than immediately post-fire (Montes-Helu et al. 2009). It has also been demonstrated that the evapotranspiration is considerably higher for regenerating deciduous forest stands compared to evergreens (Amiro et al. 2006a). Conversely, sensible and ground heat fluxes reveal a sharp increase shortly after the fire event. Consequently soil and air temperatures are markedly higher after fire occurrence (Wendt et al. 2007). The measured temperature differences between burned and unburned control plots are generally up to 2-8 K (Amiro et al. 1999; Bremer and Ham 1999; Wendt et al. 2007; Montes-Helu et al. 2009). Persistency of these fire-induced microclimatic changes depends on fire severity (Beringer et al. 2003) and ecosystem type, ranging from about one year in grasslands (Bremer and Ham 1999) to up to several decades in forests (Amiro et al. 2006*b*). From a remote sensing perspective, rather few studies have analyzed spatio-temporal patterns of post-fire albedo and surface temperature. These studies that examined the effect of fire on surface heating all reported the expected temperature increase in the immediate post-fire environment (Lopez and Caselles 1991; Cahoon et al. 1994; Eva and Lambin 1998; Lambin et al. 2003), while albedo values were halved immediately after the fire (Jin and Roy 2005; Lyons et al 2008).

Traditional pre-/post-fire image differencing is impeded by temporal constraints (Key 2006, Verbyla et al. 2008, Veraverbeke et al. 2010ac). Difficulties arise from both lag timing, i.e. time since fire, and seasonal timing. Even small inter-annual phenological differences can result in the detection of false trends (Key 2006, Verbyla et al. 2008, Lhermitte et al. 2011). To anticipate these false trends Diaz-Delgado and Pons (2001) proposed to compare burned plots with unburned control plots within the same image. As such, external and meteorological variations are minimized among the compared areas. Lhermitte et al. (2010) extended this rationale by making the control plot selection method spatially explicit. In contrast to the reference plot procedure of Diaz-Delgado and Pons (2001), the pixel-based method assigns a unique unburned control plot time series to each burned pixel, and as such account is made for within-burn heterogeneity. This control plot selection is based on the similarity between time series of the burned pixel and the time series of its surrounding unburned pixels for a pre-fire year (Lhermitte et al. 2010). So far, the pixel-based control plot selection procedure has only been used to analyze fire-induced changes in vegetation (Lhermitte et al. 2010; Veraverbeke et al. 2010a).

Hence, in this paper post-fire changes in remotely sensed bioclimatic variables are monitored based on the control plot selection procedure. More specifically we aim (i) to analyze post-fire changes in surface albedo and Land Surface Temperature (LST) and (ii) to evaluate the potential of remotely sensed albedo and LST as indicators for fire/burn severity. The first aim wishes to contribute to the understanding of how fire alters the environment whereas the second goal meets the suggestion of Lyons et al. (2008) to test the potential of new metrics for assessing post-fire effects. The case study is conducted on the large 2007 Peloponnese (Greece) wildfires. The study makes use of multi-temporal Moderate Resolution Imaging Spectroradiometer (MODIS) imagery.

Data and study area

Study area

The study focuses on several large fires situated at the Peloponnese peninsula, in southern Greece (36°30'-38°30' N, 21°-23° E) (Figure 1). All the fires date from the 2007 summer. These fires were the worst natural disaster of the last decades in Greece, both in terms of human losses and the extent of the burned area. Elevations range between 0 and 2404 m above sea level. Limestone sediments cover most of the mountainous inland. Also significant outcrops of sediments occur (Institute of Geology and Mineral Exploration 1983, Higgins et al. 1996). The hilly and mountainous inland is covered with shallow and gravelly soils (European Commission 2005). The climate is typically Mediterranean with hot, dry summers and mild, wet winters. For the Kalamata meteorological station (37°4' N, 22°1' E) the average annual temperature is 17.8 °C and the mean annual precipitation equals 780 mm (Figure 2). The fires consumed more than 175 000 ha, which consisted of 57% shrub land, 21%

coniferous forest, 20% olive groves and 2% deciduous forest (Veraverbeke et al. 2010a). A pre-fire land cover map of the burned areas is given in figure 1. Black pine (*Pinus nigra*) is the dominant conifer species. The shrub layer is characterised by e.g. *Quercus coccifera, Q. frainetto, Pistacia lentiscus, Cistus salvifolius, C. incanus, Erica arborea, Sarcopoterum spinosum*. The olive groves consist of *Olea europaea* trees, whereas oaks are the dominant deciduous species. Mediterranean-type shrub lands are highly resilient to burning due to both obligate seeder and resprouter fire-adapted strategies. They regenerate as a rule in a couple of years (Trabaud 1981, Capitaino and Carcaillet 2008) in a so called autosuccession process (Hanes 1971). Conversely, the recovery of the forests is considerably slower and can take up to several decades (Viedma et al. 1997, van Leeuwen et al. 2010).

FIGURE 1 HERE

FIGURE 2 HERE

Data

MODIS satellite time series were used in this study. The MODIS sensor is onboard the Terra and Aqua satellites and provides daily observations at 1:30 AM (Aqua ascending node), 10:30 AM (Terra descending node), 1:30 PM (Aqua descending node) and 10:30 PM (Terra ascending node) local time (Justice et al. 2002). Terra MODIS 16-day vegetation indices (1 km) (MOD13A2) (Huete et al. 2002), combined Terra/Aqua MODIS 16-day albedo (1 km) (MCD43B3) (Schaaf et al. 2002), Terra MODIS 8-day LST (1 km) (MOD11A2) and Aqua MODIS 8-day LST (1 km) (MYD11A2) with 1 K accuracy (Wan 2008) tiles covering the study area were acquired from the National Aeronautics and Space Administration (NASA) Warehouse Inventory Search Tool (WIST) (https://wist.echo.nasa.gov) for the period 01/01/2006 till 31/12/2009. NDVI, broadband (0.3-5.0 μm) white-sky albedo (α), LST_d, LST_n and associated Quality Assurance (QA) layers were subsequently extracted. We are aware that by using low resolution imagery, spatial heterogeneity is sacrificed to some degree (Key 2006), however recent research has highlighted the importance of the temporal dimension of post-fire effects (Veraverbeke et al. 2010a, 2011; Lhermitte et al., 2). This explains our choice for low resolution MODIS imagery which is characterized by its high temporal frequency. The preprocessing steps included subsetting, reprojecting, compositing and creating continuous time series. The study area was clipped and the NDVI, α, LST and QA layers were reprojected into the Universal Transverse Mercator (UTM) with the World Geodetic System 84 (WGS 84) as geodetic datum. Subsequently, the 8-day LST layers were composited in 16-day composites using the Maximum Value Composite (MVC) criterion (Holben, 1986). As such, the temporal resolution of the LST composites matches the NDVI and α composites' temporal resolution. By applying the MVC criterion high LST values are favored. This is justified as previous research mainly indicated the importance of the post-fire temperature increase (Lopez and Caselles 1991; Cahoon et al. 1994; Eva and Lambin 1998; Amiro et al. 1999; Bremer and Ham 1999; Lambin et al. 2003; Wendt et al. 2007; Montes-Helu et al. 2009). After compositing a local second-order polynomial function, also known as an adaptive Savitzky-Golay filter (Savitzky and Golay 1964), was applied to the time series as implemented in the TIMESAT software (Jonsson and Eklundh 2004) to replace bad observations. The TIMESAT program allows the inclusion of a preprocessing. These masks are translated into weights, zero and one, that determine the uncertainty of the data values. Disturbed observations were identified using the cloud, aerosol and snow algorithm flags of the QA layers. These flags consist of binary layers which permit to assign a zero weight value to disturbed observations. Consequently these data do not influence the filter procedure. Due to the low altitude (0-1000 m) of the burned areas, these locations do not experience a permanent snow cover in the Mediterranean winter. In our study region, snow cover thus does not heavily impact ecosystem functioning. For this reason we totally excluded snow effects from the analysis. Only the values of the masked observations were replaced to retain as much as possible the original NDVI, α and LST values.

Methodology

Control pixel selection

To minimize external and phenological variations a pixel based control plot selection method (Lhermitte et al. 2010) was implemented. This control pixel selection makes use of time series similarity and spatial context. The selection is based on the similarity of NDVI, α, and LST time series between burned pixels and their surrounding unburned pixels during the pre-fire year 2006 and the averaged Euclidian distance *D* was used as dissimilarity measure:

$$D = \frac{\sqrt{\sum_{t=1}^{N}(sNDVI_t^f - sNDVI_t^x)^2 + (s\alpha_t^f - s\alpha_t^x)^2 + (sLSTd_t^f - sLSTd_t^x)^2 + (sLSTn_t^f - sLSTn_t^x)^2}}{N} \quad (5)$$

where $sNDVI_t^f$ is the burned focal pixel standardized NDVI time series, $sNDVI_t^x$ is the unburned candidate control pixel standardized NDVI time series, $s\alpha_t^f$ is the focal pixel standardized α time series, $s\alpha_t^x$ is the candidate control pixel standardized α time series, $sLSTd_t^f$ is the focal pixel standardized day-time LST time series, $sLSTd_t^x$ is the candidate control pixel standardized day-time LST time series, $sLSTn_t^f$ is the focal pixel standardized night-time LST time series, $sLSTn_t^x$ is the candidate control pixel standardized night-time LST time series, while N is the number of observations in the pre-fire year (*N*=23). The time series were standardized to provide equal weight to all data layers during the control pixel selection procedure. This standardization was accomplished by the following formula:

$$sX = \frac{X - X_{mean}}{X_{sd}} \quad (6)$$

where sX is the standardized NDVI, α, or LST, X is the original NDVI, α, or LST, X_{mean} is the spatio-temporal mean NDVI, α, or LST of all pixels, while X_{sd} represents the spatio-temporal NDVI, α or LST standard deviation of all pixels.

For valid control plot estimates, control pixels must correspond to the focal pixel in case the fire had not occurred. Firstly, this implies identical pre-fire characteristics for both control and focal pixels. Secondly, it means similar post-fire environmental conditions. To determine the appropriate control pixel selection criteria, the method of Lhermitte et al. (2010) was calibrated to our dataset based on post-fire similarity, since we wish to estimate how the NDVI, α and LST would have behaved in case of no fire occurrence. In this context, the accuracy of the control pixel selection is assessed by looking at the pre- and post-fire similarity of fictively burned pixels. This approach allows to effectively assessing how parameters c, the number of control pixels, and $w{\times}w$, the window size around the focal pixel, affect the post-fire similarity. In this context, 500 unburned pixels were randomly selected and a fictive burning date was set for these pixels at the same composite date the real fire event took place. Subsequently, the sensitivity of dissimilarity criterion D to c and $w{\times}w$ was assessed for each of these pixels by comparing the outcome for varying number of control pixels (c = 1, 2,…, 15) and varying window sizes (3×3, 5×5,…, 25×25). Not only the most similar control pixel was considered because a beneficial averaging that removes random noise in the time series has been perceived in previous research (Lhermitte et al. 2010). As a result the averaged time series of the two (or more) most similar pixels potentially provides better results. Evaluation consisted of measuring the temporal dissimilarity D for the 500 fictively burned sample pixels one year pre-fire and one year post-fire. This allows to determine how well pre-fire similarity is maintained after a fictive burning date and how pre-/post-fire changes in similarity are related to the number of control pixels (c) and window size

($w \times w$). More information on the control pixel selection procedure can be found in Lhermitte et al. (2010) and Veraverbeke et al. (2010a).

Analysis method

The control plot selection procedure allowed generating two-year post-fire time series of NDVI, α, and LST (at 1:30 AM, 10:30 AM, 1:30 PM and 10:30 PM local time) as best estimates of how these variables would have behaved without fire occurrence. We aim to quantify the fire-induced changes in α and LST between focal and control pixels and to investigate their relation with the changes in NDVI provoked by fire. The mathematical formulation of these changes is:

$$dX_t = X_t^f - X_t^c \tag{7}$$

where X_t^f is the NDVI, α or LST value of the focal burned pixels at time t, X_t^c is the NDVI, α or LST of the control pixels and dX_t is the difference in NDVI, α or LST between focal and control pixels. The statistical significance of this difference is assessed by performing a z-test of the null hypothesis that dX_t follow a normal distribution with mean 0. Results are separately analyzed for different land cover and fire/burn severity classes. Land cover types were determined based on the classification of Veraverbeke et al. (2010a) resampled to a 1 km resolution (Figure 1). As a proxy for fire/burn severity we used a three-class equal interval dNDVI-stratification. For assessing immediate post-fire effects the NBR generally results in a stronger correlation with field data than the NDVI (Epting et al. 2005, French et al. 2008), however the NDVI's ability of capturing the severity of fire-induced changes has been proven in a multitude of studies (a.o. Isaev et al. 2002; Diaz-Delgado et al. 2003; Chafer et al. 2004; Hammill and Bradstock 2006, Lhermitte et al. 2011). Specifically for the Peloponnese burns Landsat dNDVI data related reasonably well with field data of severity (R^2=0.46, Veraverbeke et al. 2010b). To account for both immediate fire effects and vegetation recovery, which is prominent in a Mediterranean ecosystem over a two-year post-fire period, we considered the NDVI appropriate. While we recognize the spatial generalization of low resolution MODIS imagery compared to Landsat, previous research in the study area demonstrated a relatively high correlation between downsampled Landsat and MODIS spectral indices (R^2=0.45-0.59, Veraverbeke et al. 2010a, 2011). The choice for MODIS imagery is governed by its repeated temporal sampling, which is beneficial for considering the temporal dynamics of the post-fire environment (Veraverbeke et al. 2010a, 2011; Lhermitte et al. 2011). We consider a dynamic dNDVI-stratification with three classes (LS: low severity, MS: moderate severity, HS: high severity) for each composite data separately as reliable means to present and summarize results (White et al. 1996; Chafer et al. 2004; Hammill and Bradstock 2006; Escuin et al. 2008). By applying a separate stratification for each time step we take into account the temporal component of post-fire effects (Key 2006; Lentile et al. 2006; Veraverbeke et al. 2010a). As we will conduct a distinct analysis for each land cover type, we did not use the relative version of a differenced spectral index as proposed by Miller and Thode (2007) to account for heterogeneity in pre-fire cover when assessing fire effects.

Results

Control pixel selection

Figure 3A reflects *D* in function of varying number of control pixels and window size for a pre-fire year. It shows the median temporal similarity of the 500 unburned sample pixels. The median is used instead of the mean as it is more robust in the presence of outlier values. Two main effects are observed in the figure. Firstly, the number of control pixels chosen influenced the dissimilarity measure due to an averaging effect. The strength of this averaging effect was dependent on window size: the averaging effect became more important for larger window sizes. Secondly, there was a consistently decreasing trend in pre-fire *D* when window size enlarged. This feature appeared regardless of the number of control pixels chosen. This finding contrasts with what is visible in figure 3B, which represents the post-fire *D* in function of varying number of control pixels and window size. Here, one can see that *D* obtained an optimum for intermediate window sizes. For the large window sizes *D* started increasing again. As a result, differences between pre- and post-fire similarity enlarged for large windows. This effect originates from the possible selection of distant pixels that have higher probability of showing different post-fire environmental conditions in larger windows (Lhermitte et al. 2010). As we wish to estimate the post-fire behavior of NDVI, α and LST, post-fire similarity is the decision criterion to determine the control plot selection setting (Veraverbeke et al. 2010a). Based on figures 3A-B the control pixel selection was calibrated by taking the average of the seven most similar pixels out of 120 candidate pixels (11×11-1), which corroborates findings of Lhermitte et al. (2010) and Veraverbeke et al. (2010a).

FIGURE 3 HERE

Figure 4 shows the relationship between the pre- and post-fire similarity *D* for the approach with the seven most similar pixels out of 120 candidate pixels. It reflects how pre-fire *D* provides an indicator for post-fire *D*. The majority of the pixels exhibit a linear relationship, however, two types of outliers occur. The first type of outliers represents data with relatively high pre-fire *D*. For these points the selection results in a suboptimal control pixel. The second type of outliers has relatively elevated post-fire *D* values. These are pixels for which changes occurred after the fictive burning date. Figure 4 shows that the outliers only represent a small fraction of the data cloud. As such, pre-fire *D* can be considered as a good indicator for post-fire *D* for the majority of the pixels.

FIGURE 4 HERE

Post-fire NDVI changes

The forthcoming sections summarize results of the post-fire changes in NDVI, α and LST. To minimize the occurrence of numbers in the text, tables 1 and 2 tabulate some absolute values of changes for exemplary moments. In this respect, tables 1-2 are complementary to figures 5-8.

Figures 5A-D show the post-fire development of focal and control pixels' mean NDVI per land cover type. One can clearly infer the immediate post-fire drop. This drop was more explicit for forests than for shrub land and olive groves. After this initial decrease, the effects of both vegetation regeneration and seasonality became apparent. Figures 5E-H display the post-fire dNDVI values per land cover type. For all land cover type the magnitude of the dNDVI change decreases when time elapses, however, inter-annual differences remain visible. The crosses in the figure indicate when the mean value significantly deviates from zero ($p < 0.001$). Except from some observations of the deciduous forest class, all post-fire NDVI changes are statistically significant.

FIGURE 5 HERE

Post-fire α changes

In figures 6A-D the post-fire trends in α for control and focal pixels are plotted per land cover type. One can see an immediate post-fire α drop for all covers. During the one-year post-fire summer the focal pixels' α of the evergreen covers (shrub land, olive groves and coniferous forest) excelled the control pixels values. This α increase was even more explicit during the second post-fire summer. During winter periods α changes are small. In figure 6E-H one can see the temporal development and significance of dα values per land cover type. In contrast with the majority of the summer observations, winter changes in α are not significant for most of the observations. Post-fire α changes per severity class are presented in figures 6I-L. The magnitude of the post-fire drop was related to fire severity and land cover class. For forested covers the α decrease was more explicit. For deciduous forest for example the α drop was up to 0.039 (0.012) for the HS class ($p < 0.001$). For the evergreen land cover types the α change of the HS class already became positive during the first post-fire winter. In the subsequent post-fire summers this resulted in an increased α of for example 0.016 (0.009) for coniferous forest ($p < 0.001$) two summers post-fire. α changes in LS and MS classes were minor. Except for the immediate post-fire drop, differences in α changes between the severity classes are less obvious for deciduous forest.

FIGURE 5 HERE

Post-fire LST_d changes

Results of the MODIS Terra and Aqua LST analyses revealed very similar trends. As a consequence only the Aqua LST analysis is presented. Figure 7A-D depict the mean LST_d of the control and focal pixels per land cover class. In all land covers, the fire caused a clear LST_d increase immediately post-fire and during the subsequent summer periods, while in winter changes are minor. The magnitude of the LST_d increase during subsequent summers became less explicit as time elapsed. In figures 7E-H the mean $dLST_d$ is plotted for the two-year post-fire period. Regardless of land cover type, one can see that the post-fire LST_d changes are significant during summer periods, whereas during winter periods many observations did not reveal a significant difference. Figures 7I-L present the $dLST_d$ changes per severity class. It is clear that the magnitude of the $dLST_d$ change depends on land cover and severity class. For the HS class of coniferous forest, for example, the immediate post-fire $dLST_d$ increase equaled 8.4 (3.0) K, while during the first and second post-fire summer $dLST_d$ values of respectively 5.4 (2.3) K and 1.7 (1.2) K were obtained ($p < 0.001$). During winter changes were minor and even sporadically negative, although these observations were not significant.

FIGURE 7 HERE

Post-fire LST_n changes

Figure 8A-D depict the two-year post-fire temporal evolution of mean LST_n of the control and focal pixels per land cover class. In these plots it is very difficult to discriminate between the control and focal pixels. Thus, changes in LST_n were very small. This is also illustrated in figures 8E-H, which show the mean $dLST_n$ values per land cover type. Results show a tendency of a post-fire LST_n decrease. Except for the persistent significance of the post-fire LST_n decrease over coniferous forest, the majority of changes were insignificant. Figures 8I-L present the mean $dLST_n$ per severity class. The relationship between severity class and $dLST_n$ was also only clear for coniferous forest. For the HS class of coniferous forest for example, a consistent LST_n decrease was observed up to values of -1.4 (1.0) K during the one-year post-fire winter.

FIGURE 8 HERE

TABLE 1 HERE

TABLE 2 HERE

Discussion

Control pixel selection

The strength of the control pixel selection procedure is its ability to mimic a burned pixel's behavior as there had not been a fire. The method therefore assesses the similarity in the temporal profiles of a burned pixel and its closest unburned neighbor pixels. By doing so, the procedure implicitly tends to select control pixels which exhibit similar vegetation (e.g. type, density, etc.) and environmental (e.g. topography, geology, climatology, etc.) conditions. The actual selection relies on pre-fire similarity as post-fire similarity information is unavailable after the burning date. However, only considering pre-fire time series would not account for inter-annual meteorological variations. For this reason, a calibration was set up based on 500 fictively burned pixels. This calibration allows assessing the relationship between pre- and post-fire similarity. As inferred from figure 3B, in contrast with figure 3A, the most optimal setting tends to select control pixels relatively close to the burned pixels. This effect arises from the selection of distant pixels with different post-fire meteorological conditions for larger window sizes (Lhermitte et al. 2010; Veraverbeke et al. 2010). Figure 4 demonstrates that pre-fire similarity is a valid indicator of post-fire similarity for the majority of the pixels. For some pixels, however, the selected control pixel will be suboptimal. This is especially true for control pixels which experienced considerable changes, such as land management practices, after the fire date. A comprehensive discussion on the control pixel selection procedure can be found in Lhermitte et al. (2010) and Veraverbeke et al. (2010).

Post-fire NDVI changes

Figure 5 confirms the utility of the NDVI for monitoring fire-induced changes. The NDVI time series, however, are also subject to seasonal variations. The timing of image acquisition, both in terms of lag and seasonal timing, thus impacts the NDVI response (Key 2006; Verbyla et al. 2008; Veraverbeke et al. 2010a; Lhermitte et al. in press). The seasonality of the NDVI response also depends on land cover type. In our study, deciduous forest shows markedly higher seasonal variations than evergreen species. Despite of these temporal constraints, the fire-induced changes in NDVI were clearly more persistent than changes in α and LST (see figures 6-8). Except for some winter observations over deciduous forest the NDVI appears to be a good discriminator between control and focal pixels. In contrast, seasonality dominates the temporal profiles of α and LST variables. The usefulness of these variables to discriminate fire-affected areas, thus, heavily depends on assessment timing.

Post-fire α changes

The effects of fire on α are multiple. Firstly, an immediate post-fire decrease in α is observed. This decrease was up to 0.039 (0.012) for the HS class in deciduous forest. This outcome is in line with previously published findings that report α drops in the range of 0.01-0.05 (Beringer et al. 2003; Jin and Roy 2005; Amiro et al. 2006*a*; Lyons et al. 2008). Two of these studies were also based on MODIS imagery (Jin and Roy 2005; Lyons et al. 2008). Lyons et al. (2008) observed a merely slight decrease of 0.012 (0.005), while the average α drop of 0.024 reported by Jin and Roy (2005) more closely approximates our values. The main reason for the immediate post-fire α decrease is the large-scale replacement of living vegetation with black carbon on the surface. Char materials strongly absorb the incoming sunlight and as such they cause a significant reduction of the reflection-to-incoming sunlight ratio. However, this effect had a relatively short duration, as during the first post-fire winter period, which is a period of heavy rainfalls in the Mediterranean, most of the char materials are removed by fluvial and aeolian forces (Pereira et al. 1999). In figure 6 one can see that the control pixels α values reveal a typical seasonality, which is closely connected with moisture conditions. α values are clearly lower during wet winter periods than during dry summer periods. However, as shown in figure 6, α values of undisturbed plots do not significantly differ from those of burned plots during winter. This suggests, different from findings of Tsuyuzaki et al. (2009), that the seasonal variations in surface moisture and the removal of black carbon more importantly drive the α recovery than the early regeneration of vegetation. It is, however, also recognized that leaves and branches of regenerating species have a higher α than mature species (Betts and Ball 1997; Amiro et al. 2006*b*). The combination of char removal and regenerating species cause an α increase during the post-fire summer periods. This increase was even more explicit for the second post-fire summer than for the first. This can be explained by the fact that after the first winter period the majority of surface's char coating has been removed and early vegetation regeneration has started, but after the second winter period even more of this char material is ablated and vegetation continued regenerating. This implies the exposure of highly reflective soil and rock combined with regenerating species, which results in an α increase (Lyons et al. 2008). These changes in post-fire summer α depend on fire/burn severity. The magnitude of summer α change is proportionally related to the degree of severity (see figure 5). In a long-term study (30 years post-fire), Amiro et al. (2006*a*) ascertained that the α increase progressively weakens as regenerating vegetation matures. Thus, where the immediate fire effect results in an increased absorption of radiative energy, the long-term effect generally is an increased albedo (Amiro et al. 2006*a*; Randerson et al. 2006). The quantification of these effects, together with an accurate estimation of the amount of greenhouse gasses emitted by the fire and the subsequent post-fire carbon sequestration of regenerating vegetation, are necessary for a holistic comprehension of the effect of wildfires on regional and global climate. In this context, Randerson et al. (2006) comprehensively demonstrated that, although the first post-fire year resulted in a net warming, the long-term balance was negative. As such they concluded that an increasing fire activity in the boreal region would not necessarily lead to a net climate warming. However, these findings were restricted to the boreal eco-region and a similar net balance has not yet been formulated for more quickly recovering ecosystems, such as in fire-prone (sub)tropical and mediterranean regions.

Post-fire LST changes

Besides assessing fire-induced changes in LST with respect to lag and seasonal timing, MODIS imagery also permits a study of diurnal differences. Immediately post-fire LST_d increases. The magnitude of this increase depends on land cover and fire/burn severity class. For the HS class of coniferous forest the focal pixels' mean excelled the control pixels' mean with 8.4 (3.0) K. This is very similar to the 2-8 K immediate post-fire temperature day-time temperature increases reported by other studies (Lopez and Caselles 1991; Cahoon et al. 1994;

Eva and Lambin 1998; Amiro et al. 1999; Bremer et al. 1999; Lambin et al. 2003; Wendt et al. 2007; Montes-Helu et al. 2009). This effect has, however, only a very short duration as by the onset of the wet winter, LST_d differences are minor. These findings corroborate with an analogous study that assessed the influence of the deforestation on LST_d (Manoharan et al. 2009). These authors reported that LST_d is 4 to 8 K higher during the dry season for deforested regions compared to nearby forests. However, during the wet season LST_d of deforested and forested plots reach similar values. One can infer the same trend from figure 6. During the one-year and subsequent post-fire summer seasons mean LST_d increases strongly attenuate. This attenuation can be contributed to vegetation regeneration processes (see figure 4) and char removal. The summer LST_d increase is the driving force of the synchronous increase in sensible and ground heat fluxes (Wendt et al. 2007). Little research has been conducted so far to assess the post-fire changes in LST_n. The range of changes in LST_n is relatively small. This makes it difficult to infer post-fire trends for this variable. The fire-induced changes in LST_n.are only persistent over coniferous forest. For this cover type a clear relation between fire/burn severity and $dLST_n$ also exists. During the one-year post-fire winter for example LST_n drops with -1.4 (1.0) K for the HS class over coniferous forest. It is important to mention that the MVC criterion favors the detection of post-fire LST increases, while it diminishes the observation of cold extremes. This potentially results in a slight underestimation of the post-fire LST_n.decrease. Generally spoken, fire, thus, creates a more extreme environment with warmer days and colder nights. Another striking result lies within the fact that both $dLST_n$ and $dLST_d$ observations of the last pre-fire composite of the evergreen cover types are significantly higher than zero. This potentially opens perspectives to use remotely sensed LST data as a real-time fire risk indicator (Manzo-Delgado et al. 2009).

Relation between fire-induced changes in α, LST and fire/burn severity

Fire-induced changes in α and LST show a marked seasonality. This results in significant changes immediately post-fire and in summer periods and insignificant differences during winter periods. Changes in NDVI, in contrast, are clearly more persistent. For α and LST the magnitude of fire-induced changes is smaller than seasonal amplitude, while for vegetation indices (VIs) the post-fire drop dominates the temporal profiles. This questions the proposal of Lyons et al. (2008) to use pre-/post-fire differenced satellite-derived albedo data as indicator of fire/burn severity. Fire/burn severity assessment timing already is a serious issue when working with VIs (Key 2006; Verbyla et al. 2008; Veraverbeke et al. 2010*ac*). Introducing biophysical parameters with high seasonal amplitude would only hamper this more. Especially because fire/burn severity is traditionally estimated based on Landsat imagery (French et al. 2008), which is frequently detracted by cloudy observations (Ju and Roy 2008). Only the first post-fire observation of these variables shows some potential to be used a fire severity indicator. Additionally, changes in LST are not only dependent on a plot's fire/burn severity but also on the meteorological conditions of the acquisition period. This feature limits the comparability of LST changes of different fires across space and time. For these moments when changes in α and LST_d are significant, the magnitude of these changes has indeed a very close relation with a plot's fire/burn severity, as estimated by its NDVI change (see figures 6-8). This elucidates the importance of vegetation as an important regulator of surface energy fluxes (Xiao and Weng 2007; Amiri et al. 2009; Manoharan et al. 2009; Tsuyuzaki et al. 2009). Fire thus creates a more arid environment with enhanced diurnal and seasonal temperature fluctuations. Vegetation regeneration, however, progressively tempers this effect and facilitates the long-term ecosystem recovery (Amiro et al. 2006*a*; Tsuyuzaki et al. 2009). While the immediate post-fire changes in α and LST_d observed in this study are consistent with previous results obtained in other ecosystems (a.o. Jin and Roy 2005; Lyons et al. 2008, Lopez and Caselles 1991; Cahoon et al. 1994; Eva and Lambin 1998;

Amiro et al. 1999; Bremer et al. 1999; Lambin et al. 2003; Wendt et al. 2007; Montes-Helu et al. 2009) our analysis also incorporated seasonal changes. To date, rather few studies have assessed the interference between fire-provoked changes and seasonality. It is obviously recognized that this seasonality depends on the regional climate. In regions experiencing a prominent period of snow cover, this feature will heavily influences seasonal cycles of energy fluxes (Betts and Ball 1997).

Conclusions

In this study the pixel-based control plot selection procedure allowed a multi-temporal assessment of the effects of the 2007 Peloponnese (Greece) wildfires on local climate during a two-year post-fire period based on MODIS satellite imagery. Post-fire changes in vegetation, α and LST were dependent on land cover type and fire/burn severity. Post-fire NDVI time series were dominated by their post-fire NDVI drop, while changes in α and LST were highly dependent on seasonality. Therefore VIs are more persistent to detect burns and to discriminate severity levels. Surface α sharply decreased immediately after the fire event, however, during subsequent summer period α increased, while during winter α changes were minimal. LST_d was higher after the fire. This increase was especially obvious during summer periods. The temperature increase attenuated as time elapsed, as a consequence of regenerating vegetation. Changes in LST_n were very small and almost not significant, except over coniferous forest where LST_n slightly decreased. The magnitude of these changes is proportionally related with a plot's fire/burn severity, as assessed by the post-fire NDVI drop. This study provides insights on the multi-temporal changes in energy fluxes in a fire-altered environment, which have important ecological implications.

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Fig. 1. Pre-fire land cover map of the burned areas (after Veraverbeke et al. 2010a).

Fig. 2. Ombrothermic diagram of the Kalamata (Peloponnese, Greece) meteorological station ($37^{o}4'1''$ N $22^{o}1'1''$ E) 1956-1997 (Hellenic National Meteorological Service, www.hnms.gr)

Fig. 3. Median dissimilarity *D* of the 500 sample pixels in function of varying number of control pixels and window size for (A) a pre-fire year and for (B) a post-fire year. For the post-fire year, the same control pixels setting as in the pre-fire year is preserved. The grayscale reflects the temporal similarity, while the white areas in the upper-left corner represent impossible combinations (number of control pixels > 8, for 3×3 window size).

Fig. 4. Post-fire similarity *D* in function of pre-fire similarity *D* for the approach with the seven most similar pixels out of 120 candidate pixels.

Fig. 5. Two-year post-fire temporal evolution of mean NDVI of control and focal pixels for shrub land (A), olive groves (B), coniferous forest (C) and deciduous forest (D); and two-year post-fire temporal evolution of mean dNDVI for shrub land (E), olive groves (F), coniferous forest (G) and deciduous forest (H). The crosses in E-H indicate that the mean significantly differs from zero ($p < 0.001$). In G-H standard deviations are plotted with vertical bars.

Fig. 6. Two-year post-fire temporal evolution of mean α of control and focal pixels for shrub land (A), olive groves (B), coniferous forest (C) and deciduous forest (D); two-year post-fire temporal evolution of mean dα for shrub land (E), olive groves (F), coniferous forest (G) and deciduous forest (H); two-year post-fire temporal evolution of mean dα per fire/burn severity classes for shrub land (I), olive groves (J), coniferous forest (K) and deciduous forest (L). The crosses in E-H indicate that the mean significantly differs from zero ($p < 0.001$). In G-H standard deviations are plotted with vertical bars. In I-L LS, MS and HS stand for respectively low, moderate and high severity.

Fig 7. Two-year post-fire temporal evolution of mean LST_d of control and focal pixels for shrub land (A), olive groves (B), coniferous forest (C) and deciduous forest (D); two-year post-fire temporal evolution of mean $dLST_d$ for shrub land (E), olive groves (F), coniferous forest (G) and deciduous forest (H); two-year post-fire temporal evolution of mean $dLST_d$ per fire/burn severity classes for shrub land (I), olive groves (J), coniferous forest (K) and deciduous forest (L). The crosses in E-H indicate that the mean significantly differs from zero ($p < 0.001$). In G-H standard deviations are plotted with vertical bars. In I-L LS, MS and HS stand for respectively low, moderate and high severity.

Fig. 8. Two-year post-fire temporal evolution of mean LST_n of control and focal pixels for shrub land (A), olive groves (B), coniferous forest (C) and deciduous forest (D); two-year post-fire temporal evolution of mean $dLST_n$ for shrub land (E), olive groves (F), coniferous forest (G) and deciduous forest (H); two-year post-fire temporal evolution of mean $dLST_d$ per fire/burn severity classes for shrub land (I), olive groves (J), coniferous forest (K) and deciduous forest (L). The crosses in E-H indicate that the mean significantly differs from zero ($p < 0.001$). In G-H standard deviations are plotted with vertical bars. In I-L LS, MS and HS stand for respectively low, moderate and high severity.

Table 1. Post-fire mean (sd) NDVI, α, and LST changes of control and focal pixels per land cover type for some exemplary moments (29-Aug-07: first post-fire observation, 19-Dec-07: post-fire winter, 27-Jun-08: one-year post-fire summer, 20-Dec-08: one-year post-fire winter, 26-Jun-09: two-year post-fire summer and 19-Dec-09: two-year post-fire winter)

		29-Aug-07	19-Dec-07	27-Jun-08	20-Dec-08	26-Jun-09	19-Dec-09
Shrub land	Mean NDVI control (sd)	0.46 (0.06)	0.60 (0.05)	0.50 (0.06)	0.62 (0.06)	0.52 (0.06)	0.69 (0.05)
	Mean NDVI focal (sd)l	0.30 (0.06)	0.47 (0.10)	0.38 (0.06)	0.53 (0.07)	0.44 (0.07)	0.65 (0.07)
	Mean α control (sd)	0.140 (0.012)	0.120 (0.011)	0.149 (0.012)	0.122 (0.012)	0.142 (0.011)	0.127 (0.015)
	Mean α focal (sd)	0.117 (0.018)	0.114 (0.020)	0.154 (0.014)	0.124 (0.021)	0.151 (0.014)	0.135 (0.020)
	Mean LST_d control (sd) (K)	312.1 (2.1)	285.3 (1.7)	313.1 (2.5)	283.6 (2.0)	310.0 (2.5)	290.4 (1.5)
	Mean LST_d focal (sd) (K)	316.6 (2.9)	285.7 (1.9)	315.2 (2.6)	283.7 (1.7)	311.2 (2.6)	290.0 (2.1)
	Mean LST_n control (sd) (K)	291.4 (1.6)	275.0 (1.7)	292.6 (1.6)	274.0 (1.3)	290.5 (1.8)	282.0 (1.5)
	Mean LST_n focal (sd) (K)	291.3 (1.9)	274.8 (1.8)	292.7 (1.7)	273.9 (1.5)	290.5 (1.9)	281.5 (2.0)
Olive groves	Mean NDVI control (sd)	0.48 (0.04)	0.67 (0.04)	0.50 (0.05)	0.71 (0.03)	0.54 (0.04)	0.75 (0.03)
	Mean NDVI focal (sd)l	0.32 (0.05)	0.53 (0.09)	0.40 (0.05)	0.61 (0.06)	0.47 (0.05)	0.71 (0.06)
	Mean α control (sd)	0.137 (0.014)	0.114 (0.011)	0.146 (0.010)	0.119 (0.010)	0.138 (0.008)	0.126 (0.012)
	Mean α focal (sd)	0.115 (0.017)	0.109 (0.019)	0.149 (0.012)	0.123 (0.019)	0.146 (0.010)	0.137 (0.020)
	Mean LST_d control (sd) (K)	311.5 (1.6)	286.2 (1.2)	313.1 (1.9)	284.3 (1.5)	309.2 (2.2)	291.4 (2.3)
	Mean LST_d focal (sd) (K)	315.9 (2.6)	286.7 (1.3)	315.0 (2.0)	284.6 (1.6)	310.3 (2.3)	291.5 (1.9)
	Mean LST_n control (sd) (K)	292.6 (1.0)	277.1 (1.5)	293.9 (0.9)	275.5 (1.2)	291.3 (1.2)	283.2 (1.2)
	Mean LST_n focal (sd) (K)	292.6 (1.1)	276.8 (1.6)	294.1 (1.0)	275.4 (1.4)	291.3 (1.3)	282.9 (1.9)
Coniferous forest	Mean NDVI control (sd)	0.60 (0.06)	0.67 (0.04)	0.63 (0.06)	0.71 (0.03)	0.63 (0.05)	0.77 (0.05)
	Mean NDVI focal (sd)l	0.36 (0.09)	0.41 (0.10)	0.41 (0.08)	0.55 (0.08)	0.51 (0.07)	0.69 (0.08)
	Mean α control (sd)	0.124 (0.011)	0.100 (0.012)	0.134 (0.009)	0.102 (0.012)	0.127 (0.008)	0.102 (0.014)
	Mean α focal (sd)	0.093 (0.014)	0.088 (0.020)	0.135 (0.013)	0.102 (0.021)	0.134 (0.011)	0.108 (0.021)
	Mean LST_d control (sd) (K)	309.5 (1.9)	283.9 (1.6)	310.1 (2.2)	281.9 (1.6)	307.0 (1.5)	289.9 (1.8)
	Mean LST_d focal (sd) (K)	314.8 (3.9)	284.4 (2.1)	313.4 (2.8)	283.2 (2.0)	308.8 (2.1)	289.6 (2.2)
	Mean LST_n control (sd) (K)	291.7 (1.1)	275.4 (1.7)	292.9 (1.2)	274.5 (1.2)	290.5 (1.0)	282.4 (1.5)
	Mean LST_n focal (sd) (K)	291.2 (1.6)	274.9 (1.8)	292.7 (1.6)	274.0 (1.0)	290.2 (1.2)	281.9 (2.0)
Deciduous forest	Mean NDVI control (sd)	0.56 (0.06)	0.55 (0.04)	0.65 (0.07)	0.53 (0.06)	0.65 (0.06)	0.64 (0.06)
	Mean NDVI focal (sd)l	0.37 (0.08)	0.44 (0.07)	0.48 (0.08)	0.49 (0.05)	0.56 (0.08)	0.64 (0.06)
	Mean α control (sd)	0.137 (0.009)	0.112 (0.008)	0.142 (0.007)	0.112 (0.010)	0.135 (0.005)	0.110 (0.007)
	Mean α focal (sd)	0.109 (0.016)	0.091 (0.012)	0.140 (0.009)	0.104 (0.019)	0.133 (0.007)	0.111 (0.010)
	Mean LST_d control (sd) (K)	310.1 (2.4)	283.8 (1.3)	310.6 (2.4)	283.0 (1.9)	307.3 (1.9)	289.7 (1.6)
	Mean LST_d focal (sd) (K)	316.0 (3.7)	284.1 (1.4)	313.4 (2.7)	283.3 (2.3)	308.5 (2.0)	289.1 (1.9)
	Mean LST_n control (sd) (K)	289.6 (1.0)	273.4 (0.5)	290.8 (0.8)	272.9 (0.6)	288.9 (0.8)	280.8 (0.6)
	Mean LST_n focal (sd) (K)	289.0 (1.0)	274.0 (0.6°	290.8 (0.9)	272.7 (0.7)	288.5 (0.9)	280.2 (1.3)

Table 2. Post-fire mean (sd) dNDVI, dα, dLST$_d$ and dLST$_n$ values per land cover type and fire/burn severity class (LS: low severity, MS: moderate severity and HS: high severity) for some exemplary moments (29-Aug-07: first post-fire observation, 19-Dec-07: post-fire winter, 27-Jun-08: one-year post-fire summer, 20-Dec-08: one-year post-fire winter, 26-Jun-09: two-year post-fire summer and 19-Dec-09: two-year post-fire winter). Values which significantly differ from zero ($p < 0.001$) are italicized.

		29-Aug-07	19-Dec-07	27-Jun-08	20-Dec-08	26-Jun-09	19-Dec-09
Shrub land	Mean dα LS (sd)	*-0.013 (0.012)*	*-0.009 (0.013)*	0.000 (0.007)	0.000 (0.014)	*0.005 (0.008)*	*0.006 (0.016)*
	Mean dα MS (sd)	*-0.024 (0.014)*	*-0.006 (0.016)*	*0.005 (0.010)*	0.002 (0.018)	*0.009 (0.010)*	*0.008 (0.017)*
	Mean dα HS (sd)	*-0.032 (0.011)*	0.000 (0.020)	*0.012 (0.011)*	0.016 (0.025)	*0.012 (0.012)*	0.013 (0.023)
	Mean d LST$_d$ LS (sd) (K)	*1.8 (1.7)*	*0.2 (0.8)*	*0.5 (1.2)*	0.0 (1.1)	*0.7 (1.1)*	-0.3 (2.0)
	Mean d LST$_d$ MS (sd) (K)	*4.5 (2.5)*	*0.4 (1.1)*	*2.1 (1.9)*	0.1 (1.2)	*1.2 (1.3)*	-0.3 (2.0)
	Mean d LST$_d$ HS (sd) (K)	*6.6 (2.3)*	*0.8 (1.5)*	*4.3 (1.9)*	-0.4 (1.1)	*1.9 (1.9)*	-0.8 (2.5)
	Mean d LST$_n$ LS (sd) (K)	0.0 (0.8)	-0.1 (0.8)	0.2 (0.8)	*-0.1 (0.7)*	0.1 (0.7)	*-0.3 (1.6)*
	Mean d LST$_n$ MS (sd) (K)	-0.1 (1.1)	*-0.2 (0.8)*	*0.1 (0.8)*	*-0.2 (0.9)*	0.0 (0.8)	*-0.5 (1.6)*
	Mean d LST$_n$ HS (sd) (K)	*-0.4 (1.2)*	-0.3 (0.9)	-0.1 (0.9)	-0.3 (1.5)	-0.3 (1.4)	-1.4 (2.3)
Olive groves	Mean dα LS	*-0.015 (0.011)*	*-0.007 (0.014)*	*0.002 (0.007)*	0.001 (0.015)	*0.007 (0.007)*	*0.011 (0.017)*
	Mean dα MS	*-0.022 (0.012)*	*-0.005 (0.015)*	*0.003 (0.009)*	*0.004 (0.016)*	*0.009 (0.008)*	*0.011 (0.018)*
	Mean dα HS	*-0.029 (0.011)*	0.000 (0.015)	0.007 (0.012)	*0.030 (0.019)*	*0.019 (0.014)*	0.014 (0.028)
	Mean d LST$_d$ LS (sd) (K)	*2.8 (1.6)*	*0.3 (0.9)*	*1.0 (1.0)*	0.2 (0.9)	*0.8 (0.9)*	-0.1 (1.7
	Mean d LST$_d$ MS (sd) (K)	*4.4 (2.1)*	*0.5 (1.0)*	*1.8 (1.5)*	*0.3 (1.0)*	*1.2 (1.1)*	0.0 (1.8)
	Mean d LST$_d$ HS (sd) (K)	*6.5 (1.4)*	0.6 (1.3)	*3.5 (2.1)*	-0.9 (1.0)	*2.1 (1.7)*	0.0 (1.1)
	Mean d LST$_n$ LS (sd) (K)	0.0 (0.5)	-0.1 (0.7)	0.0 (0.5)	-0.1 (0.7)	0.0 (0.5)	-0.1 (1.4)
	Mean d LST$_n$ MS (sd) (K)	0.0 (0.6)	*-0.3 (0.6)*	*0.2 (0.6)*	-0.1 (0.8)	0.0 (0.7)	*-0.3 (1.4)*
	Mean d LST$_n$ HS (sd) (K)	-0.1 (0.6)	*-0.6 (0.7)*	0.2 (0.7)	-0.2 (1.1)	0.0 (0.7)	-0.7 (0.9)
Coniferous forest	Mean dα LS	*-0.026 (0.014)*	*-0.014 (0.018)*	-0.005 (0.011)	-0.004 (0.019)	*0.004 (0.009)*	*0.007 (0.019)*
	Mean dα MS	*-0.030 (0.012)*	*-0.011 (0.018)*	0.002 (0.012)	0.000 (0.020)	*0.007 (0.010)*	*0.006 (0.019)*
	Mean dα HS	*-0.036 (0.009)*	-0.004 (0.018)	*0.006 (0.012)*	0.003 (0.026)	*0.016 (0.009)*	*0.006 (0.019)*
	Mean d LST$_d$ LS (sd) (K)	*2.9 (2.3)*	0.3 (1.3)	*1.5 (1.7)*	0.3 (1.4)	*1.1 (1.3)*	-0.2 (2.1)
	Mean d LST$_d$ MS (sd) (K)	*5.3 (3.2)*	*0.5 (1.5)*	*3.3 (2.2)*	0.2 (1.4)	*1.7 (1.5)*	*-0.4 (2.1)*
	Mean d LST$_d$ HS (sd) (K)	*8.4 (3.0)*	0.6 (1.8)	*5.4 (2.3)*	-0.4 (1.6)	*1.7 (1.2)*	-0.3 (2.3)
	Mean d LST$_n$ LS (sd) (K)	-0.2 (0.8)	-0.2 (0.7)	0.1 (0.6)	-0.1 (0.7)	-0.1 (0.5)	-0.3 (1.4)
	Mean d LST$_n$ MS (sd) (K)	*-0.6 (1.1)*	*-0.5 (0.9)*	*-0.2 (0.9)*	*-0.5 (0.9)*	*-0.3 (0.7)*	*-0.4 (1.5)*
	Mean d LST$_n$ HS (sd) (K)	*-1.2 (1.5)*	*-1.0 (1.0)*	*-0.9 (1.1)*	*-1.4 (1.0)*	*-0.8 (0.8)*	-0.8 (1.6)
Deciduous forest	Mean dα LS	*-0.016 (0.011)*	*-0.018 (0.013)*	0.000 (0.009)	-0.013 (0.010)	0.006 (0.006)	0.000 (0.008)
	Mean dα MS	*-0.030 (0.012)*	*-0.021 (0.015)*	-0.002 (0.008)	-0.008 (0.022)	-0.002 (0.008)	0.000 (0.009)
	Mean dα HS	*-0.039 (0.012)*	*-0.026 (0.024)*	-0.006 (0.007)	0.002 (0.034)	-0.004 (0.007)	0.002 (0.012)
	Mean d LST$_d$ LS (sd) (K)	*2.8 (2.4)*	*0.4 (0.6)*	0.3 (1.4)	0.7 (0.8)	0.4 (0.6)	-0.6 (2.2)
	Mean d LST$_d$ MS (sd) (K)	*5.3 (3.2)*	*0.4 (0.8)*	*2.8 (2.1)*	0.3 (1.2)	*0.8 (1.2)*	-0.7 (2.0)
	Mean d LST$_d$ HS (sd) (K)	*8.1 (2.0)*	0.0 (1.2)	*5.0 (1.2)*	0.2 (1.1)	*2.1 (1.6)*	0.2 (2.0)
	Mean d LST$_n$ LS (sd) (K)	-0.2 (0.5)	*0.8 (0.6)*	0.5 (0.4)	-0.3 (0.6)	0.0 (0.5)	-0.6 (1.7)
	Mean d LST$_n$ MS (sd) (K)	*-0.6 (0.8)*	*0.5 (0.7)*	-0.1 (0.8)	-0.2 (0.6)	*-0.2 (0.5)*	*-0.6 (1.4)*
	Mean d LST$_n$ HS (sd) (K)	*-1.0 (0.9)*	-0.2 (0.5)	-0.5 (0.9)	0.0 (0.4)	*-0.8 (0.7)*	-0.3 (1.0)