

Research Papers Issue RP0152 January 2013

CIP - Climate Change Impacts and Policy

Division

Forest Fires in Italy: An econometric analysis of major driving factors.

By Melania Michetti

Euro-Mediterranean Center on Climate Change (CMCC) viale Aldo Moro 44, 40127, Bologna, Italy. Phone: +39 051-3782634; Fondazione Eni Enrico Mattei (FEEM) melania.michetti@cmcc.it

> Mehmet Pinar Edge Hill University (Ormskirk, UK)

This work was partially funded by the European Union Seventh Framework Programme (FP7/2007-2013) under Grant Agreement 243888 ("FUME" Project - Forest fires under climate, social and economic changes in Europe, the Mediterranean and other fire-affected areas of the world): www.fumeproject.eu Additionally, we thank the Italian Corpo Forestale dello Stato and the Joint Research Centre for providing us with data on fires as well as ISTAT for socio-economic data. Also, we want to thank Renato Rosa, Francesco Bosello, Thanasis Stengos, and Matteo Manera for their helpful comments.

SUMMARY Despite the relevant fire risk to which Italy is subject from the north to the south, very few analyses focus on this topic. This article investigates the causes of forest fires frequency and intensity in Italy during the first decade of the twenty-first century. The dynamical aspects of fire danger are explored through the use of panel data techniques, which fully capture the impacts on forest fires regarding changes in both socio-economic and climatic conditions. Italy is treated as a unique region in an initial model specification, and is then split into 3 geographical areas (north, center, and south) to capture locally specific aspects. Two different dependent variables are alternatively employed and a number of ad hoc tests are performed to corroborate the robustness of our estimates. The results highlight the importance of considering the fire situation separately for the northern, central, and southern parts of Italy. While the presence of railway networks positively affects fire risk, the impact of livestock depends on its specific composition. Favorable effects in fire reduction are represented by the increase in education levels (north and center) and touristic flows (north and south), and by the containment of illegal activities (south). Weather patterns appear to be important determinants throughout the Italian peninsula.

Keywords: Forest Fires, Forestry, Climatic and Socio-economic Drivers, Fixed and Random Effects.

JEL: C13, C23, C51, Q23.

1. Introduction and Motivation

Forestland and trees offer vital services such as commercial and recreational uses, water and climate regulation services, and carbon sequestration activity. Unfortunately, there are several forest disturbances that undermine these service provisions. Compared to other calamities such as pests, plant diseases, wind, frost etc., fire represents the most threatening one in the Mediterranean area (Alexandrian et al., 1999).

Forest fires recur year after year, with a devastating intensity. There is no natural and vegetative landscape, which has not been altered by fire. Despite the fact that during the last decades scarce precipitations along with high temperature levels have been impacting the fire risk (Moriondo et al., 2006), these two variables represent just some of the possible causes of forest fires. Fire risk depends on a number of regional specific factors (Moreno et al., 1998 and Martinez et al., 2008 and 2009; Westerling et al. 2006 for US, among others), human attitudes (Barbero et al., 1990; Martinez et al., 2008 and 2009; Pausas and Keeley, 2009), and weather patterns (Westerling et al. 2006; Pausas and Fernández-Muñoz, 2012). The combination of all these aspects is therefore responsible for generating the final scenario of fire danger.

Recent studies acknowledge that forest fire risk is common to the overall southern Mediterranean area (Pausas et al., 2008 for Mediterranean area; Miranda et al., 2008 for Southern Europe; Dimitrakopoulos et al., 2011 for Greece; Costa et al., 2011 for Portugal). Italy is not an exception since it is affected by relevant fire risk from the north to the south. A consistent number of fire events occur not only during the warm seasons, as one would expect, but also during the winter. In the last decade, 360 fire events were registered on average each year. This frequency is associated with around 40 km² of land burnt, per year, and per region. In the first quarter of 2012, 3900 forest fire events occurred corresponding to 190 km² of forest area covered by fires. Compared to the same period in 2011, Italy experienced a 165% increase in the number of fire events and a 196% enlargement of the area affected (Corpo Forestale dello Stato, 2012).²

This article fills several gaps in the literature by investigating the causes of forest fire frequency and intensity examining fire regimes during the first decade of the twenty-first century.

² For more details see <u>http://www3.corpoforestale.it/flex/cm/pages/ServeBLOB.php/L/IT/IDPagina/313</u>

First, it focuses on the Italian situation, which, so far, has been analyzed by very few investigations. It highlights signs and magnitudes of the effects considered, which are sometimes controversial in the literature. The present study initially considers the overall Italian peninsula.³ It then analyses the fire situation by classifying the Italian territory into three geographical areas (north, center , and south) to highlight differences in fire patterns across regions and to provide a more in depth investigation regarding the role of humans and the characteristics of forest fire occurrences.

Second, differently from the majority of existing analyses (Chuvieco et al., 2008; White et al., 2011), we account for both social-economic and weather patterns in the characterization of fire regimes. Most events are indeed strictly linked to human behaviors, fraudulent causes or other socio-economic conditions (Yang et al., 2007; Martinez et al. 2008 and 2009; Leone et al., 2009; Lovreglio et al., 2010; de Torres Curth et al. 2012). However, physical/weather patterns are also responsible (Chou et al., 1993; Pinol et al., 1998; Pausas, 2004; Moriondo et al., 2006; Westerling et al. 2006; Pausas and Bradstock, 2007; Pausas and Fernández-Muñoz, 2012).

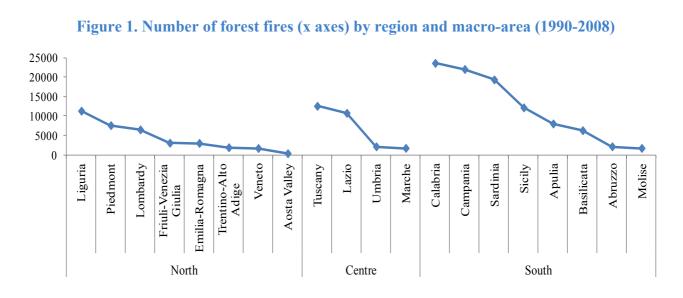
Third, on the methodological side, we implement a panel data approach fully capturing the dynamics of fire occurrence and the change in socio-economic and weather conditions in time. To corroborate the robustness of our estimates we use two, rather than just one, dependent variables, in addition to a number of *ad hoc* tests. Apart from a few exceptions, existing studies for Italy are based on the observation of simple historical trends and do not apply accurate econometric techniques to corroborate obtained results. Additionally, geographical-oriented approaches to forest fire analysis tend to account for fire realizations at some point in time (e.g., one specific year) neglecting dynamic aspects.

This paper is organized as follows. Section 2 illustrates the historical situation of forest fires in Italy while section 3 discusses main driving factors of forest fire frequency and intensity. Section 4, in addition to describing the data construction process, draws descriptive statistics on both dependent and independent variables. Section 5 offers a brief survey on methodologies useful to analyze the fire regimes, and then describes the chosen theoretical framework. Sections 6 and 7 report findings derived from different model specifications while section 8 concludes.

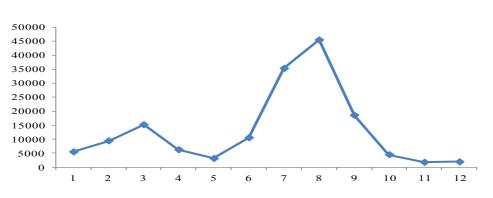
³ Examples of regional analyses are provided by Telesca and Lasaponara, 2006 for central Italy; Bajocco and Ricotta, 2008, Telesca et al. 2005, Pazienza and Beraldo, 2004 for southern Italy; Zumbrunnen et al. 2009 and Wastl et al., 2012 for northern Italy.

2. A Brief History of Forest Fires in Italy

Among the Mediterranean countries Italy represents one of the most prone areas to forest-fires.⁴ For example, Moriondo et al. (2006) find that Italy experiences the highest increase in annual extreme events in future scenarios conducted through return period analysis. Fire events cover the entire Italian peninsula, from the north to the south, however the larger wildfire events normally occur in the south (Figure 1). This explains why the few existing Italian-based analyses on fire events mostly focus on southern Italy (Pazienza and Beraldo, 2004; Bajocco and Ricotta, 2008).



The fire situation in Italy has a seasonal component. Events take place not only during the hotter periods but also during the colder ones. The most affected months appear to be February-March, July-August-September (Figure 2).

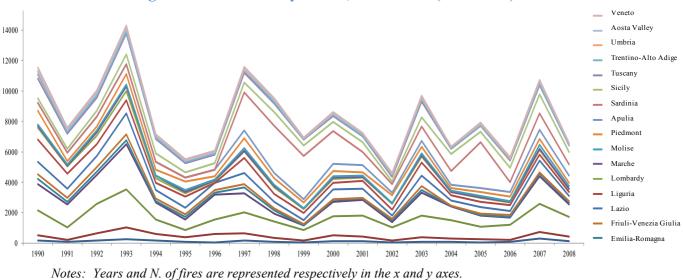




Notes: Months and N. of fires are represented respectively in the x and y axes.

⁴ See the fire history section within the European Forest Fire Information System (EFFIS) for the details of the total number of fire events, total area burnt, and the average fire size from 1985 to 2010 (http://effis.jrc.ec.europa.eu/fire-history)

Regarding medium and long-term fire patterns, during the 1990-2008 period there were several years with high frequency fire episodes, while during the last decade there were much less of them : 2003, 2005 (for some regions), and 2007 (Figure 3).





Finally, using a ten-year moving average, a downward trend in fire frequency is shown for most regions in the north and the center.⁵ For the remaining regions, especially in the south, a steady or mixed trend applies (Figure 4).

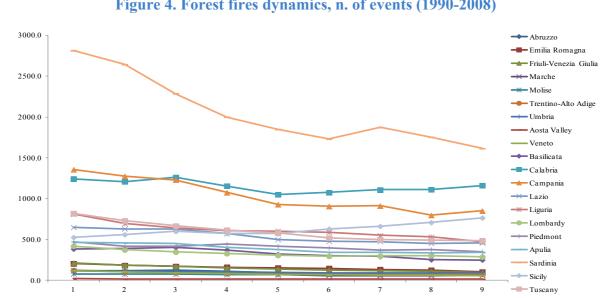


Figure 4. Forest fires dynamics, n. of events (1990-2008)

⁵ Each interval represents a 10-year average of forest fire events for each region. For example, 1 is associated to the average of fire frequency between 1990 and 1999, while 2 relates to the 1991-2000 period, and so on. Information used (from JRC) lacks data for Sardinia during 1990-1996, and for Liguria in 1996. These missing data are accounted for when the moving average trends are obtained.

3. Forest Fires Driving Forces

Notwithstanding a high number of fire events remains without a well-identified cause (Alexandrian et al., 1999; World Wide Fund, WWF, 2004),⁶ the literature typically distinguishes between natural and socio-economic conditions. This has originated two main streams of research. The first places more attention on natural-climatic or weather patterns (Chou et al., 1993; Pinol et al., 1998; Pausas, 2004; Moriondo et al., 2006; Westerling et al. 2006; Running, 2006; Pausas and Bradstock, 2007; Pausas and Fernández-Muñoz, 2012). The second emphasizes the social-economic variables that are assumed to generate higher impacts on fire ignition (Cardille et al., 2001; Leone et al. 2002; Yang et al., 2007; Martinez et al. 2008 & 2009; Leone et al., 2009; Lovreglio et al., 2010; de Torres Curth et al. 2012). Figure 5 summarizes frequently used drivers in forest fire analyses .

Variable	Relation with fire	Explanation	Studies considering the variable
Precipitation	Negative	Higher humidity and precipitation slow down the process of forest fuels dry out, reducing fire risk.	Pausas, 2004; Trouet et al., 2006; Westerling et al., 2006; Pausas and Bradstock, 2007; Trouet et al., 2010
Temperature	Positive	A rise in temperature leads to a drop in fuel moisture, and increase flammability of live and dead fuels, therefore raising the likelihood of observing fire events.	Pinol et al., 1998; Wotton et al., 2003; Pausas, 2004; Trouet et al., 2006; Westerling et al., 2006; Running 2006; Pausas and Bradstock, 2007
Drought	Negative	It depends on the combination of precipitation amounts and temperature: it causes plant mortality and impact long-run forests flammability.	Lloret et al. 2002; Breda et al. 2006; Aguado et al., 2007
population density/ growth rate	Mixed	A population enlargement may increase possible ignition causes due to human accidents. On the other hand, higher land demand, following the raise in population, could slow down the land abandonment process, e.g., the forest spontaneous re-growth.	Donoughue and Main, 1985; Serneels and Lambin, 2001; Leone et al. 2002; Mercer and Prestemon, 2005; Vadrevu et al., 2006; Syphard et al., 2007; Gellrich et al., 2007; Martinez et al., 2009; de Torres Curth et al. 2012;
Infrastructures, connections	Mixed	A greater number of roads and railways may put more pressure on wild lands raising possible ignition causes. Nevertheless, good communication routes may help fire prevention and suppression.	Cardille et al., 2001; Pew and Larsen, 2001; Martinez et al., 2009;
Agriculture and pasture intensification	Mixed	Fire is often used by shepherds and farmers to i) maintain herbaceous vegetation only; or ii) eliminate wasting harvest in borders of croplands, iii) remove pests.	Bolgiano, 1998; Kuhlken, 1999; Chuvieco et al., 1999; Leone et al. 2002; Pazienza and Beraldo, 2004; Vigilante et al., 2004; Whalley, 2005; Martinez et al., 2009
Education	Negative	More educated people may have a higher civic sense wich helps containing the number of fires due to human perverse behaviour or accidents.	Butry et al., 2002;
Unemployment Poverty level	Positive	Higher wellbeing and employment levels may discourage people from setting forests on fire for profit reasons.	Chuvieco et al., 1999; Leone et al., 2002; Butry et al., 2002; Pazienza and Beraldo, 2004; Mercer and Prestemon, 2005; Maingi and Hendry, 2007; Martinez et al., 2009; de Torres Curth et al., 2012
Depopulation of rural areas	Positive	It implies land abandonment and spontaneous colonization of natural vegetation. This, translates in additional forest biomass, and consequently in greater forestland flammability.	Le Houérou, 1987; MacDonald et al., 2000; Romero- Calcerrada and Perry, 2004; Koutsias et al. 2005; Martinez et al. 2009.
Touristic migration	The touristic use of forests for recreation could raise the probability		Atkinson and Therneau, 2000; Leone et al. 2002; Martinez et al., 2009
Presence of illegal organizations	Positive	Illegal organizations can control economical activities connected with land; set forests on fires to gain land for agriculture or pasture, retained more valuable than preserving forests for recreational use or logging.	Leone et. al, 2002; Gonzalez-Olabarria and Pukkala, 2011

Figure 5. Popular fire drivers in the literature

⁶ See special issue on Mediterranean Forests by FAO Unasylva Vol. 50, No. 197, (available at: http://www.fao.org/docrep/x1880e/x1880e00.htm). See also WWF, Forest fires in the Mediterranean: a burning issue (available at: http://ec.europa.eu/environment/forests/pdf/meeting140504_wwffirstdocument.pdf).

4. Database "Construction" and Descriptive Findings

To capture the dynamics in forest fires we constructed a balanced panel dataset for the 2000-2008 period for 19 Italian regions. It includes two dependent and around 20 explanatory variables. Although the data on forest fires is available for all 20 Italian regions, we eliminated the Aosta Valley region from our analysis due to the lack of data on most of the socio-economic and climatic variables. We believe that this exclusion has no impact on final results, since this region is the least prone area to forest fires in Italy.⁷

4.1 Dependent Variables

Two different dependent variables are used for the analysis. The first represents the frequency of forest fires, namely, the number of fire events in a given region in a given year ($lnfn_tot$). The second (lnburntot) is the area burnt in each region, in each year, measured in square kilometers. Both variables are expressed in natural logarithms, a convenient transformation which does not alter final results. The two variables are highly and positively correlated, but capture different aspects of fire dynamics. Therefore, using them both allows a richer interpretation of the results and also provides a robustness check. As shown in Table 1 there is an annual average of around 382 fire events and of 42.49 square kilometers of forest acreage destroyed per region. The lowest annual number of fire events took place in Veneto in 2004 (11 fire events), whereas the highest occurred in Sardinia in 2005 (3022 fire events). Aggregating Italian regions into three sub groups (north, center, and south) we notice that southern Italy is affected the most, followed by central and northern Italy.

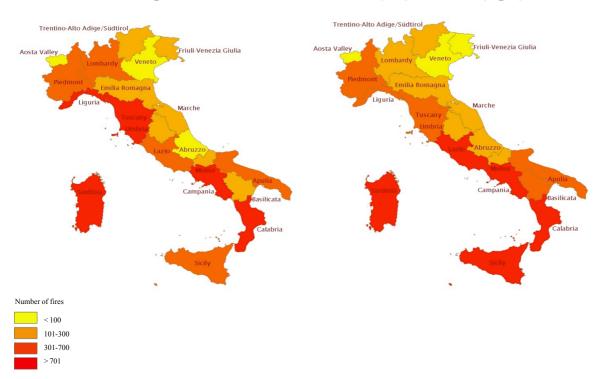
Dependent Variable	Regional Aggregation	Obs	Mean	Std. Dev.	Min	Max
# of events	North	48	156	124	11	491
# of events	Centre	60	273	233	19	1041
# of events	South	78	605	563	28	3022
Dependent Variable	Regional Aggregation	Obs	Mean	Std. Dev.	Min	Max
Area burnt in km ²	North	48	10.60	14.88	0.02	67.17
Area burnt in km ²	Centre	60	19.81	27.11	0.36	135.67
Area burnt in km ²	South	78	79.57	91.95	1.01	464.51

Table 1. Statistics on the dependent variables (2000-2008). Regions grouped in three areas

2003 and 2007 which are the most relevant years in terms of fire frequency (Figure 3), still confirm existing divergence across regions and the higher vulnerability of the south (Figure 6a/b and Table

⁷ Aosta Valley records on average 15 events, which translate into 6.5ha size of area burnt per year.

2). To control for yearly fluctuations effects on fire occurrence (Prestemon et al., 2002; Preisler et al., 2004) we add year dummies in our panel-based models.





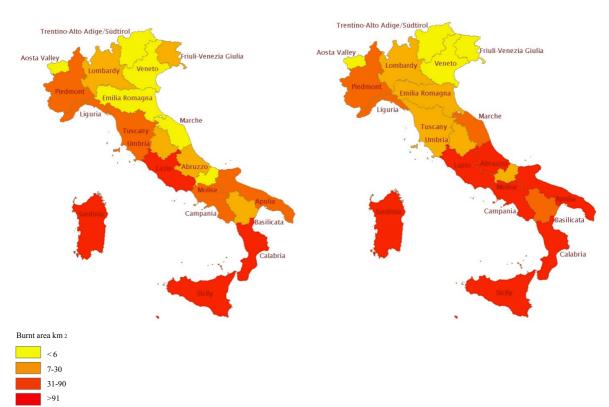


Figure 6b. Area burnt (km²) in 2003 (left) and 2007 (right)

Number of fire events in 2003 by size							
Regional Group	< 1	1 < # < 2.5	2.5 < # <5	> 5	Total events	Average size per event (in km2)	
North	1321	17	6	2	1338	0.069	
Centre	2975	47	13	3	3022	0.083	
South	5304	92	28	9	5396	0.107	
Italy	9600	156	47	14	9756	0.094	
Classification of	fire events in 2	2007 by size					
Regional Group	< 1	<i>I</i> < # < 2.5	2.5 < # <5	> 5	Total events	Average size per event (in km2)	
North	942	14	1	0	958	0.059	
Centre	2145	42	13	3	2187	0.116	
South	7249	342	135	50	7591	0.259	
Italy	10338	398	149	53	10736	0.212	

Table 2. Classification of fire events in 2003 and 2007

The monthly average of forest fire size suggests that the largest fire events take place in July and August. June and September also show high figures although 4 times lower than the mean of July and August. Interestingly, despite what one would expect, a significant number of forest fires occur during low-temperature periods, especially in February and March (Table 3).

Table 3.	Monthly	amount o	f area	burnt	during	2000-2008	(measured	in km ²)

Month	Obs	Mean	Std. Dev.	Max
January	186	0.94	4.01	41.27
February	186	1.06	3.95	34.90
March	186	1.88	4.78	42.21
April	186	0.54	1.17	7.59
May	186	0.38	1.28	15.39
June	186	3.69	10.27	94.20
July	186	14.35	32.27	191.63
August	186	14.40	28.51	195.55
September	186	3.65	6.53	46.32
October	186	0.76	3.11	34.54
November	186	0.50	1.68	12.51
December	186	0.35	2.13	20.67

Pooling the information obtained on the size and frequency at monthly averages per region and year (Tables 3 and 4), and given the outcomes of a correlation analysis, we acknowledge that the two variables are highly correlated. Yet, in some cases, their comparison helps us to draw interesting information. For instance, while in February the number of events is in line with that of the

remaining months, the total amount of forest area covered by fires is relatively high, suggesting a large *average* size.

Month	Obs	Mean	Std. Dev.	Max
January	186	12.92	55.49	723
February	186	15.02	24.14	155
March	186	27.10	38.03	187
April	186	12.06	15.13	73
May	186	9.31	14.08	79
June	186	29.89	59.42	528
July	186	92.91	146.42	1175
August	186	114.40	159.07	814
September	186	47.5	72.58	447
October	186	12.17	32.08	228
November	186	5.06	9.73	58
December	186	3.54	12.01	110

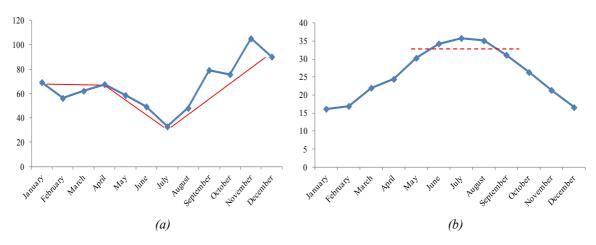
 Table 4. Monthly fire events during 2000-2008 (average number per year and regions)

4.2 Explanatory Variables: Weather Patterns

Weather patterns in the analysis are represented by precipitation and temperature, temperature excursion (i.e., the difference between the annual maximum and minimum temperature), and the number of consecutive hot days in one year. The interactions of some of these variables are also included among the explanatory ones.

Over the period considered, the annual average number of consecutive hot days for each region ranges between 0 and 43.25 (Sardinia in 2003). In the north, center, and south, on average, 2.80, 6.40, and 11.65 consecutive hot days are recorded respectively. The annual excursion in temperature ranges between 7.3 °C and 12.8 °C. Despite yearly fluctuations and inter-annual variability, general paths can be identified in precipitation levels (Figure 7 (a) and Table 5): they are higher during the winter period (September-December) and notably decrease from May to August, especially in July. Temperature (Figure 7(b) and Table 6) shows a clear seasonal effect. Its level progressively raises starting in January, peaks around July, and then decreases slowly until the January values again. This seasonal effect is normally reflected in fire events (see e.g., Bajocco and Ricotta, 2008).





Given the patterns in Figure 7 (a), we create three trend variables to account for changes in precipitation levels, which are then used to estimate our models. These are highlighted by the red line: i) precipitation from January to April (with a monthly average of 69mm during 2000-2008); ii) precipitation from May to August (with a monthly average 48.5mm during 2000-2008); and iii) precipitation from September to December (with a monthly average 88mm between 2000-2008). Regarding temperature, we focus on the summer data instead, constructing a variable related to the average June to August period (35.4°C).

Label	Obs	Mean	Std. Dev.	Min	Max
January	190	69.40	47.17	0.8	252.64
February	190	56.31	37.18	0	178.47
March	190	62.29	40.47	1.1	213.7
April	188	67.73	34.44	3.8	237.1
May	189	58.70	41.15	1.64	212.6
June	189	49.36	35.53	0.33	140.6
July	190	32.92	31.35	0.02	146.6
August	188	48.11	48.29	0	237.4
September	186	79.35	41.44	10.37	238.33
October	189	75.85	44.46	1.86	230.1
November	187	105.41	64.76	16.61	416.13
December	187	90.36	53.99	0	275.47

Table 5. Monthly precipitation levels during 2000-2008 (measured in mm)

Label	Obs	Mean	Std. Dev.	Min	Max
January	170	16.15	2.93	8.8	22.47
February	171	16.93	2.47	9.7	23.6
March	170	21.99	2.41	16.53	30.57
April	168	24.42	1.72	20	29.33
May	167	30.29	2.66	23.2	38.75
June	169	34.27	2.31	29.43	41
July	169	35.80	2.56	29.3	43.37
August	169	35.12	2.93	27	41.85
September	167	31.12	2.58	23.1	38
October	171	26.33	2.72	19	33.5
November	171	21.36	2.92	13.8	28.53
December	169	16.59	3.11	8.1	23.25

Table 6. Monthly temperature levels during 2000-2008 (measured in Degree Celsius)

4.3 Explanatory Variables: Socio-economic Factors

Several socio-economic driving factors have been identified and used as controls in the model specifications. In this subsection we summarize the main information about the variables included in the model specifications within this paper given their statistical significance. The complete list of variables can be found in the Appendix 1.

Population density varies in Italy across regions and ranges from 59 (Basilicata) to 428 people per km² (Campania). The number of people in a region in a given year is strongly subject to touristic flows. During the 2000-2008 period, apart from Campania (42 million), touristic arrivals were concentrated in northern Italy. Indeed, Veneto, Tuscany, Emilia-Romagna, Lazio, Lombardy, Trentino-Alto Adige welcomed roughly 116.5, 95, 82, 80, 79, and 74 million of tourists within a nine year period. Touristic migrations could alter the chances of ignition by accident or negligence resulting differently across regions. For example, 2007 was one of the peak years for touristic arrivals in Italy (i.e., roughly 266.5 million arrivals within 2007). This could have fostered the incidence of fire in that specific year.

Concerning economic conditions, the households' wellbeing varies significantly between the north and the south. For example, the ISTAT indicator of relative poverty reports, for 2008, shows that the percentage of population below the **poverty level** ranges between 3.9% (Emilia Romagna) and 28.8% (Basilicata and Sicily). During the whole period analyzed, on average, around 22%, 5.92%,

and 6.01% of the population was declared to be "poor" respectively in southern, central and northern Italy. According to our data, the poverty indicator is negatively correlated with the portion of population that has a **tertiary degree** in a given region, which varies significantly from the north to the south and normally increases over time. The use of land is closely linked with the **employment rate** in the agriculture sector. The percentage of population employed in this sector in 2008 varies from 1.70% (Lazio) to 9.12% (Calabria).

Italy is characterized by the presence of **illegal associations**, which control economical activities connected to agriculture and pasture practices. Their control may impact land allocation and therefore, forest fire occurrences.⁸ Especially in the past, forests have been voluntarily set on fire to create firefighting jobs or to gain land for agriculture and pasture which were retained more valuable than logging (Leone et. al, 2002). Indeed, low timber returns along with negligent forest management can result in higher fire risk (Gonzalez-Olabarria and Pukkala, 2011).⁹ To capture the effect of the presence of illegal activities/associations on human-induced fires we use the proxy variable 'number of **extortions per 1000 inhabitants**', which shows an increasing trend in time in many Italian regions. This variable may also reflect the different incidence across regions. For example, in 2008, extortions per 1000 inhabitants ranged between 0.04 (Friuli-Venezia Giulia) and 0.21 (Campania). Table 7 below summarizes this information.

Variable	Obs	Mean	Std. Dev.	Min	Max
Infn_tot (dep. var.)	186	5.36	1.14	2.40	8.01
Lnburntot (dep. var.)	186	2.72	1.54	0.02	6.14
Inpop_den	190	5.07	0.57	4.08	6.06
Inrail_den	190	4.59	0.76	2.80	5.90
rela_pov	170	12.74	8.68	2.50	30.80
Lnbovine	190	1.85	1.33	0.002	4.37
Lncaprine	190	1.15	0.66	0.32	2.63
p_ter_deg	190	7.34	1.76	3.65	12.75
p_emp_agri	190	5.52	2.94	1.53	12.79

⁸ According to Naveh (1995), throughout Europe humans have had a great role in modifying landscapes and landscapes result from the combination of different cultural views.

⁹ In Italy, the presence of illegal associations has been partially favored by the lack of law enforcement. Regulation n. 353, which dates back to November 2000 (G. U. n. 280: 30/11/2000), establishes temporal binding constraints on the use of the area covered by forest fire. Precisely, after burnt areas are identified, they must be censed by municipalities. For at least 15 years from that moment, it is prohibited to devote these lands to different uses such as agriculture, urbanization, etc. For 5 years, it is also forbidden to reforest those areas by using public funds. Despite its existence, this law has only been partially enforced and only in some Italian regions. In principle, to contain this problem the more recent regulation n. 3606 of 2007 (GU n. 204: 3-9-2007), puts a distrusting mechanism in place for defaulting municipalities. Again, despite this effort, some regions still do not provide accurate information about defaulting municipalities neutralizing the benefiting effect of this law on the reduction of forest fire occurrence.

extor_1000	190	0.08	0.04	0.02	0.21
Lnarrivals	190	5.10	1.30	1.31	7.75
Lnnhot	190	1.76	0.98	0.00	3.79
Excursion	190	9.60	0.95	7.30	12.80
mean_precq11	190	69.12	32.92	8.20	194.81
mean_precq22	189	48.51	40.13	2.57	212.60
mean_precq33	186	88.32	44.85	16.61	278.62
mean_tja	171	35.40	2.22	29.93	41.05

Notes: Variable labels and description is provided in the Appendix.

5. Methodology

5.1 Brief Survey on Existing Methodologies

Several methodologies have been used within the existing literature to explain (and/or predict) the main factors of fire risk. The choice of methodology strictly depends on the objective of the study, which can either be that of predicting future fire incidences or explaining the variation of the dependent variable. Therefore, it depends on the characteristic of the dependent variable, which can be discrete and generally dichotomous, or continuous. If, for example, we refer to fire occurrence (yes or no expressed as a 1-0 variable) or ignition index (high ignition and low ignition respectively receive the value of 1 and 0), the dependent variable is a discrete one. Finally, if we consider the total area burnt in km², the dependent variable is a continuous one.

One of the most frequently implemented techniques within fire risk analysis is the binary response regression, which takes different specifications according to the behavior of the dependent variable (i.e., logistic regression: Martinez et al. 2008 & 2009; Poisson regression: Wotton et al. 2003; Poisson, binomial or negative binomial: Venables and Ripley, 1997; Cardille et al. 2001). If its variance is greater than the mean, negative binomial regression can offer a better fit, whereas Poisson regression is normally used when the variance equals the mean.

Other methodologies use stepwise-multiple linear regressions (i.e., multivariate OLS) when the dependent variable is continuous (e.g., Vadrevu et al., 2006). In most applications, Geographic Information Systems software (GIS) is then used to gather information on fire events or visualize results through mapping.

The use of binary response regressions and of stepwise multiple linear regressions does not prevent the researcher from incurring problems of biasedness and inconsistency of the estimates due to unobserved heterogeneity across regions/areas, which are not accounted for in the analysis (Greene, 2008). The spatial heterogeneity might rise due to a lack of structural stability or homogeneity of unit observation across space. Supposedly, Italian regions are heterogeneous in terms of cultural differences (Naveh, 1995), different land cover types (Bajocco and Ricotta, 2008), different law enforcement, and the presence of local organizations. When this is the case, the fixed or random effects models should be used in the presence of panel data.¹⁰

A different methodology recently proposed consists in the classification and regression trees approach (CRT) in which the full model can be used without loss of any exogenous variables. CRT explains the variation of the categorical or numerical dependent variable with respect to explanatory variables that can include categorical and numerical data sets (De'ath and Fabricius, 2000). This approach offers various advantages and can either complement or be alternative to other statistical techniques, such as multiple regression, analysis of variance, logistic regression, and log-linear models. Unlike parametric multivariate analysis, CRT is not sensitive to strong correlations among explanatory variables (i.e., multicollinearity). For instance, Martinez et al. (2009) and Vadrevu et al. (2006) use a logit and multivariate OLS regressions respectively, in which a variable selection process is required to avoid potential multicollinearity problems among the explanatory variables prior to regressions. However, all exogenous variables could be used with the CRT analysis even though some of them are highly correlated (see De'ath and Fabricius for further information on the advantages of using the CRT approach). This methodology has recently been implemented by Sturtevant and Cleland (2007) to individuate the main exogenous determinants of forest fires in northern Wisconsin between 1985 and 2000. They classify the dependent variable according to different intensities of fire events. The relative importance of the different explanatory variables expresses the extent to which a specific variable is able to improve the model, namely to decrease the misclassification of forest fires or forest intensities for a given split, represented by their inclusion into the wrong groups (Atkinson and Therneau, 2000).

While there is a variety of cross sectional analyses investigating forest fire events, according to our knowledge, there are very few articles providing a panel data specification. Although Vadrevu et al. (2006) attempt to head towards this direction by using several years of data, they do not fully exploit the advantages of a panel data approach given their use of yearly data in a cross-sectional

¹⁰ See, e.g., Kousky and Olmstead (2010) as well as Reetz and Brummer (2011), for land use studies where binary response regressions include fixed and random effects to capture the unobserved heterogeneity across state/region.

fashion. A panel approach has been offered by Pazienza and Beraldo (2004), which examine the effects of forestry legislation on the frequency of fires in southern Italy (National Park of Gargano). However, they only focus on the southern part of Italy and account for very few socio-economic variables (unemployment rate, number of civil and industrial vehicles), disregarding many time-variant factors and totally neglecting weather patterns. By looking at municipalities, they find a low level of heterogeneity across them suggesting the use of pooled OLS regression estimation methods. Gonzalez (2007) analyzes the potential link between house pricing and the population density for the regions of Spain to explain the potential link between the house pricing and the fire events after accounting for the region and year fixed effects. Dogandjieva (2008), on the other hand, examines the relationship between land, wheat, and timber prices and forest fire incidences in four countries: Spain, Greece, Italy, and Bulgaria. It is found that the fixed effects estimation yields mixed results, confirming the existence of a link between profit motives and forest fires. Both in Dogandjieva (2008) and Gonzalez (2007), the majority of the time varying effects were excluded from their studies, potentially causing omitted variable bias.

5.2 Theoretical Framework

Aiming to overcome some of the estimation problems described in section 5.1, we propose a panel data approach to investigate the influence of both socio-economic and weather patterns on fire occurrence in Italian forests during the last decade. This approach allows us to capture not only the dynamics but also the potential changes in the relative importance of such driving factors of fire occurrences.

Both fixed and random effects models are used to account for the unobserved heterogeneity across regions and, most importantly, to obtain unbiased and consistent estimates for the time-varying explanatory variables. As explained in Wooldridge (2002), the fixed effects can be performed either by i) adding region and year dummies to the regressions (least squares dummy variable regression, or LSDV); ii) transforming variables by subtracting the regional average from both the dependent and independent variables (entity demeaned OLS regression). Given that these two approaches lead to the same coefficients - the entity demeaned OLS regression is identical to within-region estimation (Baltagi, 2008) - we choose to use the second one (equation 3) not to reduce the available degrees of freedom.

Specifically, a linear panel-data one-way model is employed to capture either the unobserved regional or time effects in the error term (time effects are tested by adding year dummies in the fixed and random effect models). This takes the following form:

$$y_{it} = \beta_m X_{itm} + \mu_i + u_{it} \qquad \text{where } t \in \{1, 2, ..., T\}, \ i = 1, ..., N; \ m = 1, ..., K$$
(1)

In (1), y_{it} is our dependent variable (either the natural logarithm of the total number of fire events, or the natural logarithm of the total area burnt in km² in a given region *i*, in a given time period *t*); X_{itm} is a vector of explanatory variables including both socio-economic and climatic factors;¹¹ μ_i the unobserved individual region effects; u_{it} the idiosyncratic errors changing in time. β_m are the parameters to be estimated either with fixed or random effects panel data specifications depending on the relation between μ_i and X_{itm} . Indeed, while fixed effect specification allows a correlation between those two (Cov(X_{itm}, μ_i) \neq 0), random effects techniques assumes independence (Cov(X_{itm}, μ_i) = 0).

If μ_i and X_{im} are correlated, coefficients can be consistently estimated by a regression on the *within* transformed data (equation 2), resulting from the difference between equation (1) and the *between* transformed data:¹²

$$y_{it} - \overline{y}_i = \beta_m (X_{itm} - \overline{X}_{im}) + u_{it} - \overline{u}_i = \overline{y}_{it} = \beta_m \overline{X}_{itm} + \overline{u}_{it}$$

$$\tag{2}$$

where :

•
$$\overline{y}_i = \sum_{t=1}^{T} y_{it}$$
, $\overline{X}_{im} = \sum_{t=1}^{T} X_{itm}$ for each $m = 1, 2..., K$

•
$$\overline{u}_i = \sum_{t=1}^l u_{it}$$

¹¹ Appendix 1 offers a detailed description of all the X_{it} variables used in our regressions and their sources. Also, it reports whether those variables are used in the final model, or just as controls and therefore excluded from the final model for statistical reasons.

Therefore, the Fixed Effect estimators (FE), $\hat{\beta}_m^{FE}$, can be obtained by using pooled OLS regression of \ddot{y} on \ddot{X} .

However, if μ_i are uncorrelated with the X_{itm} then $\hat{\beta}_m^{FE}$ are inefficient and coefficients should be estimated with random effects estimators ($\hat{\beta}_m^{RE}$). This is possible by applying the feasible feasible Generalized Least Squares method (GLS) or Random Effects model (RE) as reported below (Greene, 2008):

$$y_{it} = \alpha + \beta_m X_{itm} + v_i + u_{it}$$
(3)

where α is the common intercept and v_i are assumed to be random processes.

Given that the relation between μ_i and X_{itm} is not known *a priori* we use the Hausman specification test (Hausman, 1978) to test the correctness of the fixed effects assumptions and the Lagrange Multiplier test or LM test (Breusch and Pagan, 1980), is conducted to detect the presence of random effects.

Given the panel-data nature of our analysis, one of the main issues to be checked is the existence of an autoregressive (AR) process in the residuals. We test the presence of serial correlation performing a Wooldridge test (Wooldridge, 2002). Relying on its results we include AR(1) disturbances in both the RE and FE models. In order to test if region-specific errors are independent across regions, we further run the Pesaran cross section test (Pesaran, 2004) and find no dependence.

For each of the two dependent variables (fire frequency or fire size in logarithmic form), we estimate the model considering first all the Italian regions together (2 unrestricted model), and then separating Italy into north, center , and south (3 region-specific models), (Table 8). In doing so, we maintain the regressors constant on the right-hand side, although we then eliminate the variables resulting not statistically significant in each of the regional model. Additionally, for each of the two sets, results are reported for pooled OLS, FE, and RE models in which year dummies have been added to capture the possible time-specific shocks, common to all the regions (e.g., a policy that is effective over the entire Italian peninsula).

			Dependent variable			
		Fire	Fire	Estimations presented		
			Frequency	Size		
	Unrestricted					
	Model	Italy	Х	Х	Pooled OLS, RE , FE, AR(1)	
Geografical aggregation	Region- specific Models	North	Х	х	Pooled OLS, RE, FE	
		Centre	Х	X	Pooled OLS, RE, FE	
		South	Х	Х	Pooled OLS, RE, FE	

Table 8. Estimation Techniques

Notes: In bold the estimation techniques finally chosen

6 Empirical Findings: Unrestricted or Full-sample Model

We initially analyze the full sample (unrestricted model) for both dependent variables. Related results, for each dependent variable, are reported in Table 9 and Table 10 in which pooled OLS (column 2), FE (column 3), and RE (column 4) approaches are compared.

6.1 Unrestricted Model & Logarithm of the Number of Fire Events as Dependent Variable

Testing jointly for fixed and random effects we find the existence of regional fixed effects rather than a year effect for the FE model; year dummies are jointly significant for all other specifications in Table 9. However, from the Hausman test it results that the existing unobservable regional heterogeneity is not correlated with explanatory variables, suggesting the use of a RE model (column 4). To support the choice of such specification we conducted a Breusch Pagan LM test which confirms the presence of random effects. From the Wooldrige test we acknowledge the existence of an AR (1) serial correlation in residuals. Hence, we chose a random effect generalized least squares (RE-GLS) estimator with AR(1) disturbances to correct for it (column 5).¹³

Results show that increasing railway density by 1% raises the total number of fire events by 0.8% across regions and time. Consistent with Cardille et al. (2001) and Martinez et al. (2009), we find that railway density puts pressure on wild lands increasing the number of fire events. On the other hand, a percentage increase in relative poverty fosters fire frequency by 4.18%. In accordance with

¹³ Although the literature does not provide any specific critical value, the Baltagi-Wu LBI statistic detects a serious serial correlation when it is far below 2 (see Baltagi and Wu, 1999). As reported in Table 9, this statistic is 1.99, very close to 2 indicating that auto-correlated residuals (fourth column) disappear when an AR(1) term is included in the regression (column 5).

de Torres Curth et al. (2012), although in opposition to Leone et al. (2002) and Martinez et al. (2009), we report that the fire events are higher in the areas where poverty levels are high. Similarly to Leone et al. (2002) and Martinez et al. (2009) we conclude that touristic flows impact positively the number of forest fires: 1% increase in tourist arrivals per km² leads to 0.24% raise in the total number of fire events.

Finally, we find that depending on the extent to which land is used, intensification in the agriculture activity either puts pressure on, or generates protection against, forest fires (Chuvieco et al., 1999; Leone et al. 2002; Vigilante et al. 2004; Pazienza and Beraldo, 2004; Martinez et al., 2009). For example, a percentage increase in the number of people working in the agriculture sector has the effect of decreasing fire frequency by 11.4%. Nevertheless, grazing activity generates mixed results depending on animal species. Specifically, assuming that both bovine and caprine elements per km² increase by 1%, the number of fires respectively decreases by 0.18% and increases by 1.16%. We are not aware of similar empirical evidence from other studies. In fact, despite the fact that livestock intensity has been considered a major driver of forest fires (Chuvieco et al. 1999; Leone et al. 2002; Martinez et al., 2009), to our knowledge there is no separate analysis on different livestock compositions. This highlights the need of additional investigation useful to build tailored fire-containment policies.

As for climatic factors, the only variable found to be significant is the average number of consecutive hot days in a year. Indeed, a 1% increase in this variable leads to a 0.24% increase in the yearly frequency of forest fires. This finding is in line with other studies supposing that drier seasons boost fuel flammability, thereby fostering the likelihood of observing fire events (Pinol et al., 1998; Pausas, 2004; Westerling et al., 2006). Both temperature and precipitation do not seem to explain the variation in the total number of forest fires.

Overall, forest fire variation across Italian regions is mostly driven by socio-economic factors rather than by climatic ones. Using the best specification, according to the empirical evidence (RE model), these variables altogether are capable of explaining 81% of the total variability in forest fire frequency.

VARIABLES	Pooled OLS	Fixed effects	Random effects	Random effects-AR1
Inpop den	-0.4303	-4.5695	-0.2433	-0.3273
1 1	(0.323)	(3.425)	(0.343)	(0.257)
Inrail den	0.8341***	0.2740	0.7581***	0.8083***
_	(0.182)	(2.969)	(0.241)	(0.163)
rela pov	0.0313	0.0506**	0.0436**	0.0418**
	(0.019)	(0.019)	(0.018)	(0.017)
Lnbovine	-0.2937***	-0.1167***	-0.1488*	-0.1774**
	(0.061)	(0.039)	(0.077)	(0.080)
Lncaprine	1.2471***	-1.7234	1.0869***	1.1569***
	(0.163)	(1.115)	(0.255)	(0.184)
p ter deg	0.1644*	-0.1472**	0.0183	0.1200
<u></u> 6	(0.080)	(0.068)	(0.089)	(0.077)
p emp agri	-0.1161**	-0.1449**	-0.1390***	-0.1142**
p_omp_ugn	(0.047)	(0.069)	(0.054)	(0.049)
extor 1000	6.6286**	-1.5464	1.4671	2.9137
	(3.087)	(2.299)	(2.396)	(2.422)
Lnarrivals	0.2748*	0.2093**	0.2215*	0.2491**
	(0.138)	(0.085)	(0.122)	(0.110)
Lnnhot	0.3297***	0.2563***	0.2740***	0.2460***
	(0.084)	(0.077)	(0.083)	(0.083)
Excursion	-0.0388	0.1235	-0.0535	-0.0602
	(0.114)	(0.083)	(0.104)	(0.088)
maan nraag11	0.0004	-0.0005	0.0015	
mean_precq11				0.0010
	(0.001)	(0.001)	(0.002)	(0.002)
mean_precq22	-0.0027	0.0007	-0.0009	-0.0012
22	(0.002)	(0.001)	(0.001)	(0.001)
mean_precq33	-0.0006	0.0008	0.0008	0.0009
	(0.001)	(0.001)	(0.001)	(0.001)
mean_tja	-0.0886*	0.0447	-0.0138	-0.0304
a	(0.042)	(0.043)	(0.044)	(0.043)
Constant	2.2322		1.1856	0.7700
	(2.682)		(2.539)	(2.287)
Observations	145	145	145	145
R-squared	0.825	145	145	145
R2-within	0.025	0.5391	0.5214	0.4994
R2-between		0.2465	0.8457	0.8859
R2-overall		0.1495	0.7781	0.8075
Year effects	YES	NO	YES	YES
Region effects	115	YES	1120	
Number of n	19	19	19	19
	19	17	17	19
				Rho-AR0.22Baltagi-Wu LBI1.9
Other tests for Panel		Hausman (p-val		
		Breusch Pagan	84.16***	
		Wooldridge	87.748***	
		(p-value)	(0.000)	
		Pesaran's CD	0.1515	

Table 9. Full Sample Specification (Dependent variable: Logarithm of total fire events)

6.2 Unrestricted Model & Logarithm of the Total Area Burnt as Dependent Variable

Table 10 reports results achieved by maintaining regressors unvaried, but using the natural logarithm of the total area burnt as dependent variable. In this case we find that the year effects are jointly significant in the pooled OLS, FE and RE estimations (columns 2 to 4 respectively). The Hausman test results suggest that the unobserved region specific effects embody elements, which are correlated with regressors. As a result, the FE model is the model of choice. This is in contrast with conclusions previously drawn using the alternative dependent variable. A similarity with the previous model relates to an AR (1) serial correlation in residuals resulting from the Wooldridge test. As a consequence, we propose FE estimates with AR(1) disturbances in column 5.

Similar to the previous model, railway and tourist density positively impact the expansion of the area burnt. Specifically, the railway density shows an impact, which is 5-times larger on this dependent variable than on fire frequency. Conversely to previous results, the use of land here, seems to generate a mono-directional impact, given that the higher the percentage of people working in agriculture, the amount of area covered by fire is smaller. Therefore, in this case more intense land management translates into a greater containment of fire propagation. Although the animal presence is less impacting than above, we find an interesting difference. A bigger bovine population reduces fire frequency but enlarges the total area burnt. Therefore, even though the presence of bovine elements leads to fewer fire events, if the fire takes place, we would experience an increase in the area burnt.

In opposition to the first model, population density plays a role in explaining the total area burnt. Its 1% increase drops the fire expansion by 7.3%. This could be due to a greater amount of land used for population settlement, which reduces the availability and continuity of fuel (Syphard et al., 2007) and leaves limited area for forests and fire propagation.

What deserves specific attention is the fact that while weather patterns do not explain variability in the number of fires, they play an important role in influencing the size of land burnt by fire events. As before, we report that a percentage increase in the average number of consecutive hot days per year boosts the total area burnt by 0.38%. In addition, an increase in temperature from January to September positively impacts fire extension, although with low statistical significance. Nevertheless, restricting the analysis to June, July, and August temperature levels notably

strengthens the statistical significance. Specifically, an additional degree Celsius in the average temperature in this period is associated with an 18.26% increase in the total area burnt.¹⁴ Additionally, as one could have expected, an increase of one milliliter in the monthly average precipitation between January-April and May-August decreases the total area burnt by 0.41% and 0.33% respectively. These findings are consistent with the branch of literature which supports the relevance of precipitation rates regarding fire size (Pausas 2004; Westerling et al. 2006).

Overall, our findings support Sturtevant and Clelabd (2007) and Pinol et al., (1998) statements that although the socio-economic factors are determinants of the fire frequency, larger fire events are mostly the consequence of biophysical and climatic factors. Concluding, with this dependent-variable specification the within-region variation of the socio-economic and climatic regressors explains 78% of the variability in the total area burnt.

VARIABLES	Pooled OLS	Fixed effects	Random effects	Fixed effects – AR1
Inpop_den	-0.4063	-9.5941*	-0.4063	-7.3948**
	(0.425)	(5.289)	(0.273)	(3.438)
lnrail_den	0.8417***	2.0803	0.8417***	5.8674*
	(0.166)	(4.137)	(0.144)	(3.327)
rela_pov	0.0483	0.0637**	0.0483**	0.0163
	(0.046)	(0.027)	(0.023)	(0.027)
Lnbovine	-0.2780**	0.0803	-0.2780**	0.1794*
	(0.115)	(0.112)	(0.109)	(0.094)
Lncaprine	1.5444***	-2.2080	1.5444***	0.2286
	(0.262)	(1.570)	(0.171)	(2.278)
p_ter_deg	0.1963	-0.1838	0.1963**	-0.2203
	(0.125)	(0.153)	(0.081)	(0.142)
p_emp_agri	-0.1777*	-0.2886***	-0.1777***	-0.2223**
	(0.091)	(0.097)	(0.054)	(0.091)
extor_1000	8.8122	-0.7924	8.8122***	-3.9004
	(5.220)	(3.609)	(3.279)	(3.397)
Lnarrivals	0.2953	0.2609	0.2953**	0.6514**
	(0.246)	(0.209)	(0.132)	(0.302)
Lnnhot	0.3374***	0.4304***	0.3374**	0.3785***
	(0.079)	(0.117)	(0.144)	(0.101)
Excursion	0.0191	-0.1610	0.0191	-0.0321
	(0.119)	(0.180)	(0.095)	(0.160)
mean_precq11	0.0011	0.0035	0.0011	-0.0041*
	(0.002)	(0.002)	(0.003)	(0.002)
mean_precq22	-0.0019	0.0018	-0.0019	-0.0033*
	(0.003)	(0.002)	(0.002)	(0.002)
mean_precq33	-0.0010	0.0004	-0.0010	0.0001
	(0.002)	(0.001)	(0.002)	(0.001)
mean tja	0.0163	0.1433**	0.0163	0.1826***

 Table 10. Full Sample Specification (Dependent variable: Logarithm of the total area burnt)

¹⁴ We explored the influence of possible interactions between climatic factors constructing variables such as the combination of precipitation and temperature, and found no significant results. We also checked the impacts of lagged climatic variables on forest fires and find no significant effect. The same can be concluded for non-linear weather patterns. Results are available upon request.

	(0.082)	(0.064)	(0.069)	(0.057)
Constant	-5.4141		-5.4141*	
	(4.968)		(3.132)	
Observations	145	145	145	126
R-squared	0.800			
R2-within		0.6776	0.5225	0.7819
R2-between		0.1236	0.9041	0.0003
R2-overall		0.0525	0.7996	0.0099
Year effects	YES	YES	YES	YES
Region effects		YES		YES
Number of n	19	19	19	19
				Rho-AR 0.09
				Baltagi-Wu LBI 2.15
Other tests for Panel		Hausman (p-value	e) 0.0000***	
		Breusch Pagan	44.18***	
		Wooldridge	9.243***	
		(p-value)	(0.007)	
		Pesaran's CD	0.4880	
Robust standard errors	in parentheses, whe	re *** p<0.01, ** p<0.05	5, * p<0.1	

7 Empirical Findings: Regional Models

There are convincing reasons to think that regions located in different geographical areas in Italy show specific fires patterns. This can be derived, for example, by simply observing the variability in both types of dependent variables. At the same time, we must recall that regional effects have been found to be significant in previous model specifications (see results in Table 9 and 10 on region effects). In order to check the existence of differences in estimated parameters for different geographical regions, we perform a likelihood ratio (LR) test comparing the full sample (unrestricted model) with the sub-samples of the northern, central, and southern regions of Italy (region-specific models).¹⁵ The documented systematic difference between individual subgroup models and the full sample models (Table 11 and 12) supports the need of performing estimates separately for the north, center, and south of Italy.¹⁶ Using two dependent variables for each of the subgroups, we run 6 regressions (2x3).

 $^{^{15}}$ We used the same regressors, which are in the unrestricted model, meaning that the likelihood ratio has a degree of freedom of k=15

¹⁶ Note that the log-likelihoods for the full sample and the sub-samples are obtained with the pooled random effects model by using the maximum-likelihood estimator. The degrees of freedom for the likelihood ratio test is the number of parameters (variables) used for all regressions, k=15.

	Full sample	North	Centre	South	
Observations	145	37	47	61	
Number of n	19	5	6	8	
Log likelihood	-90.99	-10.79	-2.01	-18.96	
Likelihood Ratio	χ^2_{LR} =-2[-90.99-(-49.85)]= 82.28 , critical value: $\chi^2_{15,0.01}$ =30.58				

Table 11. Dependent variable: Total number of events (LR test)

Table 12. Dependent variable: Total size of the area burnt (LR test)

	Full sample	North	Centre	South	
Observations	145	37	47	61	
Number of n	19	5	6	8	
Log likelihood	-150.1	-18.26	-27.00	-40.46	
Likelihood Ratio	χ^2_{LR} =-2[-150.1-(-8)	χ^2_{LR} =-2[-150.1-(-85.72)]= 128.76 , critical value: $\chi^2_{15,0.01}$ =30.58			

In the following tables we report results for the three sub-geographical samples, for the two dependent variables. Only statistically significant variables are reported. Remaining variables, although used as controls, have been discarded from the three models by following the backward elimination technique (for further discussion on the backward elimination procedure see Agresti and Finlay, 1997; Menard, 2002). According to this method, starting from all the variables in the model the non-significant ones will be sequentially removed. In particular, by looking at the variance inflation factor (VIF) and the Pearson correlation coefficient, we eliminate the variables, which are both insignificant and correlated with the significant variables.¹⁷

We are aware that, although widely used within applied econometrics, this approach may be challenged by statisticians. They would claim that a t-test resulting lower than a critical value, may be due to two different reasons: either the value of the coefficient is actually 0 or the empirical evidence is not enough to reject the null hypothesis (i.e., the hypothesis is not "accepted", yet "not rejected"). If we consider the second case, eliminating the variables retained not statistically significant, would entail the risk of producing distorted estimates.

In light of this we argue that maintaining all the regressors in place would have, on the one hand, avoided the aforementioned problems, yet on the other hand, would have produced other inconveniences. Specifically, including also variables whose coefficients result equal to 0 reduces the estimation accuracy, since more degrees of freedom than what is strictly needed are used. This problem is even more relevant when the number of observations is not as high as the number of

¹⁷ Hair et al. (1995) and Kennedy (1992) suggest that the variance inflation factor (VIF) greater than 10 causes the serious multicollinearity problem. In related literature, Martinez et al., (2009) and Vadrevu et al. (2006) conduct a variable selection process to avoid potential multicollinearity among the explanatory variables, e.g., the Pearson correlation coefficient and variance inflation factor.

explanatory variables whose coefficients have to be estimated. This is precisely our case, given that disaggregating the full sample of regions fractionates the total number of observations into three groups. In this respect, to decide how big a sample size should be, relative to the number of observations, the literature offers a ratio measure, which compares the sample size (nominator) with the number of free parameters (denominator). Tanaka (1987) suggests 20 as the rule of thumb while Bentler and Chou (1987) propose the ratio 5:1. Using the second source as a reference (the first appears unrealistically high), our ratios show that we are at the border of sufficiency in terms of sample size. Therefore, we chose to follow the backward elimination approach rather than incurring different, yet significant problems.

7.1 Regional Models & Logarithm of the Number of Fire Events as Dependent Variable

We develop the same estimation methods (pooled OLS, FE, and RE) to check which model is the best specification for the sub-sample models. When the dependent variable is the natural logarithm of the total number of events from the Hausman and Breusch Pagan tests, the pooled OLS is found to be the best specification for all geographical aggregations.¹⁸ Results are shown in Table 13 where we only report the significant variables. These regressions, therefore, include the variables, which remain after the backward elimination technique mentioned in the previous section.

A common result across regional models, is that both railway density and the presence of caprine elements put pressure on forest land. Other factors influence fire frequency in an expected direction (Table 13). In particular, the presence of bovine animals, the level of education (as reported in de Torres Curth et al., 2012), tourism, and precipitation levels are relevant for the northern region; education and temperature for the center; and precipitation levels as well as extortion activity for the south. Therefore, in southern regions illegal activities represent an additional driver, providing the opportunity to create firefighting jobs or gain land for agriculture, or pasture, which are retained more valuable activities (Leone et al., 2002).

¹⁸ The Hausman test suggests using the random effects estimation, meaning that the unobserved heterogeneity across regions is not correlated with explanatory variables. However, a Breusch Pagan LM test suggests that we cannot reject the null hypothesis that the variance of residuals across regions is zero at 10% level of significance. This entails that there is no significant difference across regions within a given geographical classification.

VARIABLES	North	Centre	South
lnrail_den	1.0019***	1.3390***	0.7541***
—	(0.123)	(0.179)	(0.084)
Lnbovine	-0.1147*		
	(0.045)		
Lncaprine	0.9603***	3.0181***	1.1120***
	(0.111)	(0.420)	(0.086)
p_ter_deg	-0.2070***	-0.1015*	
	(0.030)	(0.040)	
Lnarrivals	-0.4092**		
	(0.144)		
extor_1000			3.9801***
			(0.726)
lnnhot		0.6132***	
		(0.093)	
mean_precq11	-0.0113**		
	(0.003)		
mean precq22			-0.0142***
			(0.002)
mean_precq33	-0.0074*		
	(0.003)		
Constant	4.0503*	-3.1483**	0.9360**
	(1.595)	(1.021)	(0.379)
Observations	37	54	70
R-squared	0.830	0.807	0.898
Year effects	NO	NO	YES
Robust standard erro	ors in parentheses, wh	ere *** p<0.01, **	p<0.05, * p<0.1

Table 13. OLS Dependent variable: In (total number of events)

7.2 Regional Models & Logarithm of the Total Area Burnt as Dependent Variable

We conduct similar regressions and tests as in section 7.1 when the dependent variable is the natural logarithm of the total area burnt and regions are grouped into north, center and south. Once more, for all the geographical aggregations we find that the best specification is the pooled OLS. Given that within geographical groups no unobserved heterogeneity is found, the pooled regressions show similar results for both dependent-variables models (Table 14).¹⁹

For northern regions the statistically significant regressors are mostly the same. There is only one additional significant variable: a percent increase in the bovine elements per km^2 drops the fire frequency by 0.11%. Therefore, we can conclude that our results on the northern area are robust and not sensitive to a change in the dependent variable.

¹⁹ The Pearson correlation coefficients between the natural logarithm of total number of events and the natural logarithm of total number of events are 0.87, 0.88 and 0.88 for the northern, central and southern geographical specifications respectively.

Despite the differences in magnitude we can reach the same conclusion for the central part of Italy. Specifically, climatic factors slightly differ in the two models: a percent raise in the average number of consecutive hot days increases the total number of events by 0.61%. Nevertheless, a one-millimeter increase in the average precipitation rate between May and August is associated with around a 1% decrease in the total area burnt. Also, an additional degree Celsius in the average temperature between June and August translates to a 32.79% rise in the total area burnt.

Finally, for the southern part of Italy illegal activities explain the fire frequency, yet they have no impact on the area burnt. In contrast to the northern area, touristic flows positively affect the number of events suggesting a possibly insufficient risk management and forestland protection, or a law-enforcement problem. As for climatic variables, precipitation influences the area burnt with expected signs.

VARIABLES	North	Centre	South
lnrail_den	1.2736***	1.1389***	0.8627***
	(0.192)	(0.092)	(0.104)
Lnbovine		-0.4423***	-0.3171*
		(0.062)	(0.138)
Lncaprine	1.0674***	4.3214***	1.1036***
	(0.192)	(0.232)	(0.164)
p_ter_deg	-0.3316*	-0.2793***	
	(0.120)	(0.063)	
Inarrivals	-0.6235**		0.1773*
	(0.177)		(0.088)
mean_precq11	-0.0118**		-0.0079**
	(0.003)		(0.003)
mean_precq22		-0.0135**	-0.0185**
		(0.004)	(0.007)
mean_precq33	-0.0116***		
	(0.003)		
mean_tja		0.3279***	
		(0.050)	
Constant	1.6953	-13.5858***	-0.5032
	(1.708)	(2.548)	(0.896)
Observations	37	54	70
R-squared	0.851	0.783	0.899
Year effects	NO	NO	YES
Robust standard erro	ors in parentheses, whe	ere *** p<0.01, ** p<0.	05, * p<0.1

Table 14. OLS Dependent variable: In (total area burnt)

8. Concluding Remarks and Discussion

Using panel data techniques we analyze the determinants of forest fires frequency and size for the Italian regions during the 2000-2008 period. We first investigate the situation for all the regions pulled together. Then, lead by evidence on their heterogeneity, we specify three regional models for north, center, and south, according to the incidence of forest fires and their geographical location.

We also investigate two dependent variables in each of the abovementioned models: the number of fire events and total km² of burnt area regressed on both socio-economic and climatic factors. The most appropriate regression technique for each model (fixed and random effects, pooled OLS, etc.) has been selected through appropriate testing.

Despite the heterogeneity across Italian regions and the existence of locally-specific driving factors, some general conclusions and policy implications can be discussed.

First, improving safety in the railway network is expected to have a supportive impact in reducing fire events and size throughout Italy. Weather patterns also appear to be important determinants. Additionally, the composition of livestock seems to be relevant to address the problem of forest fire. In opposition to the negative effect of bovine presence reported in some cases, caprine grazing is an element of pressure on forestland, from the north to the south. In particular, bovine grazing, which has almost no impact on reducing fire frequency, seems to help in containing the spread of fire. This conclusion, normally referred to as the "grazing reduces blazing" argument, is well supported by the literature. Indeed, it is claimed that the introduction of livestock in forest areas functions as a natural undergrowth eliminator, i.e., prevents fire amplification by removing plant biomass (Whalley, 2005). A less obvious effect on fire is generated by the presence of caprine animals affecting positively both fire frequency and extension. This effect may find its explanation in more than one reason. For example, in order to gather minor forests for pasture, shepherds normally introduce nonnative grass increasing fuel loads. Alternatively, they may start small fires to obtain better grazing grass. On the other hand, caprine excessive pasture may imply the consumption of the youngest and greenest components of vegetation thereby increasing the portion of drier, mature, and dead material which is therefore more inflammable (Blasi et al., 2005; Bernetti, 2005). This is especially true in the case of a mineral shortage in soil, also resulting from adverse weather conditions. In fact, this leads animals to strip bark from trees and browse upper branches causing tree deterioration and death, increasing, in turn, fire prone materials. Finally, recent studies recognize that the incidence of grazing on fire may depend on vegetation structure, and grazing intensity (e.g., Leonard et al., 2010). Specifically, in places where part of the vegetation is unpalatable, selective consumption by herbivores may increase the proportion of dead fuel and therefore fire occurrence.

Apart from the mentioned ones, the remaining socio-economic conditions result to be more locally specific. A good analysis requires regional details. By dividing Italy into north, center, and south we find that results from the two dependent-variable specifications are comparable and sometimes homogeneous within the same geographical area. For example, increasing education levels decreases frequency and intensity of fires in the north and the center. As for the south, where the worst Italian burning situation takes place, we acknowledge i) illegal activities as a cause of fire frequency and ii) tourism presence as an element of explanation for the variation in fire size.

In sum, our results suggest that given this concept of "locality" for a driving factor, an accurate and ex-ante definition of fire risk in a specific area becomes crucial. This would help implementing an *ad hoc* weather forecasting, taking into account seasonality issues, and developing a tailored monitoring and prevention plan. This process entails the consideration of past policies and related results to design more effective actions in the future.

Furthermore, land management, and in particular, grazing and fuel control could concretely contain the incidence of forest fires. Further research is needed to shed light on the unknown impact of different grazing levels on fire. Clarifying this relation would make a valuable contribution to the understanding of forest conservation in Italy.

9. References

Agresti, A., Finlay, B., 1997. Statistical Methods for the Social Sciences, third ed. Prentice Hall, Upper Saddle River, New Jersey.

Aguado, I., Chuvieco, E., R. Boren, R., Nieto, H., 2007. Estimation of dead fuel moisture content from meteorological data in Mediterranean areas. Applications in fire danger assessment. Int. J. Wildland Fire. 16, 390-397.

Alexandrian, D., Esnault, F., Calabri, G., 1999. Forest fires in the Mediterranean area. In Unasylva (FAO). 0041-6436, Volume 50, 197:35-41.

Atkinson, E.J., Therneau, T.M., 2000. An introduction to recursive partitioning using the RPART routines, The Mayo Foundation, Rochester, Minnesota.

Bajocco, S., Ricotta, C., 2008. Evidence of selective burning in Sardinia (Italy): which land cover classes do wildfires prefer? Landscape Ecol. 23, 241-248.

Baltagi, B. H., 2008. Econometric Analysis of Panel Data, fourth ed. John Wiley & Sons, Ltd, West Sussex.

Baltagi, B.H., Wu, P.X., 1999. Unequally spaced panel data regressions with AR(1) disturbances. Economet. Theor. 15, 814-823.

Barbero, M., Bonin, G., Loisel, R., Quezel, P., 1990. Changes and disturbances of forest ecosystems caused by human activities in western part of the Mediterranean basin. Plant. Ecol. 87(2), 151-173.

Bentler, P.M., Chou, C.P., 1987. Practical issues in structural modeling. Sociol. Method. Res. 16, 78-117.

Bernetti, G., 2005. Atlante di selvicoltura. Ed. Agricole, Bologna.

Blasi, C., Boitani L., La Posta, S., Manes, F., Marchetti, M., 2005. Stato della biodiversità in Italia - Contributo alla strategia nazionale per la biodiversità. Palombi Editori.

Bolgiano, C., 1998. The Appalachian Forest: A Search for Roots and Renewal. Stackpole Books, Mechanicsburg, Pennsylvania.

Breda, N., Huc, R., Granier, A., Dreyer, E., 2006. Temperate forest trees and stands under severe drought: a review of ecophysiological responses, adaptation processes and long-term consequences. Ann. Forest Sci. 63, 625-644.

Breusch, T.S., Pagan, A.R., 1980. The Lagrange Multiplier Test and its Applications to Model Specifications in Econometrics. Rev. Econ. Stud. 47, 239-253.

Butry, D.T., Pye, J.M., Prestemon, J.P., 2002. Prescribed fire in the interface: separating the people from the trees, in: Outcalt, K.W. (Ed.), Proceedings of the Eleventh Biennial Southern Silviculture Research Conference. USDA Forest Service, Asheville, NC, pp. 132-136 (General Technical Report GTR-SRS-48).

Cardille, J.A., Ventura, S.J., Turner, M.G., 2001. Environmental and Social Factors influencing Wildfires in the Upper Midwest, United States. Ecol. Appl. 11, 111-127.

Chou, Y.H., Minnich, R.A., Dezzani R.J., 1993. Do fire sizes differ between Southern California and Baja California. Forest Sci. 39, 835-844.

Chuvieco, E., Giglio, L., Justice, C., 2008. Global characterization of fire activity: towards defining fire regimes from earth observation data. Glob. Change Biol. 14, 1-15.

Chuvieco, E., Salas, F.J., Carvacho, L., Rodriguez-Silva, F., 1999. Integrated fire risk mapping, in: Chuvieco, E. (Ed.), Remote Sensing of Large Wildfires in the European Mediterranean. Springer-Verlag, Berlin, pp. 61-84.

Corpo Forestale Dello Stato, 2012. Report Year 2012, http://www3.corpoforestale.it/flex/cm/pages/ServeBLOB.php/L/IT/IDPagina/313

Costa, L., Thonicke, K., Poulter, B., Badeck, F.-W., 2011. Sensitivity of Portuguese forest fires to climatic, human and landscape variables: subnational differences between fire drivers in extreme fire years and decadal averages. Reg. Environ. Change. 11, 543-551.

de Torres Curth, M., Biscayart, C., Ghermandi, L., Pfister, G., 2012. Wildland-urban interface fires and socioeconomic conditions: A case study of a Northwestern Patagonia city. Environ. Manage. 49, 876-891.

De'ath, G., Fabricius, K.E., 2000. Classification and Regression Trees: A powerful but yet simple technique for ecological data analysis. Ecology. 81, 3178-3192.

Dimitrakopoulos, A. P., Vlahou, M., Anagnostopoulou, Ch. G., Mitsopoulos, I. D., 2011. Impact of drought on wildland fires in Greece: implications of climatic change? Clim. Change. 109, 331-347.

Dogandjieva, R., 2008. Forest fires in Southern Europe: An Econometric Analysis of the existence of Economic Incentives for Fire Arson, Honors Thesis. Department of Economics, University of Richmond.

Donoghue, L.R., Main, W.A., 1985. Some factors influencing wildfire occurrence and measurement of fire prevention effectiveness. J. Environ. Manage. 20, 87-96.

FAO, 1999. Mediterranean Forests. Unasylva 197.

Gellrich, M., Baur, P., Koch, B., Zimmermann, N.E., 2007. Agricultural land abandonment and natural forest re-growth in the Swiss mountains: A spatially explicit economic analysis. Agr. Ecosyst. Environ. 118, 93-108.

Gonzalez, L., 2007. Forest Fires and the Housing Boom: Evidence from Spain. UPF Working Paper No. 1060.

Gonzalez-Olabarria, J.R., Pukkala, T., 2011. Integrating fire risk considerations in landscape-level forest planning. Forest. Ecol. Manag. 261, 278-287.

Greene, W.H., 2008. Econometric analysis, sixth ed. Pearson Prentice Hall, Upper Saddle River, New Jersey.

Hair, J.F. Jr., Anderson, R.E., Tatham, R.L., Black, W.C., 1995. Multivariate Data Analysis, 3rd ed. Macmillan, New York.

Hausman, J.A., 1978. Specification tests in econometrics. Econometrica. 46, 1251-1271.

Kennedy, P., 1992. A Guide to Econometrics, Blackwell, Oxford.

Kousky, C., Olmstead, S., 2010. Induced development in risky locations: fire suppression and land use in the America West, Working paper. Washington, DC: Resources for the future.

Koutsias, N., Martinez, J., Chuvieco, E., Allgower, B., 2005. Modelling Wildland Fire Occurrence in Southern Europe by Geographically Weighted Regression Approach, in: De la Riva, J., Perez-Cabello, F., Chuvieco, E. (Eds.), Fifth International Workshop on Remote Sensing and GIS Applications to Forest Fire Management: Fire Effects Assessment, Zaragoza, pp. 57-60.

Kuhlken, R., 1999. Settin' the woods on fire: rural incendiarism as protest. Geogr. Rev. 89, 343-363.

Le Houérou, H.N., 1987. Vegetation wildfires in the Mediterranean basin: evolution and trends. Ecologia mediterranea. 13(4), 13-24.

Leonard, S., Kirkpatrick, J. & Marsden-Smedley, J., 2010. Variation in the effects of vertebrate grazing on fire potential between grassland structural types. J. Appl. Ecol. 47, 876-883.

Leone, V., Lovreglio, R., Martinez-Fernandez, J., 2002. Forest fires and anthropic influences: a study case (Gargano National Park, Italy), in: Viegas X (Ed.), Forest fire research and wild-land fire safety. Mill Press, Rotterdam, pp. 11-28.

Leone, V., Lovreglio, R., Martin, M.P., Martinez, J.M., Vilar, L., 2009. Human factors of fire occurrence in the Mediterranean, in: Chuvieco E (Ed.), Earth observation of wildland fires in Mediterranean ecosystems. Springer, Berlin, pp. 149-170.

Lloret, F., Calvo, E., Pons, X., Diaz-Delgado, R., 2002. Wildfires and landscape patterns in the Eastern Iberian Peninsula. Landscape Ecol. 17, 745-759.

Lovreglio, R., Leone, V., Giaquinto, P., Notarnicola, A., 2010. Wildfire cause analysis: four casestudies in southern Italy. iForest 3:8-15 [online: 2010-01-22]. http://www.sisef.it/iforest/show.php?id=521

MacDonald, D., Crabtree, J.R., Wiesinger, G., Dax, T., Stamou, N., Fleury, P., Gutierrez Lazpita, J., Gibon, A., 2000. Agricultural abandonment in mountain areas of Europe: environmental consequences and policy response. J. Environ. Manage. 59, 47-69

Maingi, J.K., Henry, M.C., 2007. Factors influencing wildfire occurrence and distribution in eastern Kentucky, USA. Int. J. Wildland Fire. 16, 23-33.

Martinez, J., Chuvieco, E., Martin, P., 2008. Estimation of risk factors of human ignition of fires in Spain by means of logistic regression, Proceedings of Second International Symposium on Fire Economics, Planning and Policy: A Global View, General Technical Report PSW-GTR-208, 265-278.

Martinez, J., Vega-Garcia, C., Chuvieco, E., 2009. Human-caused wildfire risk rating for prevention planning in Spain. J. Environ. Manage. 90, 1241-1252.

Menard, S., 2002. Applied logistic regression analysis, 2nd ed. Sage Publications, Thousand Oaks, California.

Mercer, D.E., Prestemon, J.P., 2005. Comparing production function models for wildfire risk analysis in the wild-land–urban interface. Forest Policy Econ. 7, 782-795.

Miranda A.I., Marchi, E., Ferretti, M., Millan, M., 2008. Forest Fires and Air Quality Issues in Southern Europe, in: Bytnerowicz A., Arbaugh M., Andersen C., Riebau A. (Eds.), Wildland Fires and Air Pollution. Elsevier Series "Developments in Environmental Science 8", Elsevier.

Moreno JM, Vázquez A, Vélez R (1998) Recent history of forest fires in Spain. In: Moreno JM (ed) Large Fires. Backhuys Publishers, Leiden, pp. 159-185.

Moriondo, M., Good, P., Durao, R., Bindi, M., Giannakopoulos, C., Corte-Real, J., 2006. Potential impact of climate change on fire risk in the Mediterranean area. Clim. Res. 31, 85-95.

Naveh, Z., 1995. Interaction of landscapes and cultures. Landscape Urban Plan. 32, 43-54.

Pausas, J.G., 2004. Changes in fire and climate in the eastern Iberian Peninsula (Mediterranean basin). Clim. Change. 63 (3), 337-350.

Pausas, J.G., Bradstock, R.A., 2007. Plant persistence fire traits along a productivity and disturbance gradient in Mediterranean shrublands of SE Australia. Global Ecol. Biogeogr. 16, 330-340.

Pausas, J. G., Fernández-Muñoz, S., 2012. Fire regime changes in the Western Mediterranean Basin: from fuel-limited to drought-driven fire regime. Clim. Change. 110, 215-226.

Pausas J. G., Keeley, J. E., 2009. A burning story: the role of fire in the history of life. Bioscience. 59(7), 593-601.

Pausas, J. G., Llovet, J., Rodrigo, A., Vallejo, R., 2008. Are wildfires a disaster in the Mediterranean Basin?—a review. Int. J. Wildland Fire 17(6), 713-723.

Pazienza, P., Beraldo, S., 2004. Adverse effects and responsibility of environmental policy: the case of forest fires. Corporate Social Responsibility and Environmental Management. 11, 222-231.

Pesaran, M.H., 2004. General diagnostic tests for cross section dependence in panels. IZA Discussion Paper Series, 1240.

Pew, K.L., Larsen, C.P.S., 2001. GIS analysis of spatial and temporal patterns of human-caused wildfires in the temperate rainforest of Vancouver Island, Canada. Forest Ecol. Manag. 140, 1-18.

Pinol, J., Terradas, J., Lloret, F., 1998. Climate warming, wildfire hazard, and wildfire occurrence in coastal eastern Spain. Clim. Change. 38, 345-357.

Preisler, H.K., Brillinger, D.R., Burgan, R.E., Benoit, J.W., 2004. Probability based models for estimating wildfire risk. Int. J. Wildland Fire. 13, 133-142.

Prestemon, J.P., Pye, J.M., Butry, D.T., Holmes, T.P., Mercer, D.E., 2002. Understanding broadscale wildfire risks in a human dominated landscape. Forest Sci. 48, 685-693.

Reetz, S.W.H., Brummer, B., 2011. Determinants of Land Use Change Dynamics in the Margins of Protected Forest Areas: Evidence from Central Sulawesi, Indonesia, 2011 International Congress, August 30-September 2, 2011, Zurich, Switzerland.

Romero-Calcerrada, R., Perry, G.L.W., 2004. The role of land abandonment in landscape dynamics in the SPA 'Encinares del rio Alberche y Cofio, Central Spain, 1984-1999. Landscape Urban Plan. 66, 217-232.

Running, S.W., 2006. Is Global Warming cause more, larger wildfires?. Science. 313, 927-928.

Serneels, S., Lambin, E.F., 2001. Proximate causes of land-use change in Narok District, Kenya: a spatial statistical model. Agr. Ecosyst. Environ. 85, 65-81.

Sturtevant, B.R., Cleland, D.T., 2007. Human and biophysical factors influencing modern fire disturbance in northern Wisconsin. Int. J. Wildland Fire. 16, 398-413.

Syphard, A.D., Radeloff, V.C., Keeley, J.E., Hawbaker, T.J., Clayton, M.K., Stewart, S.I., Hammer, R.B., 2007. Human influence on California fire regimes. Ecol. Appl. 17, 1388-1402.

Tanaka, J.S., 1987. "How big is big enough?": Sample size and goodness of fit in structural equation models with latent variables. Child Dev. 58, 134-146.

Telesca, L., Amatulli, G., Lasaponara, R., Lovallo, M., Santulli, A., 2005. Time-scaling properties in forest fire sequences observed in Gargano area (southern Italy). Ecol. Model. 185, 531-544.

Telesca, L., Lasaponara, R., 2006. Emergence of temporal regimes in fire sequences. Physica A. 360, 543-547.

Trouet, V., Taylor, A.H., Carleton, A.M., Skinner, C.N., 2006. Fire-climate interactions in forests of the American Pacific coast. Geophys. Res. Lett. 33, 1-5.

Trouet, V., Taylor, A.H., Wahl, E.R., Skinner, C.N., 2010. Fire-climate interactions in the American West since 1400 CE. Geophys. Res. Lett. 37, 1-5.

Vadrevu, K.P., Eaturu, A., Badarinath, K.V.S., 2006. Spatial distribution of forest fires and controlling factors in Andhra Pradesh, India using Spot Satellite Datasets. Environ. Monit. Assess. 123, 75-96.

Venables, W.N., Ripley, B.D., 1997. Modern applied statistics with S-PLUS. Springer-Verlag, New York, New York, USA.

Vigilante, T., Bowman, D.M.J.S., Fisher, R., Russell-Smith, J., Yates, C., 2004. Contemporary landscape burning patterns in the far North Kimberley region of north-west Australia: human influences and environmental determinants. J. Biogeogr. 31, 1317-1333.

Wastl, C., Schunk, C., Leuchner, M., Pezzatti, G.B., Menzel, A., 2012. Recent climate change: Long-term trends in meteorological forest fire danger in the Alps. Agriculture and Forest Meteorology. 162-163, 1-13.

Whalley, W., 2005. Grassland regeneration and reconstruction: the role of grazing animals. Ecological Management and Restoration. 6, 3-5.

Westerling, A.L., Hidalgo, H.G., Cayan, D.R., Swetnam, T.W., 2006. Warming and earlier spring increase western US forest wildfire activity. Science. 313, 940-943.

White, C.A., Perrakis, D.D.B., Kafka, V.G., Ennis, T., 2011. Burning at the edge: Integrating biophysical and eco-cultural fire processes in Canada's parks and protected areas. Fire Ecology. 7, 74-106.

Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data, MIT Press Cambridge, Massachusetts.

World Wide Fund, 2004. Forest fires in the Mediterranean: a burning issue.

Wotton, B.M., Martell, D.L., Logan, K.A., 2003. Climate Change and People Caused Forest Fire Occurrence in Ontario. Clim. Change. 60, 275-295.

Yang, J., He, H.S., Shifley, S.R., Gustafson, E.J., 2007. Spatial patterns of modern period humancaused fire occurrence in the Missouri Ozark Highlands. Forest Sci. 53, 1-15.

Zumbrunnen, T., Bugmann, H., Conedera, M., Burgi, M., 2009. Linking forest fire regimes and Climate – A historical analysis in a dry inner Alpine Valley. Ecosystems. 12, 73-86.

Var. name	Description	Derivation	Source of data	Use	Var. type
lnfn_tot	Number of fire events	ln (N of fires events)	JRC and CFS ²⁰	Used for main model	DV1
Inburntot	Fire extension	ln (Size of land burnt in km ²)	JRC and CFS	Used for main model	DV2
lnpop_den	Population density	ln (Total population/regional area in km ²)	Elaboration from ISTAT	Used for main model	SED
lnrail_den	Railway density	ln (km of regional railways/ regional area in km ²)	ArcGIS maps ²¹	Used for main model	SED
rela_pov	Relative poverty	Average €/month	ISTAT ²²	Used for main model	SED
Inbovine	Bovine elements	ln (Total bovine elements/regional area in km ²)	Elaboration from ISTAT	Used for main model	SED
Incaprine	Caprine elements	ln (Total caprine elements/regional area in km ²)	Elaboration from ISTAT	Used for main model	SED
p_ter_deg	% of total population holding tertiary degree ²³	(Population with tertiary degree/Total population)*100	Elaboration from ISTAT	Used for main model	SED
p_emp_agri	% Employment in the agricultural sector	(Number of people employed in the agricultural sector/Total number of employees)*100	Elaboration from ISTAT	Used for main model	SED
extor_1000	Number of extortions every 1000 inhabitants	(Total number of extortions in the region/Total population in the region)*1000	Elaboration from ISTAT	Used for main model	SED
Inarrivals	Number of tourist arrivals	In (Total number of tourist arrivals/ regional area in km ²)	Elaboration from ISTAT	Used for main model	SED
Innhot	Annual average number of hot days	ln (Annual average number of hot days)	Elaboration from CRA-CMA ²⁴	Used for main model	GPD
excursion	Annual average of temperature excursion	Annual average of temperature excursion	ISTAT elaboration ²⁵	Used for main model	GPD
mean_precq11	Monthly average precipitation of the first 4 months of the year	(Total precipitation between January and April in millimetres) /4	Elaboration from CRA-CMA	Used for main model	GPD
mean_precq22	Monthly average precipitation of the second 4 months year	(Total precipitation between May and August in millimetres) /4	Elaboration from CRA-CMA	Used for main model	GPD
mean_precq33	Monthly average precipitation of the last 4 months year	(Total precipitation between September and December in millimetres) /4	Elaboration from CRA-CMA	Used for main model	GPD
mean_tja	Monthly average temperature from June to August	(Total average temperature in June, July and August) /3	Elaboration from CRA-CMA	Used for main model	GPD
lnpop_den_f	Female population density	ln (Total female population/regional area in km ²)	Elaboration from ISTAT	Additional control	SED
lnpop_den_m	Male population density	ln (Total male population/regional area in km ²)	Elaboration from ISTAT	Additional control	SED
lncow_bufa	Cow and buffalo elements	In (Total cow and buffalo elements/regional area in km ²)	Elaboration from ISTAT	Additional control	SED
Inpigs	Pig elements	ln(Total pig elements/regional area in km ²)	Elaboration from ISTAT	Additional control	SED
Inovine	Ovine elements	ln (Total ovine elements/regional area in km ²)	Elaboration from ISTAT	Additional control	SED
Inequidae	Equidae elements	ln(Total equidae elements/regional area in km ²)	Elaboration from ISTAT	Additional control	SED
p_emp_ind	% Employment in the industry sector	(Number of people employed in the industry sector/Total number of employees)*100	Elaboration from ISTAT	Additional control	SED

Appendix 1. List of variables with relative description

²⁰JRC: Joint Centre (http://effis.jrc.ec.europa.eu/); Research CFS: Corpo Forestale dello Stato (http://www3.corpoforestale.it/flex/cm/pages/ServeBLOB.php/L/IT/IDPagina/3888) ²¹ See ArcGIS maps at <u>http://www.mapcruzin.com/free-italy-arcgis-maps-shapefiles.htm</u> ²² According to ISTAT "A household is defined as poor in relative terms if its consumption expenditure is equal to or

below the relative poverty line, which is calculated on the basis of data from the household consumption survey. For a two-member household it is the average monthly expenditure per person [...]." (More on this at: <u>http://noi-italia2012en.istat.it/index.php?id=7&user_100ind_pi1%5Bid_pagina%5D=107&cHash=39abf23d62a1111bd4edefe150</u> d82ec7) ²³ Tertiary education: Bachelor Degree and PhD

²⁴ The CRA-CMA is the Italian Consiglio per la Ricerca in Agricoltura - Unità per la Climatologia e la Meteorologia applicate all'agricoltura (More on this at: <u>http://old.politicheagricole.it/ucea/forniture/index3.htm</u>)²⁵ ISTAT elaboration from CRA-CMA data.

n omn son	% Employment in the service	(Number of people employed in	Elaboration from	Additional	SED
p_emp_ser	sector	the service sector/Total number of employees)*100	ISTAT	control	SED
unemp_tot	Total unemployment rate	(Total number of people unemployed at a region/Total labour force at the region)*100	Elaboration from ISTAT	Additional control	SED
unemp_f	Female unemployment rate	(Total number of female unemployed at a region/Female labour force at the region)*100	Elaboration from ISTAT	Additional control	SED
unemp_m	Male unemployment rate	(Total number of male unemployed at a region/Male labour force at the region)*100	Elaboration from ISTAT	Additional control	SED
ill_asso_1000	Number of illegal associations every 1000 inhabitants	(Total number of illegal association in region/Total population of the region)*1000	Elaboration from ISTAT	Additional control	SED
fraud_1000	Number of frauds every 1000 inhabitants	(Total number of frauds in a region/Total population of the region)*1000	Elaboration from ISTAT	Additional control	SED
smug_1000	Number of smuggling every 1000 inhabitants	(Total number of smuggling in a region/Total population of the region)*1000	Elaboration from ISTAT	Additional control	SED
crime_1000	Number of crimes every 1000 inhabitants	(Total number of crimes in a region/Total population of the region)*1000	Elaboration from ISTAT ²⁶	Additional control	SED
Build_price	Average price of building logs	Average price of building logs among different log categories (€/m3)	Elaboration from ISTAT	Additional control	SED
Peeled_price	Average price of log to be peeled	Average price of logs to be peeled among different log categories (€/m3)	Elaboration from ISTAT	Additional control	SED
Veneer_price	Average price of veneer logs	Average price of veneer log among different log categories (€/m3)	Elaboration from ISTAT	Additional control	SED
Saw_price	Average price of saw logs	Average price of saw log among different log categories (€/m3)	Elaboration from ISTAT	Additional control	SED
Pulp_price	Average price of pulpwood (round and split)	Average price of pulpwood among different categories (€/m3)	Elaboration from ISTAT	Additional control	SED
Ind_wood_price	Average price of other industrial round wood	Average price of veneer log among different log categories $(\notin/m3)$	Elaboration from ISTAT	Additional control	SED
Innights	Number of nights spent by tourists	In (Total number of nights spent by tourists/ regional area in km ²)	Elaboration from ISTAT	Additional control	SED
T_mean	Average annual temperature	Average annual temperature for region (measured in degrees Celsius)	ISTAT elaboration ²⁷	Additional control	GPD
T_min	Average annual maximum temperature	Average annual maximum temperature for region (measured in degrees Celsius)	ISTAT elaboration	Additional control	GPD
T_max	Average annual minimum temperature	Average annual minimum temperature for region (measured in degrees Celsius)	ISTAT elaboration	Additional control	GPD
precip	Average annual precipitation total for regions	Average annual precipitation total for regions measured in millimetres	ISTAT elaboration	Additional control	GPD
Diff00-09	Relative difference of the average total precipitation from the mean of the year 2000-2009	Relative difference of the average total precipitation from the mean of the year 2000-2009 (measured percentage deviation)	ISTAT elaboration	Additional control	GPD
prec_jan TO prec_dec	Monthly average precipitation for January,, December	Monthly average precipitation at a given region in January, February,, December	Elaboration from CRA-CMA	Additional control	GPD
t_jan TO t_dec	Monthly average temperature for January,, December	Monthly average temperature at a given region in January, February,, December	Elaboration from CRA-CMA	Additional control	GPD

 ²⁶ For more detail on this see http://www.istat.it/agricoltura/datiagri/foreste/forgloss.html
 ²⁷ ISTAT elaboration from CRA-CMA data (Weighted average calculated for each elaboration considering the extension of the individual regions for temperature and precipitation).

Forest Fires in Italy: An econometric analysis of major driving factors.



© Centro Euro-Mediterraneo sui Cambiamenti Climatici 2013

Visit **www.cmcc.it** for information on our activities and publications.

The Euro-Mediteranean Centre on Climate Change is a Ltd Company with its registered office and administration in Lecce and local units in Bologna, Venice, Capua, Sassari, Viterbo, Benevento and Milan. The society doesn't pursue profitable ends and aims to realize and manage the Centre, its promotion, and research coordination and different scientific and applied activities in the field of climate change study.

