The Long-Term Impact of Forest Fires on Carbon Sequestration in Europe

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Abstract

Greenhouse gas emissions from wildfires are substantial, and yet were given very little scrutiny in the Kyoto Protocol until very recently. The main reason for this was the assumption that forests would naturally recover fully over time, an assumption now largely challenged by on-site carbon sequestration studies. In this study, we produce the first large scale assessment of long-term forest recovery from wildfires, contributing to a better understanding of the environmental damages from forest fires and their economic valuation. Utilizing a matching strategy for fires of 2000, we find that after 18 years, on average, fire-damage has caused 61% reduction in the presence of forests and at least a 26% average reduction of carbon stored. The costs of compensation for this loss alone rise to estimates over $5.9 billion, while not doing so impedes the effectiveness of climate change policy. With more accurate data soon-to-be released to public, these estimates are likely to be even larger.

JEL classification: Q23, Q28, Q54, C21
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1. Introduction

It is now widely accepted that the 3.4 million square meters of land that burn every year, representing about 2 percent of global land area, pose a very serious threat to climate stability. As much as 16% of global GHG emissions could be caused by fires every year (Rossi et al., 2016; Climate Watch, 2021). This estimate is at the same level as the contribution of the transport sector. The number of wildfires has further increased over the past few years (WWF, 2020) and, in 2019 and 2020, exceptionally devastating wildfires have destroyed vast areas of forest and wildlife in Brazil and Australia.[1]

Yet, for a very long time, the international community imperfectly accounted for greenhouse gas emissions (GHG) from forest fires. Both under the Kyoto Protocol of 1997 and the accounting provisions of 2006 by the IPCC, wildfires were considered to be "neutral over time" due to ecological recovery (Johns, 2020). This gave way to substantial loopholes in GHG accounting from fires. For instance, Fry (2007) notes that a fire started on farmland had to be accounted for but that, if a fire escaped into "unmanaged" forest, then the resultant emissions were no longer covered by the inventory. Only in 2019 did a refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories acknowledge that natural disturbances (including wildfires) had to be fully accounted for (Ogle et al., 2019).

Uncertainties on the long-term impacts of forest fires on land use and carbon sequestration may have contributed to the delays in accounting for their contribution to climate change. Recent scientific evidence suggests that fires may have a substantial impact on long-term carbon storage on bunt areas (e.g. Hurteau and Brooks, 2011; Caon et al., 2014; Francos et al., 2018), but assessments are limited in scope by the need to gather precise data on carbon storage on vast areas of land and over large periods of time. Furthermore, ecological assessments alone are often insufficient to understand the magnitude of the carbon loss because carbon storage depends as much on ecological factors as on post-disaster land use and land management.

In this study, we intend to provide a large-scale picture of long-term recovery rates from forest fires in Europe, based on the latest ecological evidence for on-the-ground and below ground carbon sequestration, while accounting for economic mechanisms, especially potential changes in land use after forest fires took place. Relying on the CORINE Land Cover (CLC) inventory to focus on the forest fires that happened in the late 1990s and early 2000s, we implement a matching method to look at the impact these fires on land use many years later, in 2018. we create a control group consisting of nearby, similar areas that did not undergo a fire, and therefore control for the likely evolution of burnt areas between 1990 and 2018, had they not burnt. we furthermore overlay the most recent maps of carbon storage and net primary productivity (an indicator of vegetation growth and carbon storage) to assess long term impacts until 2020.

To the best of our knowledge, this analysis constitutes the first multinational study of the average recovery rate forests from existing fires. So far, most assessments of post-fire recovery rates have been conducted at a much small scale through case studies (e.g. Dumontet et al., 1996; Verma and Jayakumar, 2012). A second contribution regards the application of our methodology beyond land use changes. Because our matching method identifies control and treatment groups with a calibration on pre-sample

[1] Damages from forest fires also include severe biodiversity loss, the emergency evacuation of more than half a million people annually, and an estimated 340,000 premature deaths annually from respiratory and cardiovascular diseases caused by forest smoke (Chen et al., 2021).

data on land use from 1990, it can be used to estimate impacts on any European map of bio-physical factors after 2000.

The production of the scientific data on such indicators at the scale, accuracy, and fine detail that we require is still ongoing, with several large-scale projects taking place at the moment. One appropriate example would be the Naturemap Earth project (https://naturemap.earth/). However, this study shows how we will be able to use our matching estimator in the future, in conjunction with the right ecological data, to identify the impact of forest fires on a large array of key ecological indicators with substantial economic implications, especially biodiversity loss and carbon sequestration. It is therefore proof-of-concept for the constitution of a full research paper on the ecological implications of forest fires in Europe, and their long-term economic valuation.

In this manuscript, we employ this method on biomass carbon density and net primary productivity as indicators of carbon sequestration. we find that the fires have impacted total biomass carbon density in burnt forests with a decrease of 12.86 MgC ha^{-1} after 10 years. This is 28% of the carbon storage capacity that the forests otherwise would have had. It is accompanied by the fact that even after 20 years, though there is relative recovery in the burnt forests in terms of productivity, the carbon storage contributions associated is only 0.96 MgC ha^{-1} on average, annually. This stark contrast is less than 10% of the differential the carbon density, after twice the amount of time. In economic terms, the overall carbon sequestration loss from the analyzed in this study estimated to be USD 5.95 billion in 2010 for fires that occurred in 2000. The marginal cost of rapid abatement will reach up to USD 1 billion, for 2030, if these losses are not compensated[2]. These figures of course, only considers the impact of fires of 2000. Since social cost of carbon is not a constant value, so long as the lost carbon is not re-captured, total costs estimated here will only increase in time. However, aside from costs associated with uncaptured carbon, long-term impact on carbon sequestration can induce pressure on biodiversity offset policies. As land for biodiversity offsetting policies become scarce, the competition effects generated will further inflate the value of land with high capacity for carbon sequestration, leading to increased costs associated. While difficult to quantify, we provide examples of recent studies on how this supply constraint has already caused related offset policies to fail and induced social conflicts due to clashing economic interests under scarce resources.

Considering the very recent changes in policy consensus regarding wildfires, our findings show that they have had long-term effects, even prior to views established on their increased frequency and severity due to climate change. Wildfire occurrence in Europe as early as 2000, shows significant and long-lasting impact on carbon sequestration. This presents a necessity for reevaluating the current approaches on both climate change policies such as biodiversity offsetting, impact of fire-damage, and how to manage these effects, going forward. One important issue which needs resolving has to do with climate commitments allowing for loopholes regarding emissions. Past drafts allowing for exclusion of emissions due to natural disturbances, as well as the aforementioned exclusion of long-term impacts from the Kyoto Protocol misrepresent the true danger that wildfire emissions represent for the climate (Fry, 2011). Further, forest management policies represent one dimension by which "avoided emissions" (climate-friendly activities which do not actively reduce emissions, but contribute far less GHG into the atmosphere than alternatives) could be used as a means to avoid taking active steps to fight climate change (LRI, 2019). The concerns over Paris Agreement allowing countries to "bank" surplus avoided emissions in one period of commitment, in order to increase relative emissions in the next in exhaustion

[2] The figures expressed are all in 2007 USD. The "marginal cost of rapid abatement", as discussed by McKinsey & Company (2009), regard costs of reaching zero or negative net global emissions by the end of this century. Hence, the costs assume no advancements made in terms of compensation of lost biomass carbon at hand, until 2050.

of these banked emissions, is especially problematic in the context of forest management, as reforestation activities could be accounted as such. My results go to either incentivize taking more active steps, as forest fires render avoided emissions by forestry significantly less reliable without effective forest management strategies or incentivize actually implementing a robust and effective prevention and management policies regarding wildfires. With new understanding of the long-term losses now known, the trade-off between effective versus economic forest management policies can also be better settled. As these policies would no longer mean mere costs for environmental protection, but they also translate to significant economic gains in the long-term.

In the remainder of the manuscript, we will be first going over the history of related works, methodological approaches, and policy stances expressed in the past, and pinpoint our contributions to the literature in this context, with Section 2. Section 3 will detail the various data we have used, the state of Europe vis-à-vis land use and carbon sequestration, as well as the systemic issues inherent to technologies we exploit for our methodology. In Section 4, we will introduce the baseline matching model, point out the inherent assumptions and qualities of the approach which could be the most problematic for its validity, and provide individual cases as to why they hold in this context. Section 5 will provide individual accounts of the impacts done on land use, the two indices regarding carbon sequestration, and their temporal progression, while setting up some preliminary discussion on their meaning. A more comprehensive discussion is provided in Section 6, first contextualizing and connecting the ecological impacts, then, mention the economic costs these impact estimates represent, and finally the policy implication which connect these two dimensions of ecology and economy. Once the central discussion of the manuscript is completed, Section 7 will go back to review some of the secondary and tertiary factors on the model regarding consistency which are not particularly problematic in nature for our approach, but important to exhaust the details of, nevertheless. Section 8 will further this discussion on validity, but less theoretically, and more through quantitative assessments of robustness checks, involving various parameters of our model to ensure that central results remain just as significant. Finally, Section 9 will reiterate the central premises and the conclusions of the study, overall summing the study and emphasizing its implications.

2. Literature Review

2.1. Background

Due to the multi-dimensional impacts of forest fires, their effects have been analyzed and measured through several different methods and approaches. Depending on the discipline of analysis associated, the earlier examples could be scientifically driven and focused on the damage done to ecological vigor, soil conditions and fauna (e.g. Heyward and Barnette, 1934; Heyward and Tissot, 1936; Beadle et al., 1940); geographically driven and focus on descriptive, spatial patterns and accounting of total damages (e.g. Graves, 1910; Plummer, 1912); or economically driven, which was usually based on applying economic theories for assessment of insurance risks, property damage and modelling fire management costs (e.g. Coyle, 1929; Dallyn, 1933). Generally marked by the almost mutually exclusive approaches that these disciplines took in determining what "impact" referred to, the ecological and economic effects of wildfires were considered qualitatively related, but usually, quantitatively disconnected. As the advancement of associated methods, technologies, and knowledge in these areas grew, the gap between these various impact analyses began to converge in application and implication. This progress was due to the further research in climate sciences regarding greenhouse gasses in the 1950's and 1960's (particularly starting with works such as Plass, 1956; Keeling, 1960), supported by advances in technology such as remote sensing technologies, allowing much larger scale, geographical observation of ecological indicators, and also in economics, through better understanding and formulating the downstream economic costs of climate phenomenon (e.g. the climate-economy models, beginning with the IIASA climate model of Nordhaus, 1977; application of social cost theories on carbon, such as Adams et al., 1993). Throughout this progress, while there has been anecdotal if not qualitative documentation of lasting impact of wildfires on biomass and carbon (e.g. Crutzen and Goldammer, 1993; Dumontet et al. 1996; or the conceptual model of fire impact by Cochrane and Schulze, 1999), the general consensus regarding impact of fires on carbon storage of vegetation, particularly from the perspective of policymakers, was that they were a net wash beyond short-term (Johns, 2020). Hence, plans focusing on climate action such as no net loss (NNL) strategies, GHG emission quotas, or natural offsetting policies did not account for long-term effects of wildfires on carbon sequestration. However, as mentioned prior, in recent years this view has started shifting, and action plans revised. More research done with more advanced methodologies, over longer periods of time, presented stronger evidence of how forest fires could have much longer lasting impact on the environment than previously thought.

2.2. Recent Discoveries

Two of the primary reasons behind the change of perception on long-term effects of fire damage on emissions and carbon sequestration were long-lasting recovery, and vegetation change. Studies such as Dore et al., (2008) demonstrate that even after 10 years of recovery, forests fail to become a net carbon sink, due to slow recovery of vegetation. These findings on longer-term impact of fires on forest recovery were also supported by later literature such as Helu et al. (2009). In terms of vegetation change, consensus-changing discoveries primarily happened in the 21st century. As Savage and Mast (2005) put, "[Currently] we have little understanding of the longer-term effects of [forest] fires on forest demography and structure". Authors then go on to show that out of 10 studied sites, the forests in half of them had transitioned into grassland or shrubs after 10 years. These vegetation are categorically less capable of capturing much carbon from the atmosphere. Similarly, later studies such as Coop et al. (2016) study forest fires in southwestern US to find that severe burns were associated with transition of forest sites to open savannas and meadows. Unlike previous assumptions of recovery, high-intensity forest fires are fundamentally changing the vegetation structure of the ecological zone. Incidentally, high-intensity and fast-spreading wildfires are considered natural for the Mediterranean basin (Caon et al., 2014). Ultimately, in both of these dimensions, forest fires are capable of significantly altering the capacity of an ecosystem to sequester carbon.

2.3. Modern Methods

Methodologically, more recent research on effects of fire-damage frequently utilize field surveys, modelling, or aforementioned remote sensing techniques, for comparative assessment of forest fire impact (e.g. Chu and Guo, 2014; Liu et al., 2019; Dai et al., 2020). Remote sensing techniques, in particular, allow for much larger, standardized, and consistent accounting of ecological properties, and its regular records make for temporal analysis on forest disturbances possible. This comes at the expense of it still being a developing technology, and as such having limitations on data availability, and depending on the type of information intended to be captured, not being nearly as accurate as a field survey (Olofsson et al., 2014). For this reason, depending on how intricate the study is, or how the data will be used, remotely sensed indicators tend to be accommodated with some preliminary field observation for error correction (e.g. Keller et al., 2001, Dai et al., 2020). Nevertheless, as both the accuracy and the availability of data has increased, satellite technologies has allowed systematic and continuous tracking of forest fires. One further opportunity which naturally follows from this is the ability to work on larger-scale comparative analyses of the effects of said fires.

Impact assessment of forest fires, regardless of the underlying technique, frequently utilize comparison of nearby plots to the "treated" areas of burnt forests, as the control group (e.g. Stephens and Moghaddas, 2005; Smith et al., 2005; Ghebreiwot et al., 2012; Miteva et al., 2015; Woo et al., 2021). This is primarily to ensure ecological comparability of counterfactuals, as even if from the same genus, plant-life in different environmental conditions will have significant biochemical diversity and respond to disturbances in significantly different ways. In terms of field surveys, the amount of labor needed for this condition limits them to relatively small-scale research, cross-sectionally. Knutson et al. (2014) evaluates the long-term impact (areas burnt once since 1970 in various years, field survey done from 1990 to 2003) of forest fires. For long-term impact assessment, remote sensing techniques generally suffer from temporal limitations, due to lack of information going farther back enough. Further, Woo et al. (2021) finds that simple geospatial matching of nearby plots based on observed indicators may not provide well balanced matches. Considering its methodological similarity to our work, this is particularly important to take into account.

2.4. Economic Impacts

One of the most commonly used dimensions by which forest fires are translated to economic impacts is through the theory of Social Cost of Carbon. First introduced by William Nordhaus in 1977, his explicitly describes the issue of carbon emission as a fiscal question. Interpreted as the shadow price for a carbon tax, the estimates for social cost of have since became central to policymaking. It is also widely criticized for being a reductive measure (Neumayer, 2000), and vary significantly due to high model dependency (Wang et al., 2019, finds this range at -50 to 8,752 USD per ton of carbon). The theory has since been developed to provide more nuanced and realistic estimates. McKinsey & Company (2009) provides a multi-sectoral pathway with a range of scenarios involving measures taken to reach stabilization in emissions by 2060, with the so called "rapid abatement cost". Studies such as Ackerman and Stanton (2012) revises old estimates and produces 16 different plausible estimates based on climate sensitivity and using multiple models commonly used for policy projections. With these estimates, social cost of carbon allows for a range of direct monetary value to be assigned to the findings provided in this manuscript.

Outside of the simple monetary value, policies associated with combatting climate change also come with tertiary economic costs. Biodiversity offsetting is commonly used as a policy tool to ensure that the emissions and ecological damages of the private sector will be balanced by the land "re-created" in compensation. Usually in the context of a "credit system", the viability of this offsetting relies on available supply land, which, studies like Sonter et al. (2020) and Calvet et al. (2019) find not to be the case. Wildfires, in this context, go to exacerbate the scarcity of resources and the competition effects which arise.

In light of this information, our study contributes to the growing literature on the long-term impact of fires, both in terms of the demographic composition changes, and the productive capacity of the remaining post-fire forests. Further, with its full scale exceeding the European continent, it is the largest impact assessment study on this topic, in scale. It is among the few studies which evaluate the average impact of fires among different climatic zones and genera of forests (studies of fires in US could also be considered in this category). Hence, it's applicability transcends localized, context-specific findings. Methodologically, we present a novel framework which is able to evaluate the impact not just on land use, but on any bio-physical indicator associated with forests. Firstly this allows other ecological studies to be conducted on impacts of forest fires with negligible changes to the model, so long as the associated data can be found (e.g. biodiversity, fire management policy). Secondly, due to its reliance on common remote sensing data (i.e. land use classification), it can just as easily be calibrated for studies in other countries and ecologies.

3. Data and Descriptive Statistics

3.1. Burnt Areas and Land-Use

Land use information is provided by satellite images of the CLC inventory of the European Environmental Agency (Kosztra et al. 2017). CLC is a pan-European land cover map which combines national databases and remote sensing information into 44 distinct sub-classes covering 39 countries in continental Europe. They detail five primary classes of land for each pixel of observation: "artificial surfaces", "agricultural areas", "forest and seminatural areas", "wetlands", and "water bodies" (full specifics on the coverage area, pixels, and the land classes can be found in Appendix). With a resolution of 100 by 100 meters, which amounts to 2.99 billion pixels in extent, per year, this is one of the coarsest accounts of land use for the European continent in whole. As such, we have decided to use a resolution of 400 by 400 meters as the spatial unit, primarily due to technical feasibility of the project given the time constraints. The dataset spans 28 years in total, consisting of five cross-sections representing the years: 1990, 2000, 2006, 2012 and 2018. In order to assess the long-term effects of forest fires, primary focus will be on burnt forests in earlier periods (e.g. 1990 and 2000) and their recovery in later periods.

Burnt areas were identified based on the designated category of the same name, defined as fire-damaged regions of "forests, moors and heathlands, sclerophyllous vegetation, transitional forest-shrub formations, areas with sparse vegetation" (Kosztra et al. 2017). This means even though there is a defined subset of subclasses a given "burnt pixel" can be, this subset is strictly larger than forests. As such, given a burnt region, there is no direct information as to whether they consisted of trees, bushes, or some other form of vegetation, which experienced fire damage. Addressing this issue of ambiguity will be central to the methodology utilized in this paper to assess effects of forest fires.

Fig. 1 — Spatial distribution of burnt areas in the pan-European region between 1990 and 2000, inclusively. Isle of man is also provided at the top right corner. 10 km proximity around burnt pixels are colored red with for clarity. The map is color graded based on land use categorization of CLC inventory standards. The pan-European region includes the EU-member countries, EFTA members, EU candidate countries, and potential candidates. Further information on the pixel classification standards can be found in the Appendix.

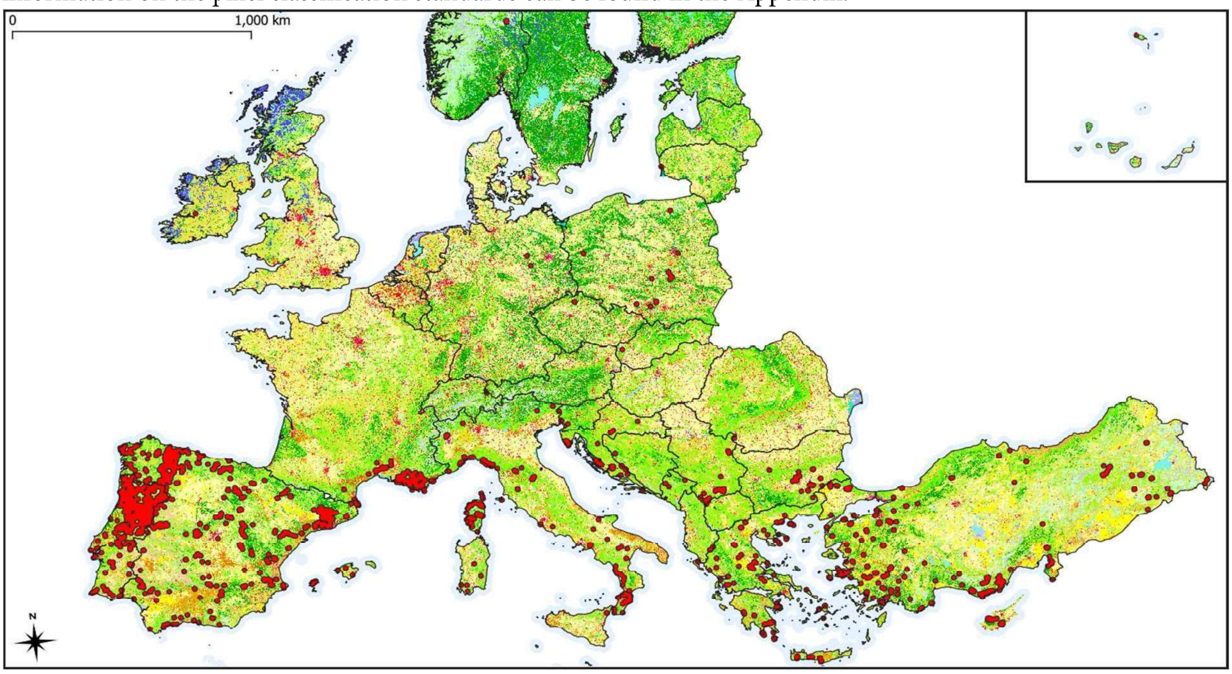


Table 1 — Descriptive statistics on land use in the pan-European region, by year.

		% Share of Land by Year				
Categories	Description	1990	2000	2006	2012	2018
Forests	Broad-leaved, coniferous, and mixed forests.	24.42%	28.48%	28.72%	29.26%	29.29%
Artificial Surfaces	Built and otherwise non-natural areas.	3.59%	3.39%	3.68%	3.93%	3.99%
Agricultural Areas	All areas occupied by agricultural purposes including agro-forestry.	53.10%	43.06%	42.50%	42.21%	42.15%
Natural grasslands, moors, and heathland		5.07%	6.71%	6.80%	6.65%	6.64%
Sclerophyllous vegetation, transitional woodland-shrubs		7.57%	7.63%	7.41%	6.98%	6.94%
Burnt areas	Fire-damaged areas[a].	0.046%	0.030%	0.024%	0.015%	0.039%
Other	Sparse vegetation, wetlands and water bodies	6.21%	10.70%	10.86%	10.95%	10.95%
Share of forests to total land		19.95%	24.42%	28.48%	28.72%	29.26%
Share of burnt areas to burnable greenery		0.13%	0.07%	0.06%	0.04%	0.09%

Notes: "Share of forests to total land" denotes the aggregate share of "Broad-leaved forest", " Coniferous forest", and "Mixed forest" to the total land use.
a: Does not include burnt areas of natural grasslands, agricultural areas (including agro-forestry) or urban-greenery as per Kosztra et al. (2017).

Fig. 1 shows a comprehensive map of the burnt areas between the years 1990 and 2000, inclusively. Firstly, as expected, the overwhelming majority of fires have been in the Mediterranean countries. The aforementioned issues raised by Mateus and Fernandez (2014), regarding flammable forest types dominating Northern and central Portugal can be clearly observed. Within the Mediterranean region, Portugal by far has the highest share of burnt areas. Further, the prevalence of dense and frequent fires in the southern France as Ganteaume & Jappiot (2012) point out, can also be validated. But, for a more concrete understanding of the distribution of vegetation and burnt areas, this visual context will not be enough.

Table 1 provides a breakdown of land-use shares across the dataset for each period. Since forests and seminatural areas are of primary interest, they are detailed at the highest tier. "Broad-leaved forest", "Coniferous forest", "Mixed forest" are the three categories designated to encompass the forests of the pan-European region. Overall, a plurality of the land throughout the years has shifted from agricultural areas to forests and seminatural greenery, with a significant increase in the share of forests. However, over the past 10 years, there seems to have been a significant increase in forest fires, with the rate more than doubling. This, of course underrepresents the total burnt land, as forests are not the only flammable forms of vegetation.

However, it is clear that the fire damage is still a persistent problem. In order to get a better perspective on effects of fire damage, it is important to not only investigate the data cross-sectionally, but also how burnt areas, specifically, change over time.

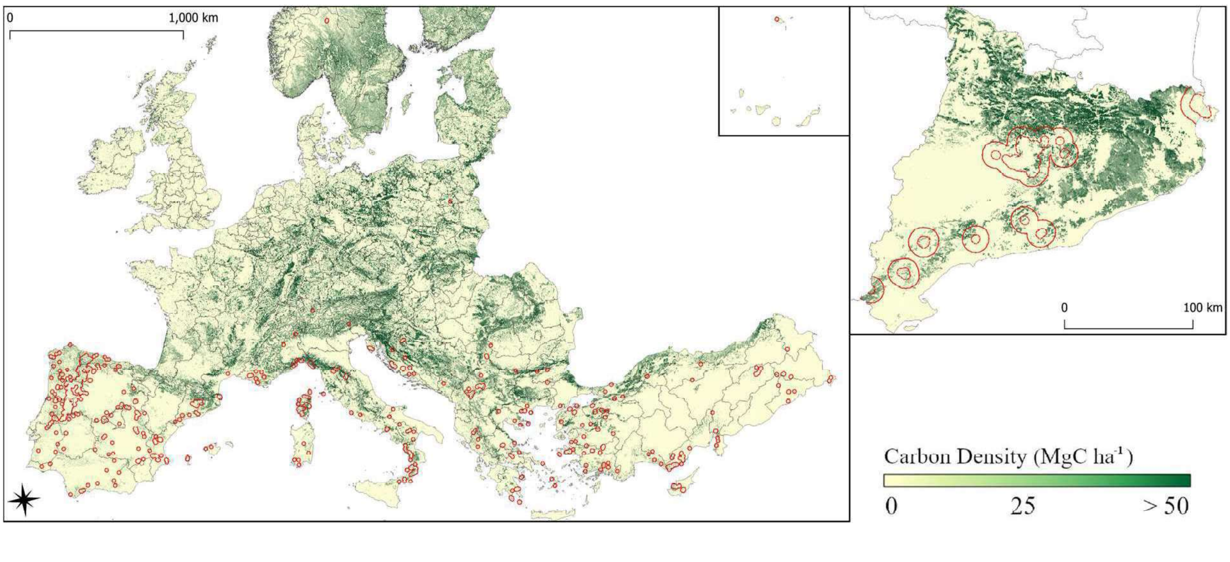
3.2. Carbon Storage & Sequestration

Carbon sequestration, in the context of our study, refers to the photosynthetic activities which allow vegetation to capture and otherwise remove carbon dioxide from the atmosphere in the long-term. Naturally, forests have far greater capacity to sequester and store carbon compared to other forms of vegetation such as grasslands or shrubs[3]. Measuring this capacity is generally done either in small scale case studies through field surveys, or through proxy variables (e.g. vegetation indices), interpolation, and filtering (e.g. Dai et al., 2020; Tao et al., 2020) are used for inference for larger scale analyses. Since the estimation of the impact forest fires requires a very fine-scale and accurate analysis, proxy variables or interpolation will cause a loss of accuracy in each step, and hence, bias in our investigation. The Nature Map project (IIASA et al., 2020) seeks to provide comprehensive and detailed measures for key bio-physical features which would be impacted by forest fires in the long-term. To our knowledge, this is the latest and most accurate set of estimations regarding indicators such as carbon sequestration and biodiversity. However, Nature Map has not been released yet. As such, we will be using second best available resources for our study. As more accurate data is released, we will have the opportunity to expand and detail the application of our research, going forward.

3.2.1. Aboveground & Belowground Biomass Carbon Density

In place of carbon sequestration, we will be using the aboveground and belowground biomass carbon density maps of Spawn et al. (2020). Measured in MgC per ha, these maps are the first harmonized and remotely sensed global maps of carbon storage of its kind. In this sense it will both allow me to observe impact of fire-damage on both vegetation and soils. Fig. 2 shows the distribution of aboveground biomass carbon density, both for our whole study area, and Catalonia, in detail. Looking at the burnt areas of Catalonia, we can already see that the burnt areas, as well as their relative proximity within 3 km, have distinctly less carbon stored than farther surrounding regions at 10 km.

Fig. 2 — Aboveground biomass carbon density map for the pan-European region (left) and for the NUTS II region of Catalonia (top right), for the year 2010. Isle of man is also provided at the top left corner of the map of Europe. 10 km perimeter around burnt areas of 2000 are outlined in red in both maps, while for Catalonia, a 3 km perimeter is further shown in dashed-red lines. Color-grading was done in accordance with Spawn et al. (2020).



[3] Though there are periods, such as during winter periods, when growing forests can become net emitters of CO_2, they are net carbon sinks over lifetime (Gorte RW, 2009). Over time, one of the primary way in which photosynthesis allow forests to store carbon to a much greater extent than other plant life is through converting CO_2 to biomass. Other vegetation usually relies on storing this carbon only in their roots.

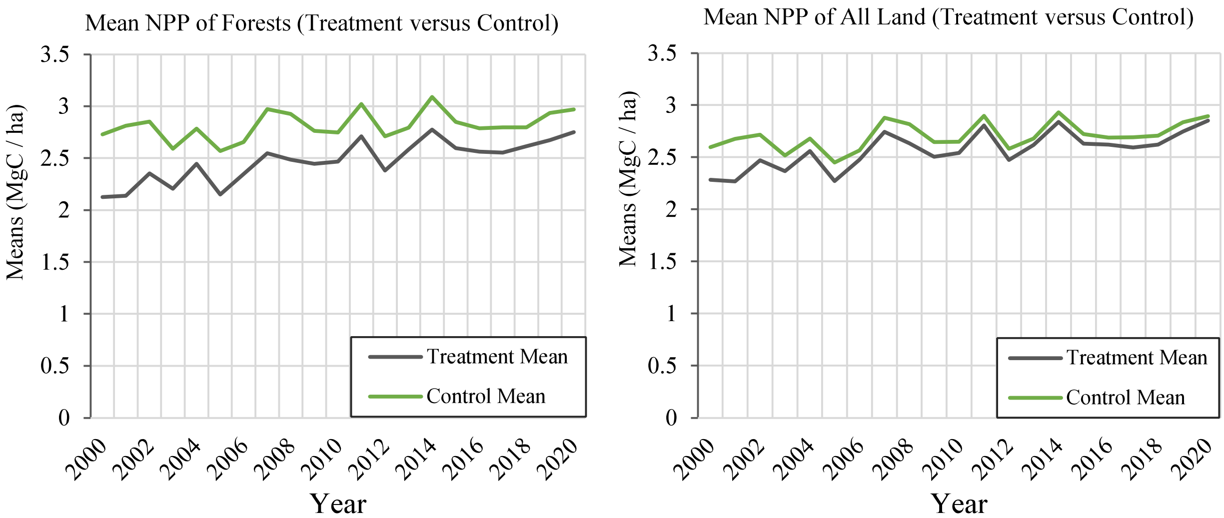
However, despite the fact that the authors utilize several other studies in validation of the final map, there are still several dimensions in which accuracy diminishes. For example, accuracy of mapping phylogenetic features of gymnosperm vegetation, such as coniferous forests, can fall as low as 55%. Other studies used for validation also have associated systemic errors which increase the cumulative uncertainty. As mentioned prior, since forests have the greatest capacity for carbon sequestration, these inaccuracies will lead to an underestimation in our data. Further, maps only provide an estimate of the year 2010. Therefore, even though this data will still allow me to observe impact of forest fires after a relatively long time, it will still not necessarily constitute a long-term analysis. In remedy, we will also be using a remotely sensed dataset on the geospatial distribution of carbon fluxes, which is available staring from the date of our study, until today: net primary productivity.

3.2.2. Net Primary Productivity

Net primary productivity (NPP) index of NASA is a measurement of the net plant productivity (photosynthetic activities which capture carbon minus the respiratory activities which produce it), ranging from 2000 to 2020, expressed in gC per m^2 annually (Running and Zao, 2021). This indicator provides a measure of the carbon storage fluxes throughout the year and it can be seen as a "flow" variable associated with the sequestration process. Observing the changes of forest productivity from 2000 onwards can capture the evolution of the underlying vegetation, after the forest fires occur. Since different types of vegetation have different levels of productivity, we would have a quantified frame of reference in understanding the fire impact.

Fig. 3 primary productivity in burnt and non-burnt areas, as given in Fig. 5. For forests, the discrepancy at first seems large, with roughly 32% difference. However, the difference seems to be shrinking over time, with similar fluctuations. By 2020, the difference drops to only 7%. Regarding means for all land, the discrepancy is even smaller, going from a difference of 12% in 2000, to 5% in 2020. As far as productivity is concerned, independent of fires, it is fair to say that there is relative recovery after 20 years. One possible argument here could be regarding the productivity which burnt forests would have had, had they not experienced fires. While fair to consider at this point, later in this

Fig. 3 — Average net primary productivity of burnt and non-burnt areas.



Notes: Means indicate the average value NPP value of the whole control and treatment groups under the baseline specification of data.

manuscript we will describe why this is not likely to be true, and why higher rates of productivity increase for burnt plots actually provides support in favor of the severity of wildfires.

3.3. Systemic Issues with Data

As mentioned previously, despite increasing accuracy and validation, there are limitations associated with remote sensing technologies. Regarding remote sensing of forest fires, specifically, Sajjad and Kumar (2018) mention issues regarding preprocessing and validation. Due to the nature of how wildfires ignite and spread, high spatial and temporal resolution is necessary to make accurate estimates. Without high spatial resolution, the impact will be underestimated due to surrounding, healthier vegetation causing an interpolative effect.

Temporal resolution can also lead to underestimation issues based on assessing the severity and frequency of fires, but since this study is not concerned with decoupling wildfires based on severity, or areas based on fire frequency, this is not a problem for our work.

Beyond simply accounting for fires, there are issues concerning any work which involves multiple geospatial datasets, in concurrence. This is because, in order to convert multiple raster information into a workable, unified dataset, methods like resampling and reprojection is usually necessary. This technically can be avoided, however, such associated methods can be much more computationally intensive. Therefore, we had to use techniques which, although conventional in the field of geography, are nevertheless approximative in nature. In order to best undertake this process, we have exclusively used nearest-neighbor methods, as it makes the least number of systematic assumptions about the data. In fact it is the only method that does not generate values which do not exist in the original dataset, in approximation.

Each of these issues ultimately contribute to *underestimating* the true effects of fires. Whether through approximation (smoothing effects), temporal mismatch (fires lose severity and become harder to capture), or due to preprocessing stage itself (approximating validation methods lower quality of "edge values"), these obstacles serve to render our estimates less significant. Forest fires, as ecological shocks, have effects which are composed of uneven patterns. Analyzing these effects at such a large scale necessarily involves utilizing satellite data with varying spatial units, coordinate reference systems, which have to be realigned and this will also cause loss of information. However, this discussion is not to prepare for an excuse for weak findings, on the contrary, it should only go to emphasize the significance and magnitude thereof, as our results represent the lower bound.

4. Methodology & Model

4.1. Baseline Specification

In order to estimate the impact of fires, we use nearest-neighbor matching which compares the regions that experience fire in the initial year T_0 with the status the same region from year T_{0+t}. Treatment groups are then, naturally, the areas which have experienced fires in 2000 but not in the prior period of observation. These are represented by pixels which are of the "Burnt areas" category in 2000 and were strictly not "burnt" in 1990. In line with prior literature (e.g. Franco-Lopez et al., 2001; Ghebreiwot et al., 2012; Woo et al., 2021), control groups are determined from the regions surrounding, but not immediately bordering, the fire-damaged plots. As will be discussed in detail, we have selected this range to be within 3 to 10 km of burnt areas in order to ensure comparability.

Thus, given a pixel j, of the land use category y, in years T_0 to T_{0+t}, the difference in probability of land use distribution due to impact of fires is estimated by our model as:

$$ATE_y = E\left[Y_{j,T_{0+t}}|X_j, T_{j,T_0} = 1\right] - E\left[Y_{j,T_{0+t}}|X_j, T_{j,T_0} = 0\right] \quad (1)$$

Where $Y_{j,T_{0+t}}$ is the dummy for land use type of pixel j, at time T_{0+t}; X_j represents the matrix of covariates associated with j, used for matching; T_{j,T_0} indicates the whether the pixel j is treated at the time period T_0; and average treatment effect (ATE) for the category y is denoted by ATE_y. Naturally, for the purposes of our study, T_0 is the year 2000, while T_{0+t} is the year 2018. The outcome of this estimation will provide a causal estimate of the long-term impact of fire-damage on distribution of land use. However, in order for our approach to correctly estimate (1), there are some key assumption which have to hold. Otherwise, we will not be able to consider the outcomes of the matched control variables as representing comparable counterfactuals for that of the treated group. Considerations central to ensuring the validity of our method will be addressed in the following discussion, while Section 7 provides a much more comprehensive and in-depth investigation on other model considerations and assumptions associated with nearest-neighbor matching, both in general and specific, to our study.

4.2. Selection

As mentioned, in the literature regarding wildfires and forestry, it is common practice to use neighboring plots of a given "treated" area as a basis for a comparison group in order to understand the average effects of the treatment. Woo et al. (2021) and Ghebreiwot et al. (2012) in particular, utilize spatial matching on latitude and longitude for estimating the respective treatment effects. In order to estimate the ATE for forest fires of 2000, we similarly use matching based on pixel coordinates with Euclidian distance through Easting and Northing. However, we also utilize exact matching of pixels in 2000 and later, based on the information we have on the land use in 1990. The discussion on the ambiguity of the past land use of burnt regions, mentioned in section 2, factors into this issue. Specifically, if we cannot determine the values of a given treated region prior to the treatment, this opens up the possibility that pre-treatment distribution of treated pixels is significantly different than that of the control group. To put it more formally, our model has to satisfy the condition:

$$\left(Y_{j,T_{0+t}}(T_{j,T_0} = 0), Y_{j,T_{0+t}}(T_{j,T_0} = 1)\right) \perp T_{j,T_0}|X_j$$

Otherwise, since different categories of land are affected by fire in different ways, we would end up with a confounding factor that "selects" for treatment groups in ways that cannot be measured or accounted for. This can also explain why Woo et al. (2021), finds low balance for the distribution of covariates when matching is only done spatially. As the authors point out: "despite proximity, it is possible that neighboring burnt and unburnt regions are not always similar in environmental conditions". This is why exact matching on the pixel categories of 1990 is essential. Being able to set up a control group which has the same land use distribution in 1990 as the treatment group, allows for a much more representative selection of control observations. Initially, with only the nearest-neighbor matching, the assumption for discounting this selection bias had to be along the lines of: "pixels which are in close proximity to burnt regions have the same environmental characteristics as the unburnt regions". Now, it can be reduced to the assumption that between 1990 and 2000, there has not been such a drastic change in land use distributions of the pixels, which would subsequently render the two groups unrepresentative of each other. Considering the relative temporal persistence of forests, our category of interest, this is a much more reasonable assumption to hold.

Exact matching further allows our model to estimate impact of forest fires on any bio-physical indicator, so long as one can reasonably argue that their values are determined by land use and are causally affected by wildfires. This is because having formed counterfactual groups on land use information, we can compare the treated and untreated observations of the bio-physical variable which are of the same vegetation type. The average damage done to the matched treated observations due to fire-damage give me the ATE estimate. This discrepancy between groups of the calibrated biodiversity data collected at time T, for example, would then give me the causal damage of wildfires on biodiversity, on average, in year T.

To sum, the baseline specification (1) regards nearest-neighbor matching on spatial coordinates, and exact matching for the past value of a given pixel. However, there may still be other factors which could cause issues of endogeneity that we might have to account for. Looking at the literature on the determining factors of forest fires, next section outlines other covariates that might be of interest for our model.

4.3. Controlling for Geographic Factors

In order to further address the issue confounding influences, there are tertiary geographic factors, which are known to affect both the chance of fires, and distribution of forests as well as land at large, that we can account for. Firstly, proximity to roads and urban settlements has long been associated with an increase in chance both of deforestation, and of forest fires, whether accidental or voluntary (e.g. Chuvieco and Congalton, 1989; Vasilaskos et al., 2009; Ganteaume et al., 2013). As such, since the "artificial surfaces" category covers roads, railways, buildings, and otherwise constructed, non-natural areas, proximity of a given burnt plot to such a land could have a significant impact on its composition, independent of wildfires. Distance to agricultural areas can also be considered as a control by extension of this logic. Next, water bodies may provide better soil conditions for forests in close proximity, allowing them to flourish more. They tend also to act as natural firebreaks which hamper, if not stop, the spread of fires (e.g. Heinselman, 1997; Mansuy et al., 2014; Nielsen et al., 2016). Distance to such areas, then, could be relevant to account for. Finally, successive fires in close proximity are also known to alter the composition of greenery as well as the soil conditions, measurably differently than incidental and non-recurrent fires (Cochrane and Schulze, 1999; Eugenio and Lloret, 2004). Having some account of how treated pixels are located compared to other, past burnt regions might represent a significant predictor for our outcome.

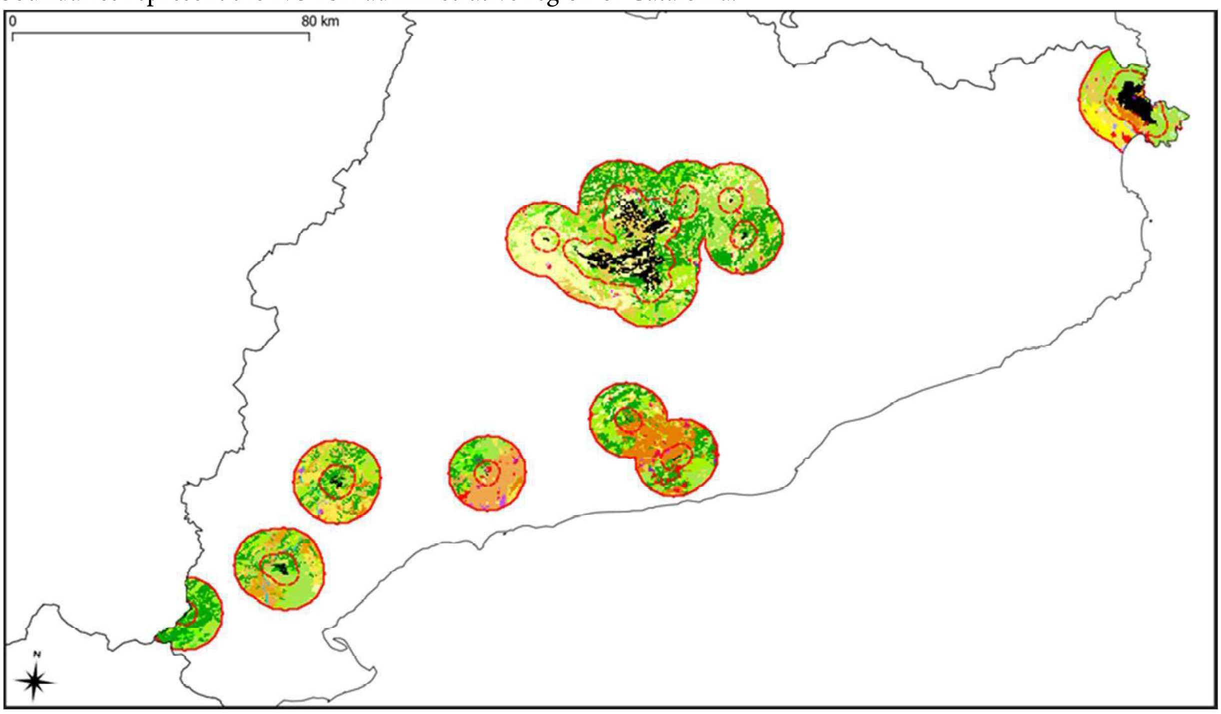
Using the data from 2000, our period of interest, to form these controls, is certainly problematic as they are endogenously determined. For example, changes in land use happening after 1990 and before 2000, which is also affected by fires would induce bias in the estimate as we cannot account for them. For example, if an agricultural or built area were to become "burnt", this would prevent me from being able to consider its distance to surrounding burnt areas. It would be as if there was no artificial surface occupying this pixel whatsoever, as far as the covariate is concerned, which naturally would induce bias in the estimation. Further, since the data is obtained through remote sensing, the year 2000 is representative. This is to say that it is compiled through processed composites from 1999 to 2001, and hence, we could be erroneously considering distance of a fire which happened in 1999, to a construction site which started in 2000 (construction sites are a distinct class CLC inventory indicating modified spaces under "anthropogenic transition" as per Kosztra et al. 2017). To alleviate these issues, we have decided to pick each of our covariates (distance to artificial surfaces, agricultural areas, water bodies and burnt regions) from 1990.

Involvement of these covariates specifies the second model we will analyze in depth. It is simply composed of an addition of four factors regarding proximity to artificial surfaces, agricultural areas, water bodies, and other burnt regions, from 1990, to the already existing covariates of the baseline model.

4.4. Stable Unit Treatment Value

The stable unit treatment value assumption (SUTVA) is particularly important for our study as unlike how CLC data presents burnt regions to be individual pixels, concretely separated from the surrounding greenery, fires do not operate so discretely. SUTVA would require that any impact on a treated observation is not "interfered" by the treatment other observations have received. This presents a problem for this study when we look at regions neighboring the burnt plots. Fire is documented to not only affect the temperature and air moisture of a given area, but even the soil contents (Dumontet et al., 1996; Verma and Jayakumar, 2012). It is difficult to argue that the soil and greenery in close proximity to the edge of a burnt plot would be completely unaffected by such a drastic and sudden change in environmental characteristics. Therefore, we could count these pixels as treated, as they have certainly been affected by the treatment to some capacity. However, then, SUTVA would be violated, as these "treated" pixels are affected by the treatment of other pixels within their group. That being said, they clearly cannot be counted as controls either, as their characteristics are no longer representative of the "population". As such, the safest option is to exclude pixels within a certain perimeter around the burnt regions from the estimation. For the baseline model this is set at 3 km, for providing a reasonable distance away from the burnt areas, while still allowing for a large enough number of observations to be in the control groups for exact matching, as well as providing acceptable levels of computational

Fig. 4 — The scope of the data selection used for the baseline specification, for NUTS II region of Catalonia. Outer red line indicates the 10 km. outer perimeter around the burnt regions, which is the spatial extent of the pixels considered as control; inner dashed red line indicates the pixels which are suspected to have been indirectly treated by the burnt regions, and hence, excluded. Color grading is done based on land use categorization of CLC inventory standards, details of which can be found in the Appendix. Black pixels represent "burnt areas". The gray boundaries represent the NUTSII administrative region of Catalonia.



intensity for the estimation. That being said, perimeters for 1 and 5 km have also been tested in section 8, ensuring robustness. Central results of the study were not affected.

In light of the discussion so far, Fig. 4 presents the scope of pixels in both the outer perimeter around the burnt regions which included to represent the controls, as well as the inner perimeter within which the control pixels were excluded as they are suspected be indirectly affected by the fires. The outer perimeter for the baseline specification of the data is set at 10 km This "radius" can also be seen as a "caliper" by which we can ensure the controls are more comparable in terms of their qualities which we cannot quantitatively observe from our data, considering the broadness of the categorical definitions used by CLC. That being said, similar to the extent of excluded pixels within the inner perimeter, we tested several radii of proximity ranging from 10 to 20 km for the outer edge. The central results were once again unaffected. These different specifications as well as their results is discussed in greater detail both under the sections of model consistency, regarding the overlap assumption, and robustness checks.

Finally, it is also important to note that for computational ease, control and treatment groups are coupled based on NUTS II regions through exact matching. As such, matching is only done based on counterfactuals in relatively close proximity. This does not cause any significant issues covariate balance for the baseline model while providing estimations much faster, though technically the extended version might have suffered due to overall lower presence of some of the geographical covariates.

5. Results

5.1. Impact on Land Use

As Rubin (2008) recommends, before commenting on the results of a model, one should make sure that the model specified sufficiently balances the covariates. Hence, before the results of either specification, we will comment on the properties of the matching process. For a fully balanced set of covariates, ideal standardized differences would be 0, while the variance ratio would be 1. With (I) shown in Table 3, we can see that matching has been quite successful by these metrics. Expectedly, with the overabundance of controls, appropriate matches were found for every treated observation. These levels indicate that covariate distribution is balanced, as they do not vary over treatment levels. The raw data for (I) indicates that while for Easting was quite balanced (and similarly, though less so, with Northing), with less than a difference of 0.1 with respect to the variance ratio, the matched data is much closer to ideal values. Based on these findings we determined that the baseline specification indeed provides good balance for covariates.

The extended specification, (II), does not show such a level of balance in all dimensions. This is partly to be expected, as the number of covariates increase, it becomes exponentially difficult to maintain the same level of overall quality in terms of matches. Further, some of the geographical covariates are very sparsely distributed, in the first place. As Table 3 specifies, artificial surfaces account for less than 4% of the total land mass. This causes some of the control groups to be at undesirably different distances to such surfaces, in comparison to the treated observations. Nevertheless, outside of two covariates (namely the distance to artificial surfaces and agricultural areas) matched data provides values much closer to the ideal. In order to address the issue balance for these two covariates, more accurate datasets could be used as support. European data on road-networks could greatly increase precision if utilized for support, as the roads at the resolution of CLC that we are using can be difficult to accurately represent. Nevertheless, even with this relative imbalance, as we will touch on next, the results are globally robust, considering the fact that ATEs associated with the covariates (e.g. impact on agricultural areas) are not statistically different in significance from specification (I) to (II).

Table 2 displays the ATEs for the baseline model estimations, denoted as (I), and its extended specification, with the covariates denoting distance to geographically relevant factors, (II). In either

Table 2 — Impact of fires on land use after 18 years.

Impact on Forests		**(I)**	**(II)**
	ATE	-0.27*** (0.0097)	-0.29*** (0.011)
	Percentage impact	-61%	-65%
Impact on Artificial Surfaces		**(I)**	**(II)**
	ATE	-0.0024 (0.0022)	-0.00045 (0.0037)
	Percentage impact	-29%	-5.3%
Impact on Agricultural Areas		**(I)**	**(II)**
	ATE	-0.028*** (0.0056)	-0.0013 (0.11)
	Percentage impact	-46%	-2.1%
Impact on Natural Grasslands, Moors, and Heathland		**(I)**	**(II)**
	ATE	0.061*** (0.0091)	0.10*** (0.0075)
	Percentage impact	+37%	+65%
Impact on Sclerophyllous Vegetation, Transitional Woodland-shrubs		**(I)**	**(II)**
	ATE	0.23*** (0.011)	0.16*** (0.015)
	Percentage impact	+73%	+53%
Impact on Burnt Areas		**(I)**	**(II)**
	ATE	0.0011 (0.0015)	0.0023 (0.0021)
	Percentage impact	+15%	+30%
Impact on Other Categories of Land		**(I)**	**(II)**
	ATE	0.016*** (0.0056)	0.019*** (0.0033)
	Percentage impact	+114%	+139%

Notes: Each impact category represents a separate estimation. "Percentage impact" refers to the ratio of average treatment effect and the mean value of the control group, indicating the percentage difference, between control and treatment groups, of which is due to the fires. Information on the observations and the group means are shared in Table 3. Abadie-Imbens robust standard errors are provided in parentheses. The indicators for statistical significance are as follows:

*** 1% significance
** 5% significance
* 10% significance

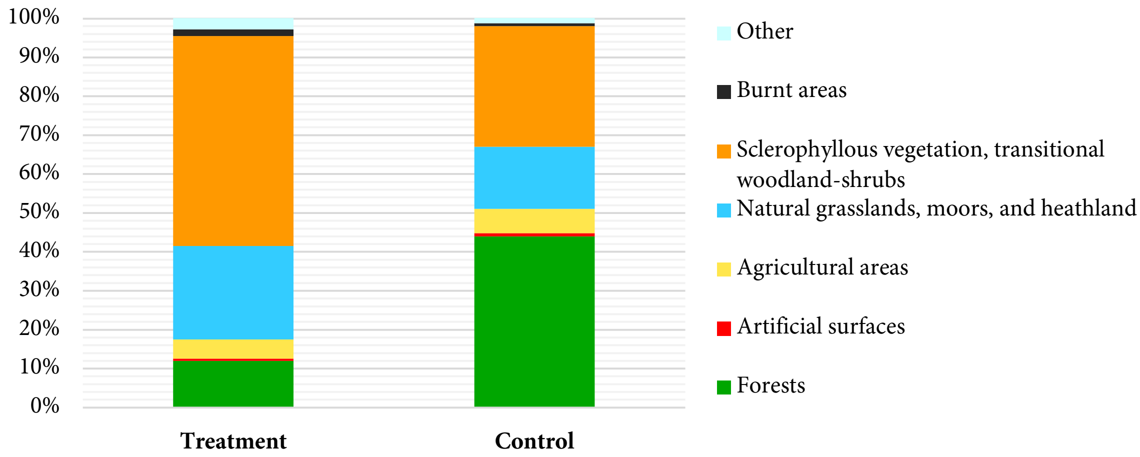
case, we can see that the central results regarding the impact on forests is both highly significant at 1% and concerning in its implications regarding the magnitude. For (I), we find that compared to the counterfactual regions, burnt plots show 61% less presence of forests, after 18 years. Forests go from covering 44% of the total surface of burnt regions, to only 12%, with majority being found to have been caused by fire damage. Going by this specification alone, the non-forest greenery (indicated by natural grasslands, moors, heathland, sclerophyllous vegetation, and transitional woodland-shrubs) significantly increase in occupation. Sclerophyllous vegetation, and transitional woodland-shrubs specifically, show an increase of 73%. This is consistent with the categorical definitions provided by the CLC standards, as the transitional woodland-shrubs, specifically, can represent "woodland degradation" and includes areas occupied by "damaged or dead trees and shrubs" (Kosztra et al. 2017). Considering the lower capabilities of such vegetation for carbon storage, we can already see strong

Table 3 — The covariate balance and estimation details on specifications (I) and (II).

	(I)		**(II)**	
Observations	Raw	Matched	Raw	Matched
Total Observations	390,927	781,854	390,927	781,854
Treated Observations	6,874	390,927	6,874	390,927
Control Observations	384,053	390,927	384,053	390,927
Standardized Differences	Raw	Matched	Raw	Matched
Easting	0.13	0.00033	0.13	-0.0031
Northing	0.055	-0.017	0.055	-0.027
Distance to artificial surfaces	—	—	-0.037	-0.16
Distance to agricultural areas	—	—	-0.022	-0.12
Distance to past burnt regions	—	—	0.17	0.13
Distance to water bodies	—	—	0.12	-0.047
Variance ratio	Raw	Matched	Raw	Matched
Easting	1.065	0.99	1.065	0.99
Northing	0.71	1.082	0.71	1.12
Distance to artificial surfaces	—	—	0.74	0.73
Distance to agricultural areas	—	—	0.94	0.68
Distance to past burnt regions	—	—	1.28	1.01
Distance to water bodies	—	—	1.24	0.92
Outcome Means	Treatment	Control	Treatment	Control
Forests	0.12	0.44	0.12	0.44
Artificial Surfaces	0.0058	0.0084	0.0058	0.0084
Agricultural Areas	0.049	0.062	0.049	0.062
Natural Grasslands, Moors, and Heathland	0.24	0.16	0.24	0.16
Sclerophyllous vegetation, transitional woodland-shrubs	0.54	0.31	0.54	0.31
Burnt areas	0.017	0.0075	0.017	0.0075
Other	0.029	0.014	0.029	0.014
Number of matches	2		2	

Notes: Each category represents the share percentage of land group to which their pixels belong. Thus, the outcome means for the categories sum up to 1, barring approximations used for reporting, for each group.

Fig. 5 — Land use distribution in burnt and non-burnt areas in 2018.



Notes: Each category is selected based on the categories of Table 1. Average treatment effects indicate the difference in mean share of a given category between the two groups, on a scale of 0 to 1, of which are due to fires. Error bars for average treatment effects indicate the Abadie-Imbens standard errors.

implications regarding the effects on carbon sequestration. Burnt regions areas as well as artificial surfaces were found not to have been significantly affected, while minor impact (in absolute values) can be observed on agricultural areas and regions primarily occupied other forms of land use (-0.028 and 0.016, to be specific). The statistical insignificance of burnt areas indicate potential for fire recurrence, there will be more consideration of this possibility in the discussion section. Ultimately, the central results of (I) are undeniably strong in magnitude and highly significant. It shows that wildfires indeed degrade forests to the extent that even after 18 years, more than half of them fail to comparably regenerate.

The resulting distribution of land can be seen in Fig. 5. There is an overwhelming decrease of forests, while a stark increase in various grasslands, shrubs, and otherwise vegetation known to hold much smaller biomass and ability to sequester carbon in the long-term. Without the specification (II), however, one could consider this transition in vegetation as due to proximity to some of the aforementioned geographical factors. Perhaps these areas were deforested not due to wildfires, but instead, logging activities. It could be that there are qualities which render forests that are likely to burn, also attractive for logging. Hence, we might have seen the same trend regardless. To examine this, the results extended model (II) would be useful to understand.

For (II), central findings are not just reaffirmed but impact on forests and some vegetation has *increased* in magnitude, while staying just as significant. With 65% lower presence, we are almost looking at only a third of the forests able to recover, on average. For less productive vegetation such as grasslands, moors and heathlands, the fire impact increased their presence by 65%. These results provide further evidence that long-term impact on forests, as past literature analyzed at smaller scales, is significantly negative, despite fact that the scale of the study covers various climates, genera of vegetation, and geographies. These aspects are further investigated in the section on robustness checks, with relevant variations on both methodological parameters and data specifications.

5.2 Short and Medium-term Impacts

Aside from estimating the impact only for 2018, it will be useful to have a broader perspective on the evolution the impacts of wildfires on forests. For this purpose, we have also estimated the impact of fires of 2000, for prior years. This discussion will provide a more temporal dimension to the impact we are interested in observing and show how the vegetation covering these regions change over time.

Despite the persistence of their effects, fires naturally tend to have the strongest impact on forests in the short-term, weakening in its effects in time. This should imply that the impact should be the strongest on forests in 2006, lowering it only to be replaced by a transitional and much less dense

Table 4 — Impact of fires on land use for the years 2000, 2006, and 2012.

Impact on Forests	**(III)**	**(IV)**
ATE	-0.32***	-0.30***
	(0.0086)	(0.0094)
Percentage impact	-68%	-65%
Impact on Artificial Surfaces	**(III)**	**(IV)**
ATE	-0.0039*	-0.0030
	(0.0018)	(0.0021)
Percentage impact	-60%	-37%
Impact on Agricultural Areas	**(III)**	**(IV)**
ATE	-0.025***	-0.028***
	(0.0052)	(0.0056)
Percentage impact	-47%	-46%
Impact on Natural Grasslands, Moors, and Heathland	**(III)**	**(IV)**
ATE	0.047***	0.059***
	(0.0093)	(0.0090)
Percentage impact	+28%	+36%
Impact on Sclerophyllous Vegetation, Transitional Woodland-shrubs	**(III)**	**(IV)**
ATE	0.28***	0.25***
	(0.0090)	(0.010)
Percentage impact	+90%	+86%
Impact on Burnt Areas	**(III)**	**(IV)**
ATE	0.0068**	0.0053***
	(0.0032)	(0.0011)
Percentage impact	+91%	+318%
Impact on Other Categories of Land	**(III)**	**(IV)**
ATE	0.016***	0.013**
	(0.0055)	(0.054)
Percentage impact	+137%	+93%

Notes: Each impact category represents a separate estimation. "Percentage impact" refers to the ratio of average treatment effect and the mean value of the control group, indicating the percentage difference, between control and treatment groups, of which is due to the fires. Information on the observations and the group means are shared in Table 5. Abadie-Imbens robust standard errors are provided in parentheses. The indicators for statistical significance are as follows:

*** 1% significance
** 5% significance
* 10% significance

form of vegetation. Depending on the severity and frequency of fires, both forest and recovery characteristics might change (Stevens-Rumann and Morgan, 2016). So we could observe a change in the categories of vegetation which prevail such drastic impacts. With specifications, (III) and (IV), as shown in Tables 4 and 5, this is exactly what we observe. There is not much to mention regarding covariate balance, as they area expectedly the same, but in terms of magnitudes of impact, a more complete story can be seen. We can first observe that the impact on forests decline in time, from 68% lower presence on average, to 61% in (I).

This decline is also accompanied by a strong presence of transitional woodland-shrubs and sclerophyllous vegetation, as expected. There also seems to be an increased presence of grasslands, moors and heathlands. Perhaps, in line with Stevens-Rumann & Morgan (2016), as the damaged areas recover, transitional vegetation begins to decline and be replaced by relatively more vigorous

Table 5 — The covariate balance and estimation details on specifications (III), and (IV).

	(III)		**(IV)**	
Observations	Raw	Matched	Raw	Matched
Total Observations	390,927	781,854	390,927	781,854
Control Observations	6,874	390,927	6,874	390,927
Treated Observations	384,053	390,927	384,053	390,927
Standardized Differences	Raw	Matched	Raw	Matched
Easting	0.13	0.00033	0.13	0.00033
Northing	0.055	-0.017	0.055	-0.017
Variance ratio	Raw	Matched	Raw	Matched
Easting	1.066	0.99	1.066	0.99
Northing	0.71	1.082	0.71	1.082
Outcome Means	Treatment	Control	Treatment	Control
Forests	0.10	0.47	0.12	0.46
Artificial Surfaces	0.0017	0.0066	0.0081	0.0042
Agricultural Areas	0.033	0.053	0.043	0.061
Natural Grasslands, Moors, and Heathland	0.22	0.16	0.24	0.16
Sclerophyllous vegetation, transitional woodland-shrubs	0.59	0.29	0.55	0.29
Burnt areas	0.015	0.0074	0.012	0.0017
Other	0.034	0.012	0.028	0.012
Number of matches	2		2	

Notes: Since each category represents the share percentage of land group their pixels belong to, the means for the categories add up to 1 for each group, barring approximations.

grasslands. Though this is simply a speculative possibility, as these estimations cannot decipher such a relation causally. Ultimately, if (I) and (II) explain *what* happened in the long-term, these findings provide a quantitative account of *how* it happened, which paints a richer picture. That being said, the ecological progression of the burnt areas observed follow lines which are both sensible and supported by the literature.

5.3. Impact on Carbon Sequestration

5.3.1. Biomass Carbon Density

As an indicator of sequestered carbon, impact on biomass carbon density is crucial for understanding the ecological impact of wildfires. Since our matching strategy gives temporal dynamics of land use, covering both pre- and post-treatment times, we can exploit this setting to estimate impact on other indicators. Instituting this strategy on biomass carbon, Table 6 provides estimates for the impact of fires on aboveground (AGBC) and belowground biomass carbon density (BGBC). As expected, the largest impact is on forests, on both accounts, with 32% and 18% decreases due to wildfires respectively in 2010, on average. Combining the above and belowground total counterfactual carbon stock (through outcome means of Table 7), we can see that the total decrease is roughly 28%. This means after 10 years, more than a quarter of the carbon that would have been stored had wildfires not happened, is still lost. This sums to a total of 12.86 MgC per ha. This represents the total amount of carbon per hectare that would have to be compensated in order for the effect of wildfires to be nullified.

A figure like 28% already indicates long-lasting fire-damage however, it is important to remember that even in 2012, presence of forests decreased by 65% due to forests on average, while being replaced largely by vegetation such as grasslands and shrubs. There is a slight conflict here. In Europe's temperate climates, grasslands typically have around 10% as much carbon biomass density as forests (Watson et al., 2000). Therefore, carbon density only decreasing by 28%, while almost two thirds of the forests have disappeared, seems very unlikely, and indicates an underestimation. As discussed before, the methodological and technological issues contribute significantly here. Therefore, the

Table 6 — Impact of fires on biomass carbon density of forests, and all land, in 2010.

Impact on Forests	**(AGBC)**	**(BGBC)**
ATE	-10.58*** (0.82)	-2.28*** (0.47)
Percentage impact	-32%	-18%
Impact on All Land	**(AGBC)**	**(BGBC)**
ATE	-5.86*** (0.54)	-1.66*** (0.27)
Percentage impact	-23%	-15%

Notes: Each impact category represents a separate estimation. "Percentage impact" refers to the ratio of average treatment effect and the mean value of the control group, indicating the percentage difference, between control and treatment groups, of which is due to the fires. The units for each of the estimates are MgC per ha. The indicators for statistical significance are as follows:

*** 1% significance
** 5% significance
* 10% significance

Table 7 — The covariate balance and estimation details on specifications (AGBC) and (BGBC).

	Forests				All Land			
	(AGBC)		(BGBC)		(AGBC)		(BGBC)	
Observations	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched
Total	91,985	183,970	92,191	184,382	209,246	418,492	209,754	419,508
Treated	2,895	91,985	2,903	92,191	6,860	209,246	6,874	209,754
Control	89,090	91,985	89,288	92,191	202,386	209,246	202,880	209,754
Standardized Differences	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched
Easting	0.27	-0.00090	0.27	-0.00090	0.10	-0.00091	0.10	-0.00091
Northing	-0.35	0.016	-0.35	0.017	-0.01	0.0040	-0.01	0.0040
Variance ratio	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched
Easting	1.14	0.99	1.14	0.99	1.02	0.99	1.02	0.99
Northing	0.68	0.98	0.68	0.98	0.70	1.04	0.70	1.04
	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control
Outcome Means	19.85	33.42	9.53	12.46	17.62	25.35	9.97	11.47

Notes: Each category represents the share percentage of land group to which their pixels belong. Thus, the outcome means for the categories sum up to 1, barring approximations used for reporting, for each group.

results found here should represent a lower bound for the true impact. Studies such as Ekinci and Kavdır (2005), has found the impact of fires on overall soil organic carbon to be close to 60% lower for burnt forests in Mediterranean climate, after 8 years. Hence, it is highly unlikely that total impact belowground would be only a drop of 18%. While comparable long-term studies on live biomass carbon density are rare to find, it is similarly unlikely that a drop of more than 60% of forests would only lead to roughly 30% causal differential between the groups.

The effects on total land are slightly smaller in magnitude, but nevertheless equally significant. Since forests are a main driver of biomass carbon storage in Europe, impact on all land is likely also driven by impact on forests (Watson et al., 2000). The outcome means similarly show forests to have greater density in either dimension. Though since we did not estimate each category of land separately, these are technically speculation, in this context. That being said, the results regarding impact on all land are reflections of impact on forests, albeit to a lesser degree, with 7.52 MgC per ha lost in terms of carbon density, cumulatively.

5.3.2. Net Primary Productivity

Initially, one would expect the impact on NPP to be significantly negative, similar to the biomass carbon density. However, the trends on Fig. 3 hinted that this it could also change directions if the reason why gap closes later is partly due to fires. Fig. 6 illustrates this progression. While we see a modest decrease of roughly 4%, after about 12 years, there starts to be a relative recovery period. This effect is particularly pronounced with all land, likely due to its inclusion of non-forest vegetation, which tends to reach its productivity climax much earlier than forests. We can also see perhaps a hint of why past consensus had thought that forest fires were only a concern in the short term. As mentioned previously, impact on carbon sequestration is also done through vegetation indices and measures of primary production. However, these are measures of “flow” in sequestration. While they are indicative of changes in the “stock” variable that is carbon density, the dynamics could lead to entirely different conclusions. By the measures of NPP, effects of forest fires seem to lose significance

Table 8 — Impact of fires on average NPP of forests and all land, from 2000 to 2020.

	Impact on Forests		Impact on All Land	
ATE	0.051		0.26***	
	(0.103)		(0.077)	
Percentage impact	0.3%		1.8%	
Observations	Raw	Matched	Raw	Matched
Total	91,494	182,988	208,301	416,602
Treated	2,886	91,494	6,816	208,301
Control	88,608	91,494	201,485	208,301
Standardized differences	Raw	Matched	Raw	Matched
Easting	0.27	-0.00086	0.099	-0.00088
Northing	-0.35	0.016	-0.017	0.0040
Variance ratio	Raw	Matched	Raw	Matched
Easting	1.14	0.99	1.021	1.00
Northing	0.68	0.98	0.71	1.042
	Treatment	Control	Treatment	Control
Outcome means	13.63	15.44	14.14	14.84

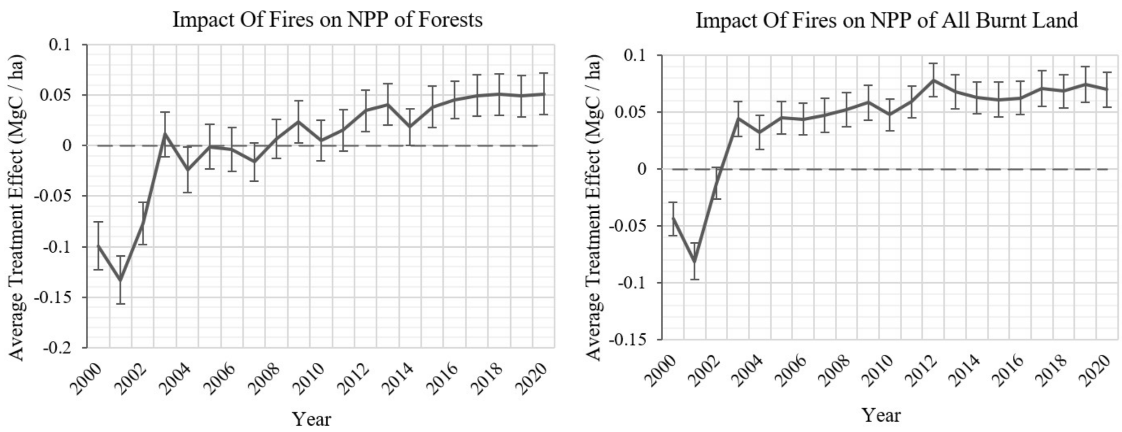
Notes: Each impact category represents a separate estimation. "Percentage impact" refers to the ratio of average treatment effect and the mean value of the control group, indicating the percentage difference, between control and treatment groups, of which is due to the fires. ATE units are gC per m^2. The indicators for statistical significance are as follows:

*** 1% significance
** 5% significance
* 10% significance

within 3 years, having negligible impact for the next 9. The true context becomes clearer after a longer-term analysis, or release of direct measures of carbon density data, such as Spawn et al. (2020). With imperfect remote sensing measures, verification via field surveys were used to fill this gap specifically.

Table 8 generalizes the NPP progression by estimating the impact on total average productivity. The impact on forests overall is insignificant, possibly since more than half the years show either insignificant, or negative impact (Specific estimation results could be found in the

Fig. 6 — Impact of fires on net primary productivity.



Notes: Average treatment effects indicate the difference in mean share between the two groups, on a scale of 0 to 1, of which are due to fires. Error bars for average treatment effects indicate the associated Abadie-Imbens standard errors.

Appendix). Estimation on all land, on the other hand, shows direct positive effect. Though it is also important to notice how small the impact is in terms of percentage: 1.8%. This means over the course of 20 years, roughly 0.26 gC per m^2, or in more conventional terms, 0.96 MgC per ha have been captured after fires.

To sum, it is clear that forest fires have had negligible on forest productivity, on average, with an upward directed, slope, indicating positive impact in the long run; the total land has benefitted modestly from the first regarding productivity. The overall positive effect seems to be continuing even after 20 years for both estimations.

6. Discussion

6.1. Connecting The Impacts

In line with findings of prior research, the fires of Europe indeed significantly change the ecological demography of the plant-life in a persisting manner. However, unlike the 50% over 10 years which Savage and Mast (2005) had found for US, the impact on European forests is quite larger with over 60%, after almost twice the period of time. This could be due to the Mediterranean basin being prone to high severity fires (Caon et al., 2014). Considering these areas are largely replaced by vegetation associated with significantly lower biomass such as grasslands and shrubs, it is then not surprising that total biomass carbon density was affected by almost 13 MgC per ha. The changes in the primary productivity at first might seem contradictory with the other findings. As the data indicates that the negative effect on primary productivity vanishes in 3 years, and if anything, becomes positive going forward. However, studies such as Kashian et al. (2006), Goulden et al. (2011) and He et al. (2012) repeatedly find that younger trees tend to be associated with greater NPP: despite their comparatively low ability to store carbon due to their much lower biomass, their rapid growth warrants much more efficient photosynthetic activities. Therefore implicitly, this confirms the drop in aboveground biomass carbon among forests. Even though as far as land use is concerned, we are still looking at forests, ones in the treatment group are very likely to be much younger trees, as they store much less carbon, and quickly recover to the extent that total impact of wildfires induce a positive impact on these forests.

This points us in the direction of a relative recovery. In the sense that parts of forests have recovered, but there is still a carbon-stock differential which persists. The amount of carbon stored in forests due to rapid increase of NPP, in comparison is negligible, in twice the period of time. While with the aforementioned availability of newer maps could indicate further recovery in the longer term, younger forests do not show realistic capacity to close the gap as carbon sinks anytime soon.

Some of the conceptual models for fire impact based on case studies in the past had estimated that full recovery of even light fires can take up to a century (Cochrane and Schulze, 1999). While mostly speculative at the time, our findings support the potential that indeed, this might be the case, and the descriptor “long-term” used in this paper might be too short for observing convergence regarding both the level effect induced by the initial fire damage on forests, and the negative growth effect regarding the sequestration capacity of the degraded vegetation.

6.2. Economics Costs

6.2.1. Social Cost of Carbon

Though the information presented so far could be misconstrued as only being ecological, there are direct, long-term economic impacts associated with our findings. One dimension of this impact is the cost of carbon storage itself. The most appropriate literature associated with quantifying the cost of

GHG emissions utilize the concept of Social Cost of Carbon (SCC). This perspective of seeing emissions as a fiscal issue allows to consider wildfires as an exogenous financial shock in the form of a loan taken, with an associated interest rate. As this loan does not have a due date, the longer it is not paid, the higher the cost.

The estimations on SCC range from \$20 per ton of CO_2 in 2021-2030 period (Fankhauser, 1994), which is widely regarded to be a conservative estimate, up to \$1,550 per ton of CO_2 in 2007 USD (Ackerman and Stanton, 2012). As such, it is possible to estimate a range of direct monetary cost on the impact on forests. Though it is important to note that these calculations are generally criticized for oversimplifying the true costs (e.g. Neumayer, 2000). McKinsey & Company (2009), also provides estimates of marginal abatement cost, based on the scenario where atmospheric CO_2-equivalent concentration peaks at 480 ppm in 2060's, before declining. This cost is placed somewhere between \$90 and \$150 in 2007 USD, by 2030. Table 9 provides the estimates for each of the aforementioned estimations, as well as estimates of one more commonly used model by Interagency Working Group (2010). Despite the already high estimates for a single year of wildfires, ranging from \$111 million to \$5.95 billion, it is important to remind that these figures are not constant over time. Ackerman and Stanton (2012)'s first estimate for the worst-case scenario of high-severity, high damages, and low discount rate is only for 2010. Meaning, the costs which needs to be incurred by this given year in order to compensate the loss of carbon captured. *Ceteris peribus*, in 2050, this estimate increases by almost 60%, as the damages associated with the released, yet uncaptured carbon rise. On the other hand, it should be note that these estimates are highly model dependent, different models consider different aspects of carbon loss, which are valued differently, albeit with scientifically compliant methods. Though Mediterranean climates are likely to be on the worse end of the parameter calibration if region-specific estimates were to be provided. These figures are ultimately to give a general idea of the scale of damage being done, by expressing it in monetary terms.

6.2.2. Cost of Biodiversity Offsetting

Outside of the direct cost through SCC, there are non-monetary, yet nevertheless economic costs associated with lower rates of carbon sequestration. Costs associated with supply constraints are of relevance here. Sonter et al. (2020) mentions the lack of land for offsetting: due to lack of available land for achieving NNL of biodiversity, none of the cases they have studied at a multinational scale, had succeeded. Even post compensation, selective institutions of NNL policies fail to slow the biodiversity declines. Naturally, the less productive a land gets in terms of carbon sequestration (e.g. due to fire damage), the more land will be needed to reach the associated minimum requirements. Lack of available land can also lead to increased competition: Calvet et al. (2019) finds that offset policies can induce social conflicts and competition among farmers, when large parts of land is occupied by agricultural purposes, such as France, with 51% of its total area denoted to be under cultivation. Once again, this competition effect will have direct economic costs associated. Though this impact can be evaluated much more accurately through Nature Map's biodiversity indicators, once released (IIASA et al., 2020), our findings on the share of forests lost due to fires, the loss of sequestration, as well as literature on the devastating effects of wildfires on biodiversity (e.g. Letnic et al., 2005; Kodandapani et al., 2008; Pastro et al., 2011) can still give us some idea on the matter. It is thus safe to say that these findings alone warrant a conversation on the economic dynamics and long-term viability of offset policies in, particularly in the Mediterranean basin, as climate change effects intensify. Without proper

Table 9 — Social Cost of Carbon from wildfires of 2000, based on various estimates.

	Source of SSC Estimates				
SSC Cost	Fankhauser (1994)	M&C (2009): Low	M&C (2009): High	IWG (2010): DICE avg.	A&S (2012): Worst scenario
By 2010	—	—	—	$144,810,003 ($28)	$4,943,326,854 ($892)
By 2030	$110,836,925 ($20)[a]	$498,766,162 ($90)	$831,276,937 ($150)	—	—
By 2050	—	—	—	$330,994,293 ($64)	$5,947,553,705 ($1,550)

Notes: Associated marginal costs are provided in parentheses and expressed in 2007 USD. The estimates are fond by converting per hectare estimates of carbon loss to total MgC loss using pixel size and amount, then, the loss is converted from carbon to CO_2 (as done in Breisinger, 2012 or EIB, 2020). Each estimates is then multiplied by the SSC estimate of the given literature.

a: Not expressed in 2007 USD, due to the author not providing a basis year for the dollar value of their estimate.

fire management and prevention strategies, biodiversity offsetting will be less and less feasible in countries like Portugal or Italy.

6.2.3. Cost of Irreversible Ecological Damage

Tucker et al. (2020), in describing the most important, common, yet uncompensated problems regarding Biodiversity and Ecosystem Services (BES), mentions the "limitations on ecological feasibility" of restoring ecosystems. Denoting that only the simple, and low-complexity ecosystems can be fully restored. Anthropogenic ecosystems such as urban vegetation are also provided as example, but as for the rest, restoration is argued to only be partially feasible. This is because "their biodiversity and services are the result of millions of years of complex biophysical interactions that are not fully understood, measurable or replicable." The wildfires which our study regards, categorically exclude "simpler" ecosystems such as urban greenery, or damaged farmland. As such, most of the fire impact we have estimated fall into the latter category for partial restoration. This presents an important reason why there are other, difficult to measure losses associated with fire damage, and looking at the forest types and sequestration capacity of forests likely will not be enough to account for them.

Each one of these costs, environmental, monetary, or otherwise, point to the necessity of better fire management strategies. The severity as well as the regional scope of our findings, combined with the costs and challenges associates with implementation of NNL policies, clearly stress the importance of thorough preventative measures regarding wildfires and P&R strategies for forests.

6.3. Policy Implications

With the importance that natural preservation and restoration (P&R) strategies represent for European countries going forward, and NNL being seen as a necessary minimum achievement, (EC, 2020), one of the primary implications of our findings regard long-term economic gains associated with preservation of nature. More than one quarter of the forests failing to measurably recover after 18 years of a fire suggests that in order for P&R strategies to succeed as intended, these long-term affects need serious consideration. As pointed out by other natural research done on Mediterranean countries (e.g. Mateus & Fernandes, 2014; Molina-Terrén et al., 2019), with the increasing effects of climate change on severity and frequency of fires, fire management strategies have to play a stronger role in adaptation. This adaptation is due partly due to the fact that Mediterranean climates will be affected the most severely, but also partly due to contemporary policy framework, which is considered either inadvertently contributive to, or ineffective in prevention of, forest fires. To understand why the institutional and structural factors is particularly important, a deeper perspective should be in order.

6.3.1. Forest Management

In European counties, in the Mediterranean region in particular, there forest management policies have had multiple institutional issues, ranging from conflicts of interest to negligence. Lovreglio et al. (2010) identifies policies regarding seasonal forest workers as an exacerbating factor for voluntary forest fires in Southern Italy. These policies were argued to incentivize the usage of voluntary fires as an instrument to "force or maintain" seasonal employment. For Portugal, Mateus & Fernandes (2014) point to political and institutional factors behind persistent wildfires, which refers to how inconsistent and reactionary the government responses have been prior to the 2003 and 2005 wildfire crises. Even after these crises, authors find that Portuguese Forest Service as well as the National Fire Fighting Service, has continued to go through copious structural changes. These changes are identified as clear signals showing a "lack of understanding" of its role by policy makers. For a broader scale analysis, Molina-Terrén et al. (2019) look at Spain, Portugal, Greece, and Italy in the context forest fires and associated fatalities. Primary aspect authors found to have been lacking is, expectedly, effective prevention policies. Authors recommend an in-depth revision of the prevention policies, particularly regarding prevention planning in urban areas. These institutional factors, having persisted to this day, present a growing issue of insufficient adaptation and unpreparedness for wildfires. As a consequence, the worse the problem gets, it will be all the harder for the effects on forests to be mitigated. The short-term damage caused due to impact on biodiversity, and the long-term damage due to impact on carbon sequestration will intensify.

However, remedy is likely not to come from a centralized body. Continent-wide analyses such as Lazdinis et al. (2019) point out that European forest management is too polycentric for EU-level forest management policies to be feasible or practical. Therefore, a top-down enforcement for overcoming regional, institutional issues are difficult to implement, even become harder to ensure, and likely not to be optimal due to "EU-level steering" of priorities. Instead, they offer that sustainable forest management can be done by exploiting the diversity of regional of both governance and ecology by building a more localized approach. Therefore, in terms of the issues regarding local institutional problems and economic conflicts of interests, our findings could go to exemplify how purposeful forest fires might have much more costly drawbacks than once thought. With hundreds of millions, if not billions of dollars' worth of long-term costs incurred, seasonal employment becomes a negligible plus in the short-term. Further, the competition effects intensified by wildfires will prevent nations from being able meet their nationally determined contribution targets, as per their commitments under Paris Agreement. Each of these points build a case incentivizing local actors to prioritize the primary purpose of forest management policies: actually managing forests.

6.3.2. Accounting for Climate Change Action

Both Paris Agreement and the Kyoto Protocol has been widely criticized for their inadequate forest land use, land use change, and forestry (LULUCF) related emissions. Initially, the Kyoto Protocol did not provide and rules on how LULUCF emissions should be integrated into the overall accounting system proposed (Krug, 2018). Even within this system, natural disturbances could be excluded from accounting anyways (Johns, 2020). Even after deliberations which determined that certain disturbances should be considered, there were accounting loopholes which allowed for exclusions of emissions accounting for fires in unmanaged land, or the drafted *force majeure* defense (Fry, 2007; LRI, 2010). *Force majeure* defense in particular, which referred to "unforeseen or irresistible events" was asked by non-governmental organizations to be deleted because it legally provides means by which countries can avoid their reduction obligations. Natural disturbances could be discounted wholesale under this defense.

Paris Agreement has also been noted not to have specific rules on how LULUCF emissions should be accounted for or responded to. These were instead guidelines which encouraged countries to set nationally determined contributions, with no definitional direction on what LULUCF categories, activities or pools should be accounted, or how, or through which methods (Krug, 2018). While there are certain political and economic interests (particularly in conflict between European and continental American nations) which puts some of the deliberations into a deadlock (Fry, 2011), in the context of wildfires, this is also due to the consideration that such natural disturbances are negligible in effect and difficult to quantify. Evidence shown in this manuscript not only contributes to the already growing literature showing these effects are not negligible, but also provides the first evidence that they can be accounted at the international level.

As UNFCCC (2019) specifies for Conference of the Parties (COP24), regarding the accounting methods for LULUCF related emissions, that any such endeavors on considering the emissions on natural disturbances be compliant with the IPCC guidelines. It is useful then, that the revision of the 2006 guidelines in 2019 provided a much-needed emphasis on wildfire emissions accounting (Johns, 2020). However, a standardized system of accounting for long-term impacts still remains. In this sense, one clear direction for accounting and reduction policies would involve a deliberation in favor of more standardized, and unambiguous methods for reporting on the impacts of forest fires. The more quantitative evidence is found regarding the persistent effects of fire-damage, the more incentive there will be for considering them in more rigid ways which are free of contextual loopholes.

7. Model Consistency

Given the comprehensive discussion on the baseline model, central results, and the implications thereof, there are secondary technical details which could be useful to exhaust in ensuring the validity of our approach. These assumptions are still inherent to matching and to the conceptual approach we are taking, but they are of lesser importance in terms of the potential issues they might represent for the model. There are also decisions on model parameters, which have to be taken into account for a robust procedure. This section provides deeper investigation into each of these elements.

7.1. Overlap

Second key assumption regards the overlap of control and treatment groups. It can be viewed in the context of this study as the assumption that given the covariates, any observed pixel has a non-zero and non-total probability of being treated:

$$1 > \Pr\,(T_{j,T_0} = 1 | X_j) > 0$$

Therefore, we would like to make sure that the controls and the treatments included, in terms of their covariate distributions have an overlapping "region" within which the observations can be reasonably argued to have the possibility of being treated. For the purposes of this study's baseline specification, we can consider the overlapping region to correspond to a geographic region with respect to strictly the Easting and Northing[1]. Any control or treatment observation outside of this area we would consider as violating the overlap assumption. For this study, given the estimation specifications, we exclude any observation which is found to violate the overlap assumption, iteratively, until all observations are valid in this respect.

A more systematic way in which overlap assumption is assisted, has to do with the brief discussion on the spatial perimeters of the control group, given in section 3.3. Given, the choice of the 10 km perimeter is partly due to the computational intensity of the estimation, as it still allows for exact matching to be done with two matches, while estimations still completing in a reasonable time frame. But it is also important to note that after a certain distance it is difficult to argue that the pixels of the control group are comparably similar to the treatment pixels, in the first place. Though CLC inventory has 44 classes regarding land use, each of them are nevertheless broad categories and it is not very probable to argue that the particular genus of broad-leaved forests in a Mediterranean country would have comparable growth patterns as one from Northern European country. Therefore, even without a treatment, such two pixels might have shown significantly different signs of development. Within this unaccounted range of variability, the similarity of vegetation within local ecosystems as imposed by the outer perimeter will ensure similarity of unobserved characteristics.

7.2. Recurrence of Fires

Another important aspect to discuss regarding the findings is the possibility that when looking at 2018 for the impact of fires on forests of 2000, we are overlooking fires on some of these forests which repeatedly occur between 2000 and 2018. In order to better explore this possibility, firstly, we explore the percentage share of burnt areas that the year 2000 has in common with future observed years. Table 10 provides the breakdown of "brunt" pixels of 2000, which are repeatedly observed as burned areas in 2006, 2012, and 2018. The results never exceed 2.53%, and on average less than 2% of the plots burned in 2000 continue to be burnt in following years. Table also takes intersections on these years, to see pixels which always remain as burned areas. This rate is even smaller, where only 0.51% of the total burned regions. This translates to less than 10 km2 in terms of total surface area, in the entirety of the pan-European region. Clearly, this is a very small area, but nevertheless, we can also re-estimate the baseline model with any pixel which was also burned in later years, excluded.

Table 10 — Recurrence of fires of 2000 in later years.

Pixels burnt in years	Intersection	Pixels burnt in years	Intersection
2000 ∩ 2006	1.30%	2000 ∩ 2006 ∩ 2012	0.63%
2000 ∩ 2012	2.53%	2000 ∩ 2006 ∩ 2018	0.51%
2000 ∩ 2018	1.76%	2000 ∩ 2006 ∩ 2012 ∩ 2018	0.51%

Notes: Intersection implies a pixel is burnt in each of the given years.

[1] Conventionally latitudes and longitudes are used to refer to the location of a specific point on a map. However, CLC data uses EPSG: 3035 coordinate reference system (CRS), which is a cartesian, 2D, grid-based CRS. Under these conventions, the coordinates have the spatial unit of meters, the X-axis is referred to as "Easting", while Y-axis is referred to as "Northing".

7.3. Temporal Changes & Disaggregation of Forests

There are multiple ways to observe how burnt land transforms over time. Fig. 6 visualizes two possible algorithms to examine how land use classification of a pixel can change between observations. Each method has its own shortcomings associated. The "naïve" approach will recount a given pixel of the same type repeatedly, so long as it used to be a burnt region and is not anymore, which will cause areas that repeatedly change to be underrepresented, in relation. The "first-differences" approach on the other hand, focuses exclusively on dynamism, and as such, it will count even burnt pixels, so long as they were a different sub-class in the period prior (given that the pixel was also burnt in the initial period). However, if forest fires are to be a significant problem, with long-term negative impacts, as described by Bowd et al. (2019), there should be some indicative patterns emerging despite these shortcomings.

In order to further assess long-term effects of fire damage on land use, Table 11 provides the implementation of both algorithms mentioned, for years 1990 and 2000. This way we can also see evolution of "burnt" pixels after 28 years, albeit not through a causal lens, of course. Nevertheless, in either case, with either method, it is evident that an overwhelming majority of the regions do not become any type of forest. Considering that on average, roughly a quarter of the pixels have one of the forest classes associated, burnt regions, even after 28 years, fail to recover to a representative degree. Even under the best estimates, only about 14% of the burnt regions manage to become forests, and at worst, it is less than 1%. Mixed forests seem to show the most recovery for both 1990 and 2000. While the discrepancy between naïve and first-differences approaches of broad-leaved forests indicate that to the extent that they recover, they do so early, and not change much recovery happens in the long term. Overall, First-differences approach seems to find much less share of forests over time. This is to be expected, as once a region recovers enough for forests to emerge; they are likely to stay, over time, unless they burn again. This means first-differences will simply count these regions once, when they first emerge, and discount them the next period, and the share will fall again. In general, these results support our findings, as well as literature on post-fire regeneration, in regard to the lackluster process of recovery. The negligible recovery on disaggregated categories further substantiates the results of the robustness checks for 2006 and 2012.

Fig. 6 — Visual examples of how changes in burnt areas can be accounted. Each box represents a pixel, each color refers to a different sub-class of land, and dark gray ones, specifically, are the "Burnt areas". Both algorithms first restrict the sample to geographical locations of burnt areas of the initial year. Following this, naïve approach will simply compare the initial year of observation (e.g. burnt pixels of 2000) and compare them to pixels of the following observations at the same geographical location. If the new region is not burnt, it will be counted as having changed. First-differences approach on the other hand, as its name suggests, will instead compare each observation to its immediate successor. This means if a given pixel has changed compared to its previous observation, it will be counted as having changed.

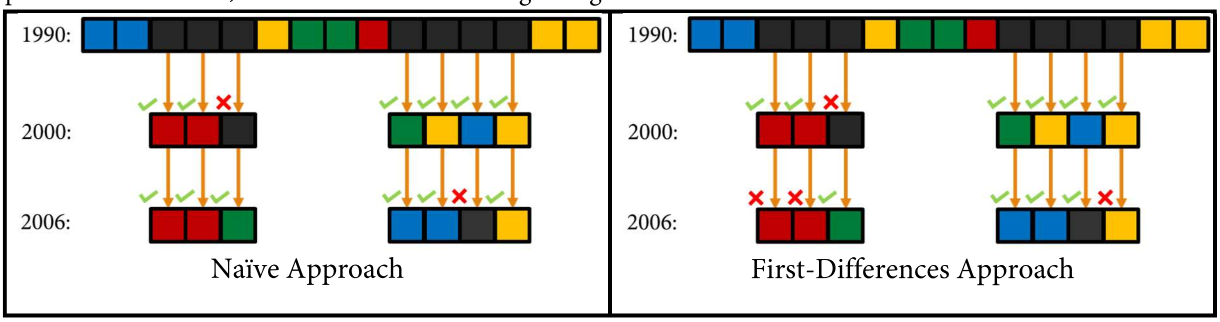


Table 11 — Temporal class changes of burnt areas in 1990 and 2000.

	Initial Year: 1990				Initial Year: 2000			
	Broad-Leaved	**Coniferous**	**Mixed**	**Total Non-Forest**	**Broad-Leaved**	**Coniferous**	**Mixed**	**Total Non-Forest**
Naïve Approach:								
2000	0.15%	0.53%	0.15%	99.17%	-	-	-	-
2006	0.24%	0.00%	1.54%	98.22%	2.09%	0.29%	5.31%	92.31%
2012	1.92%	0.67%	8.30%	89.11%	2.99%	0.32%	5.58%	91.11%
2018	1.95%	0.69%	7.26%	90.10%	3.13%	0.34%	5.39%	91.14%
First-Differences Approach:								
2000	0.15%	0.53%	0.15%	99.17%	-	-	-	-
2006	0.39%	0.00%	2.84%	96.77%	2.09%	0.29%	5.31%	92.31%
2012	3.75%	2.27%	8.19%	85.79%	0.29%	0.00%	7.44%	92.27%
2018	0.00%	0.55%	0.00%	99.45%	0.03%	6.19%	1.07%	92.70%

Notes: Each category represents share of the given class in relation to the total land use. Broad-leaved forests, coniferous forests and mixed forests are the three "Tier 4" classes in the CLC inventory which compose the general category of forests.

8. Robustness Checks

If our baseline estimation is not capturing a spurious relationship, different parameter specifications of the model, should still produce output which conforms to past literature and intuition. The following list provides a detailed account of the robustness checks performed for this purpose of validation:

8.1. Different Radii

Table 13 shows the results of the baseline model, (I), with differing inner and outer perimeters. (V) checks whether we can relax the assumption of regions being indirectly affected by the fires, and scales the inner radius to 1 km The balance seems unaffected if not marginally better for Easting and marginally worse for Northing. The central results are almost identical, with forests being affected to the same exact degree, and other vegetation losing some magnitude. The category for others also seems to have lost some precision with 5%, but otherwise, the model shows evidence in the same direction. With (VI) we try to see if extending the inner perimeter to 5 km would significantly change the results, since if it does, this could mean that even at 3 km we have a violation of the models' basic assumptions. However, this is not the case. Once again regarding balance, the covariates seem to be similarly distributed. The results are also in line with the baseline model. Agricultural areas as well as "others" lose some precision, and interestingly we gain precision with burnt regions at 1%. Though the magnitude show that we are looking at a difference of 0.55% increased presence of fires, on average, compared to the control group. So not very impactful. But otherwise, impact on both forests and vegetation remain significant and almost same in magnitude. Finally, with (VIII), we extend the outer perimeter to 20 km (while inner perimeter is left at 3 km), to assess if increasing number of controls would provide significantly better accuracy, at the exponential cost of computation time. The covariate balance once again seems to be better for Easting, but worse for Northing, so we do not gain much use in terms of representativeness. The impact estimates, on the other hand, are almost identical to (VI). These findings clearly demonstrate our model is robust to various geospatial ranges of selection regarding control groups.

Table 12 — Impact of fires on land use after 18 years, using several radii.

Impact on Forests	**(V)**	**(VI)**	**(VII)**
ATE	-0.27***	-0.28***	-0.29***
	(0.012)	(0.012)	(0.012)
Percentage impact	-63%	-63%	-65%
Impact on Artificial Surfaces	**(V)**	**(VI)**	**(VII)**
ATE	-0.0013	-0.0028	-0.0028
	(0.0029)	(0.0029)	(0.0033)
Percentage impact	-15%	-33%	-37%
Impact on Agricultural Areas	**(V)**	**(VI)**	**(VII)**
ATE	-0.017**	-0.020**	-0.018*
	(0.0071)	(0.0087)	(0.0097)
Percentage impact	-29%	-30%	-%25
Impact on Natural Grasslands, Moors, and Heathland	**(V)**	**(VI)**	**(VII)**
ATE	0.052***	0.064***	0.067***
	(0.011)	(0.012)	(0.013)
Percentage impact	+31%	+42%	+45%
Impact on Sclerophyllous XIegetation, Transitional Woodland-shrubs	**(V)**	**(VI)**	**(VII)**
ATE	0.22***	0.22***	0.22***
	(0.014)	(0.015)	(0.015)
Percentage impact	+70%	+72%	+74%
Impact on Burnt Areas	**(V)**	**(VI)**	**(VII)**
ATE	0.0018	0.0055***	0.008***
	(0.0018)	(0.0018)	(0.0022)
Percentage impact	+115%	+149%	+179%
Impact on Other Categories of Land	**(V)**	**(VI)**	**(VII)**
ATE	0.017**	0.018**	0.017*
	(0.0073)	(0.0085)	(0.0093)
Percentage impact	+122%	+126%	+116%

Notes: Each impact category represents a separate estimation. "Percentage impact" refers to the ratio of average treatment effect and the mean value of the control group, indicating the percentage difference, between control and treatment groups, of which is due to the fires. Information on the observations and the group means are shared in Table 13. Specification (V) utilizes 1 km inner perimeter, and 10 km outer perimeter; (VI) utilizes 5 km inner, 10 km outer perimeters; (VII) utilizes 3 km inner and 20 km outer perimeters. Abadie-Imbens robust standard errors are provided in parentheses. The indicators for statistical significance are as follows:

*** 1% significance
** 5% significance
* 10% significance

8.2. Monte Carlo Simulations

One other way to ensure robustness, could be through making sure the effects we have captured are not spurious to the extent that a subset of controls used as treatment group could also generate significant outcomes. To test this, we ran Monte Carlo tests, in which we randomly select a strict subset of the controls, as a substitute for the treatment group, and test if our model produces any statistically significant results. Due to timing concerns and the computationally intense nature of our matching strategy, there were some limitations we had to conform to in order to make this test valid, yet nevertheless feasible. we ran 50 iterations, only with the "Forests" category, each 2,000 observations as the treated group, the rest of the controls being used as counterfactual. Table 15 shows the results of these permutations. Only 4 out of the 50 permutations were statistically significant. Out of these 4, only 1 of them was significant at 5%, the others at 10%. Furthermore, the magnitude of each of the significant effects were less than 10% of our findings. The percentage impact of the significant estimations are between -4% and 6%.

Table 14 — Coefficient results of Monte Carlo tests.

Monte Carlo permutations:	**1 through 10**	**11 through 20**	**21 through 30**	**31 through 40**	**41 through 50**
ATE	-0.0026 (0.011)	-0.015 (0.010)	-0.0031 (0.0099)	0.0047 (0.010)	-0.0047 (0.010)
ATE	0.013 (0.010)	-0.016 (0.011)	0.0026 (0.0099)	0.0029 (0.010)	-0.0036 (0.010)
ATE	-0.014 (0.010)	0.020* (0.011)	-0.019* (0.010)	0.0043 (0.0099)	-0.0078 (0.010)
ATE	-0.0098 (0.010)	-0.010 (0.011)	-0.0002 (0.0097)	0.0054 (0.011)	0.016 (0.0099)
ATE	0.015 (0.010)	0.0032 (0.010)	-0.013 (0.011)	-0.0034 (0.010)	0.011 (0.010)
ATE	-0.0039 (0.0097)	0.025** (0.011)	0.015 (0.010)	0.0063 (0.010)	-0.010 (0.0095)
ATE	-0.0037 (0.0096)	0.019* (0.011)	0.0020 (0.010)	-0.0099 (0.0099)	-0.0022 (0.010)
ATE	-0.0086 (0.010)	-0.011 (0.010)	-0.00081 (0.011)	0.012 (0.010)	0.0011 (0.010)
ATE	-0.0025 (0.010)	0.00068 (0.011)	0.018* (0.010)	-0.0044 (0.011)	-0.0065 (0.010)
ATE	-0.00004 (0.010)	0.0041 (0.010)	0.0035 (0.010)	0.0019 (0.010)	-0.0054 (0.011)

	Minimum		Maximum	
Observations	Raw	Matched	Raw	Matched
Total	485,382	970,764	505,367	1,010,734
Treatment	1,819	485,382	1,862	505,367
Control	483,563	483,563	503,506	503,506

Notes: Average treatment effect estimations are strictly for the "forest" category. Observations are less than 2,000 and varying due to the fact that some of them defy overlap assumption, and hence have to be excluded from the estimation. Further details on each estimation can be found in the Appendix. The indicators for statistical significance are as follows:

*** 1% significance
** 5% significance
* 10% significance

While running 1000 tests, with each category of land use, with much larger number of observations, utilizing a greater coarser spatial resolution would provide much better case for our methodology, we believe this test still builds a strong case for the overall robustness of the approach.

8.3. No Coordinate Covariates

Past literature has an emphasis to use bordering regions of burnt plots for composing control groups, and the fact that we have a geospatial data makes this process very appealing. However, what would

Table 16 — Impact of fires on land use after 18 years, using only distance covariates.

Impact on Forests		**(VIII)**
	ATE	-0.29*** (0.011)
	Percentage impact	-66%
Impact on Artificial Surfaces		**(VIII)**
	ATE	-0.0029 (0.0038)
	Percentage impact	-3.4%
Impact on Agricultural Areas		**(VIII)**
	ATE	-0.00047** (0.0106)
	Percentage impact	+0.76%
Impact on Natural Grasslands, Moors, and Heathland		**(VIII)**
	ATE	0.104*** (0.0075)
	Percentage impact	+64%
Impact on Sclerophyllous Vegetation, Transitional Woodland-shrubs		**(VIII)**
	ATE	0.16*** (0.015)
	Percentage impact	+54%
Impact on Burnt Areas		**(VIII)**
	ATE	0.0020 (0.0020)
	Percentage impact	+26%
Impact on Other Categories of Land		**(VIII)**
	ATE	0.020*** (0.0032)
	Percentage impact	+147%

Notes: Each impact category represents a separate estimation. "Percentage impact" refers to the ratio of average treatment effect and the mean value of the control group. Abadie-Imbens robust standard errors are provided in parentheses. The indicators for statistical significance are as follows:

*** 1% significance
** 5% significance
* 10% significance

happen if we only had other geographic factors based on distance, to match controls? Perhaps without accounting for geolocation, our estimations would fall short of accurately assessing the impact, which could cast doubt on the accuracy of our distance-based covariates, as they are also considered in the literature as predictors. Specification (VIII) of Table 15 addresses these concerns. In terms of both impact estimations, and the covariate balance, this model is almost identical to (VIII). In fact, the results of interest, forests, have the same magnitude and standard errors. Similar to the other robustness checks so far, the results are observably unaffected by exclusion of the geolocational information. It seems the distance-based covariates are also quite accurate in finding matches which are close to those of the treatment group.

One further implication here is that so long as exact pre-treatment matching provides a precondition selecting the controls, approaches driven by geospatial similarity or geographical similarity are both adequate in providing robust and globally balanced groups. In this sense exact matching on past proved to be a strongly reliable means by which ecological counterfactuals could be assessed. Though as per initial discussion on (II), the covariate balance on geographical factor proximity proves to be less balanced. As such, the preference here would be in favor of (I) rather than (VIII) or (II).

8.3. Different Number of Matches

In a nearest-neighbor matching model it is both important to make sure there are comparable counterfactuals for the treatment group, and that the bias this might generate is taken into account. As Stuart (2010) describes, higher number of matches would mean that we are able to involve more controls per treatment observation. This will increase the balance of the estimation, as we are able to construct better counterfactuals. However, this will come at the cost of increased bias. As the number of matches increase, the average quality of the matches will be inversely affected. For the purposes of our study, though maximum number of matches could go up to 6 control observations per one treated pixel, we have considered using two non-weighted matches per treated pixel. This both provides sufficient balance in the estimation while not allowing the bias to dictate the results, for our baseline model. As a form of robustness check, though, we also report estimations with one and three matches. This way, we can discuss the bias-variance trade-off in more detail, in context.

There is another aspect of the matching which we cannot control due to technical limitations: match replacement. In matching with replacement one control observation can be used as counterfactual for multiple treatment observations, ultimately allowing for better average quality for matches which will then decrease bias, at the cost of increased variance due to lower overall number of control observations used. Possibly the most important issue to consider for non-replacement, though, is that since once a control is matched, it cannot be used again, thus matching without replacement becomes dependent on the order in which controls and treatments are assigned (Smith & Todd, 2005). Within our technical limitations, matching with replacement was the only option. And even though in our particular case, we have an overabundance of controls, and as such non-replacement would likely not have become a big issue, this aspect of matching is nevertheless important to keep in mind.

In Table 16, given the baseline model, different number of matches were applied to the primary category of interest: forests. As per the former discussion on the bias-variance trade-off associated with the number of matches, if our model is strongly dependent the number of matches we use, we should see a difference of bias, and the covariate balance, in these results. Specification (IX) matches only one control per treatment observation, and compared to (I), the covariate matches are very similar. We are marginally closer to ideal values with Easting, and farther away with Northing. While the results are exactly the same in magnitude, though with larger standard errors. Specification

Table 16 — Impact of fires on forests after 18 years, with different number of matches.

Impact on Forests	**(IX)**		**(X)**	
ATE	-0.27*** (0.012)		-0.28*** (0.012)	
Percentage impact	-63%		-63%	
Observations	Raw	Matched	Raw	Matched
Total	390,927	781,854	390,927	781,854
Treated	6,874	390,927	6,874	390,927
Control	384,053	390,927	384,053	390,927
Standardized differences	Raw	Matched	Raw	Matched
Easting	0.13	0.00017	0.13	0.00044
Northing	0.055	-0.018	0.055	-0.016
Variance ratio	Raw	Matched	Raw	Matched
Easting	1.067	0.99	1.067	0.99
Northing	0.71	1.088	0.71	1.075
	Treatment	Control	Treatment	Control
Outcome means	0.12	0.44	0.12	0.44
Number of matches	1		3	

Notes: Each impact category represents a separate estimation. "Percentage impact" refers to the ratio of average treatment effect and the mean value of the control group, indicating the percentage difference, between control and treatment groups, of which is due to the fires. The indicators for statistical significance are as follows:

*** 1% significance
** 5% significance
* 10% significance

(X) on the other hand, uses 3 matches. The covariate balance is once again, almost identical, while the magnitude of the impact is slightly higher. The difference is small enough thar arguing this is the direct result of the bias induced as a result of increased number of matches would be difficult. Nevertheless, one thing is clear: the findings are also robust to changes in parameters regarding matching.

9. Conclusions

Until recently, effects of forest fires in the long-term had been considered negligible. They would be excluded categorically, later due to loopholes, and later still due to ambiguous guidelines (Fry, 2007; Krug, 2018). This was in part due to lack of quantitative, large-scale research on the lasting impacts of forest fires. Advancing technologies and measurement methods in the last few decades allowed an opportunity to estimate bio-physical factors in greater spatial and temporal coverage, despite some drawbacks in terms of limitations regarding data and methodology (Sajjad and Kumar, 2018).

Utilizing these modern tools, and instituting a robust matching strategy, we provide the first pan-European, and the first multinational estimates of the long-term impact of forest fires, from 2000 to 2018. The first dimension regards impacts on land use, to obtain some perspective on the damage done on the ecological habitat directly. In multiple specifications of the model, we found the presence of forests to have declines by at least 61%, after 18 years, on average. These areas were primarily replaced by vegetation known to have much lower capacity to sequester carbon, such as grasslands and shrubs. Results are robust to alternative specifications of the model, the data, and several changes in model parameters.

Secondly, exploiting the matching setting calibrated on pre-treatment data, we are able to assess the impact done on other ecological indicators, on any period of time. For the purposes of carbon sequestration, though not ideal, estimations were done on the best available data: biomass carbon density of the year 2010, and progression of NPP index from 2000 to 2020. The results confirm that a drastic drop in the captured carbon stock has occurred due to fires, at 28%, while even the forests which do show presence after fires, show signs of low capacity to sequester carbon, only re-capturing about 2.1% of the carbon lost. Although the technical limitations strongly indicate that these estimates are underreport the severity of the true impact.

From an economic perspective, the monetary costs of abatement alone reach hundreds of millions of USD, while future total cost of no-action scenarios reaches almost 6 billion USD by 2050, for a single year of fires alone. Further considering the downward pressure forest fires have on resources used for climate action policies, the full range of implications of the severity of these findings diverse, for better or for worse. In this sense, our findings could serve to incentivize reprioritization of forest management strategies and goals, potentially open a way in which activities previously thought to be a net cost are seen as long-term economic benefits. From a macro-policy standpoint, these results emphasize the need for clearer and more directed accounting systems to be introduced for natural disturbances such as forest fires and means to account for long-term impacts.

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Appendix

1. Technical Information on Datasets

Table A1 — Raster data and shapefiles used in this study.

Raster Data

Name	Original Coordinate Reference System	Original Spatial Unit	Original Pixel Dimensions	Original Raster Dimensions	Original Measurement Unit	Year	Source
Aboveground Biomass Carbon	EPSG:4326 - WGS 84	Degrees	0.0028 × 0.0028	Latitude: 129,600 Longitude: 52,201	MgC per ha^{-1}	2010	Spawn et al. (2020)
Belowground Biomass Carbon	EPSG:4326 - WGS 84	Degrees	0.0028 × 0.0028	Latitude: 129,600 Longitude: 52,201	MgC per ha^{-1}	2010	Spawn et al. (2020)
CORINE Land Cover Inventory	EPSG:3035 – ETRS89-extended	Meters	100 × 100	Latitude: 65,000 Longitude: 46,000	n/a	1990; 2000; 2006; 2012; 2018	https://land.copernicus.eu/pan-european/corine-land-cover
Net Primary Productivity	EPSG:53008	Meters	463.31 × 463.31	Easting: 12,000 Northing: 12,000	gC per m^2	[2000, 2020]	Running and Zao (2021)

Shapefile Data

Name	Storage Convetion	Original Coordinate Reference System	Original Spatial Unit	Year	Source
NUTS II Regions	ESRI	EPSG:3035 – ETRS89-extended	Meters	2021	https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units/nuts
Mount Athos Autonomous State	ESRI	EPSG:2100 - GGRS87	Meters	2011	https://www.statistics.gr/digital-cartographical-data

Notes: Regions of Kosovo and Bosnia and Herzegovina are technically not included in the NUTS II Regions provided by EU. These areas were included by extending the shapefile to them using the borders of surrounding NUTS II regions. Mount Athos was included by merging the two shapefiles. Though these procedures cause some inclusion issues around the borders, the regions of interest for this study were not affected.

Table A2 — CLC class nomenclature and its association with category names used in thesis

Color	ID	CLC Tier-4 Class Name	Thesis Category Name
	1	Continuous urban fabric	Artificial surfaces
	2	Discontinuous urban fabric	
	3	Industrial or commercial units	
	4	Road and rail networks and associated land	
	5	Port areas	
	6	Airports	
	7	Mineral extraction sites	
	8	Dump sites	
	9	Construction sites	
	10	Green urban areas	
	11	Sport and leisure facilities	
	12	Non-irrigated arable land	Agricultural areas
	13	Permanently irrigated land	
	14	Rice fields	
	15	Vineyards	
	16	Fruit trees and berry plantations	
	17	Olive groves	
	18	Pastures	
	19	Annual crops associated with permanent crops	
	20	Complex cultivation patterns	
	21	Land principally occupied by agriculture with significant areas of natural vegetation	
	22	Agro-forestry areas	
	23	Broad-leaved forest	Forests
	24	Coniferous forest	
	25	Mixed forest	
	26	Natural grasslands	Natural grasslands, moors, and heathland
	27	Moors and heathland	
	28	Sclerophyllous vegetation	Sclerophyllous vegetation, transitional woodland-shrub
	29	Transitional woodland-shrub	
	30	Beaches dunes sands	Other
	31	Bare rocks	
	32	Sparsely vegetated areas	
	33	Burnt areas	Burnt areas
	34	Glaciers and perpetual snow	Other
	35	Inland marshes	
	36	Peat bogs	
	37	Salt marshes	
	38	Salines	
	39	Intertidal flats	
	40	Water courses	
	41	Water bodies	
	42	Coastal lagoons	
	43	Estuaries	
	44	Sea and ocean	

Notes: Except for the tier-class 33, "Burnt Areas", any category IDs in rage [30, 44] are included in the same category: "Other". The "NODATA" category with designated ID 48, is not considered.

Table A3 — Dates of inclusion of each country covered by CLC Inventory

Country Name	Initial Year of Coverage	Country Name	Initial Year of Coverage	Country Name	Initial Year of Coverage
Albania	2000	Greece	1990	Netherlands	1990
Austria	1990	Hungary	1990	Norway	2000
Belgium	1990	Iceland	2000	Poland	1990
Bosnia & Herzegovina	2000	Ireland	1990	Portugal	1990
Bulgaria	1990	Italy	1990	Romania	1990
Croatia	1990	Kosovo	2000	Serbia	1990
Cyprus	2000	Latvia	1990	Slovakia	1990
Czechia	1990	Liechtenstein	1990	Slovenia	1990
Denmark	1990	Lithuania	1990	Spain	1990
Estonia	1990	Luxembourg	1990	Sweden	2000
Finland	2000	Malta	1990	Switzerland	2000
France	1990	Macedonia	2000	Turkey	1990
Germany	1990	Montenegro	1990	United Kingdom	2000

Notes: As our estimation requires exact matching on 1990 values, lack of available data for some countries in 1990 causes our method to lose roughly 31% of our observations (from 10,118 to 7,017).

2. Verbose Results

Table A4 — Estimation results and distribution means for the Monte Carlo robustness checks.

Permutation	ATE	AI-Robust Std. Err.	Treated Means	Control Means	Permutation	ATE	AI-Robust Std. Err	Treated Means	Control Means
1	0.0026	0.011	0.46	0.45	26	0.015	0.011	0.45	0.46
2	0.013	0.010	0.47	0.45	27	0.0020	0.010	0.47	0.46
3	-0.014	0.010	0.45	0.46	28	-0.00081	0.010	0.47	0.46
4	0.0098	0.010	0.46	0.46	29	0.018	0.011	0.46	0.46
5	0.015	0.010	0.47	0.46	30	0.0035*	0.010	0.48	0.45
6	0.0039	0.010	0.47	0.46	31	0.0047	0.010	0.46	0.46
7	0.0037	0.010	0.45	0.45	32	0.0029	0.010	0.47	0.46
8	0.0086	0.010	0.45	0.46	33	0.0043	0.010	0.47	0.46
9	0.0025	0.010	0.47	0.46	34	0.0054	0.010	0.44	0.45
10	0.000040	0.010	0.45	0.45	35	-0.0034	0.011	0.46	0.46
11	-0.015	0.010	0.46	0.46	36	0.0063	0.010	0.46	0.45
12	-0.016	0.011	0.45	0.46	37	-0.0099	0.010	0.46	0.45
13	0.020*	0.011	0.48	0.46	38	0.012	0.010	0.46	0.45
14	-0.010	0.011	0.44	0.45	39	-0.0044	0.010	0.47	0.46
15	0.0032	0.010	0.47	0.46	40	0.0019	0.011	0.44	0.45
16	0.025**	0.011	0.48	0.46	41	-0.0047	0.010	0.47	0.46
17	0.019*	0.011	0.47	0.46	42	-0.0036	0.010	0.45	0.46
18	0.011	0.010	0.44	0.46	43	-0.0078	0.010	0.46	0.46
19	0.00068	0.011	0.48	0.45	44	0.016	0.010	0.44	0.46
20	0.0041	0.010	0.46	0.45	45	0.011	0.010	0.46	0.46
21	-0.0031	0.010	0.46	0.45	46	-0.010	0.010	0.47	0.45
22	0.0026	0.010	0.45	0.46	47	-0.0022	0.0095	0.44	0.46
23	0.019*	0.010	0.46	0.46	48	0.0011	0.010	0.48	0.46
24	-0.00020	0.010	0.47	0.46	49	-0.0065	0.010	0.47	0.46
25	-0.013	0.011	0.45	0.46	50	-0.0054	0.010	0.47	0.46

Notes: Due to spacing concerns, Abadie-Imbens Robust standard errors are given to the right of ATE estimates. The indicators for statistical significance are as follows: *** for 1% significance; ** for 5% significance; * for 10% significance.

Table A5 — Covariate balance and estimations details of the Monte Carlo robustness checks.

Permutation No	Total Raw Obs.	Total Matched Obs.	Treated Raw Obs.	Treated Matched Obs.	Control Raw Obs.	Control Matched Obs.	Easting Std. Diff. Raw	Easting Std. Diff. Matched	Easting Var. Ratio Raw	Easting Var. Ratio Matched	Northing Std. Diff. Raw	Northing Std. Diff. Matched	Northing Var. Ratio Raw	Northing Var. Ratio Matched
1	496,741	993,482	1,837	496,741	494,904	494,904	0.016	0.000033	1.04	1.00	0.014	0.00076	1.05	1.00
2	495,853	991,706	1,829	495,853	494,024	494,024	0.028	0.00038	1.01	1.00	0.024	0.004	1.08	1.00
3	496,738	993,476	1,842	496,738	494,896	494,896	0.033	-0.00027	1.02	1.00	0.018	-0.00033	1.08	0.99
4	498,191	996,382	1,841	498,191	496,350	496,350	0.046	0.00025	1.05	1.00	0.027	0.004	1.07	0.99
5	500,340	1,000,680	1,845	500,340	498,495	498,495	0.024	-0.00053	1.03	1.00	-0.0071	0.0033	1.04	0.99
6	496,168	992,336	1,836	496,168	494,332	494,332	0.031	0.00042	1.02	1.00	0.018	0.0028	1.05	1.00
7	493,745	987,490	1,830	493,745	491,915	491,915	0.0093	-0.00094	1.00	1.00	0.033	0.0062	1.04	0.99
8	498,315	996,630	1,840	498,315	496,475	496,475	0.063	-0.00034	1.08	1.00	-0.019	0.0034	1.11	1.00
9	497,743	995,486	1,851	497,743	495,892	495,892	0.057	0.00007	1.03	1.00	0.05	0.0058	1.11	0.99
10	498,172	996,344	1,837	498,172	496,335	496,335	0.011	0.00018	1.05	1.00	0.03	0.0044	0.98	0.99
11	497,236	994,472	1,844	497,236	495,392	495,392	0.069	-0.00009	1.08	1.00	0.022	0.0018	1.13	1.00
12	496,301	992,602	1,833	496,301	494,468	494,468	0.019	-0.00052	0.99	1.00	0.057	0.0017	1.05	0.99
13	490,922	981,844	1,839	490,922	489,083	489,083	0.059	0.000077	1.04	1.00	0.038	0.0017	1.07	0.99
14	495,361	990,722	1,855	495,361	493,506	493,506	0.04	-0.00029	1.04	1.00	0.027	0.003	1.12	1.00
15	495,896	991,792	1,831	495,896	494,065	494,065	0.039	0.000069	1.01	1.00	0.00063	-0.00025	1.11	1.00
16	495,157	990,314	1,830	495,157	493,327	493,327	0.056	0.000016	1.08	1.00	0.017	0.0019	1.15	1.00
17	500,428	1,000,856	1,844	500,428	498,584	498,584	0.081	-0.00026	1.08	1.00	-0.0089	0.00039	1.06	1.00
18	497,152	994,304	1,843	497,152	495,309	495,309	0.026	0.00085	1.01	1.00	0.028	0.0043	1.08	0.99
19	496,915	993,830	1,826	496,915	495,089	495,089	0.072	0.00095	1.05	1.00	0.0031	0.0011	1.12	1.00
20	491,455	982,910	1,824	491,455	489,631	489,631	0.035	-0.0004	1.06	1.00	0.0073	0.0034	1.08	0.99
21	497,278	994,556	1,842	497,278	495,436	495,436	0.059	0.000093	1.06	1.00	0.017	0.0055	1.11	1.00
22	502,241	1,004,482	1,857	502,241	500,384	500,384	0.021	-0.00011	1.00	1.00	-0.0084	0.0029	1.08	1.00
23	493,381	986,762	1,832	493,381	491,549	491,549	0.064	0.0001	1.06	1.00	-0.0038	0.0045	1.11	0.99
24	502,430	1,004,860	1,849	502,430	500,581	500,581	0.023	-0.000068	1.04	1.00	0.046	0.004	1.05	0.99
25	495,158	990,316	1,835	495,158	493,323	493,323	0.036	-0.00016	1.02	1.00	0.042	0.0024	1.03	1.00
26	499,249	998,498	1,855	499,249	497,394	497,394	0.054	-0.00051	1.06	1.00	0.0033	0.00024	1.16	1.00
27	500,146	1,000,292	1,853	500,146	498,293	498,293	0.032	0.000059	1.01	1.00	0.03	0.0026	1.07	1.00
28	501,385	1,002,770	1,857	501,385	499,528	499,528	0.041	0.000091	1.02	1.00	-0.012	0.0012	1.05	0.99

Table A5 (cont.) — Covariate balance and estimations details of the Monte Carlo robustness checks.

Permutation No	Total Raw Obs.	Total Matched Obs.	Treated Raw Obs.	Treated Matched Obs.	Control Raw Obs.	Control Matched Obs.	Easting Std. Diff. Raw	Easting Std. Diff. Matched	Easting Var. Ratio Raw	Easting Var. Ratio Matched	Northing Std. Diff. Raw	Northing Std. Diff. Matched	Northing Var. Ratio Raw	Northing Var. Ratio Matched
29	497,907	995,814	1,853	497,907	496,054	496,054	0.0046	0.00047	1.00	1.00	0.012	0.0059	1.08	1.00
30	492,077	984,154	1,854	492,077	490,223	490,223	0.022	-0.00074	1.03	1.00	-0.015	0.0057	1.10	0.99
31	494,925	989,850	1,859	494,925	493,066	493,066	0.034	0.0005	1.04	1.00	0.025	0.0048	1.08	1.00
32	496,116	992,232	1,836	496,116	494,280	494,280	0.049	-0.001	1.05	1.00	0.018	0.0061	1.08	1.00
33	496,055	992,110	1,824	496,055	494,231	494,231	0.048	-0.0004	1.05	1.00	0.027	0.00097	1.02	0.99
34	502,778	1,005,556	1,855	502,778	500,923	500,923	0.028	0.00059	1.03	1.00	0.029	0.0007	1.03	1.00
35	499,032	998,064	1,848	499,032	497,184	497,184	0.06	-0.00045	1.05	1.00	0.027	0.0016	1.03	1.00
36	499,820	999,640	1,843	499,820	497,977	497,977	0.036	-0.00041	1.02	1.00	0.012	0.0045	1.11	1.00
37	489,649	979,298	1,832	489,649	487,817	487,817	0.036	-0.00045	1.04	1.00	0.03	0.004	1.08	1.00
38	501,683	1,003,366	1,852	501,683	499,831	499,831	0.041	-0.00011	1.05	1.00	0.037	0.0034	1.00	1.00
39	500,086	1,000,172	1,862	500,086	498,224	498,224	-0.0097	-0.00024	0.98	1.00	0.027	0.0014	1.06	0.99
40	500,578	1,001,156	1,839	500,578	498,739	498,739	0.049	0.00052	1.06	1.00	0.05	0.0084	1.10	0.99
41	485,382	970,764	1,819	485,382	483,563	483,563	0.029	0.00072	1.05	1.00	0.03	0.0039	1.08	1.00
42	489,596	979,192	1,826	489,596	487,770	487,770	0.024	-0.00053	1.01	1.00	-0.0032	0.0021	1.08	1.00
43	489,636	979,272	1,833	489,636	487,803	487,803	0.037	-0.00018	1.02	1.00	-0.011	0.0047	1.04	0.99
44	499,856	999,712	1,834	499,856	498,022	498,022	-0.0053	0.00033	0.98	1.00	0.028	0.0039	1.09	1.00
45	501,119	1,002,238	1,841	501,119	499,278	499,278	0.081	0.00027	1.07	1.00	0.023	0.0031	1.11	0.99
46	494,268	988,536	1,853	494,268	492,415	492,415	0.022	0.00048	1.04	1.00	0.037	-0.0018	1.05	1.00
47	494,363	988,726	1,833	494,363	492,530	492,530	0.038	-0.00084	1.04	1.00	0.036	0.0028	1.12	0.99
48	505,367	1,010,734	1,861	505,367	503,506	503,506	0.037	0.000011	1.06	1.00	0.04	0.0026	1.13	1.00
49	491,267	982,534	1,821	491,267	489,446	489,446	0.054	-0.00089	1.07	1.00	0.001	0.002	1.11	1.00
50	502,996	1,005,992	1,840	502,996	501,156	501,156	-0.00051	-0.00055	1.00	1.00	0.044	0.0037	1.02	1.00

Table A6 — Estimation results for impact of fires on NPP from 2000 to 2021.

Impact of Fires on NPP of Forests					Impact of Fires on NPP of All Land				
Year of NPP Estimated	ATE	AI-Robust Std. Err.	Treated Means	Control Means	Year of NPP Estimated	ATE	AI-Robust Std. Err.	Treated Means	Control Means
2000	-0.027***	0.0064	0.19	0.23	2000	-0.012***	0.0040	0.19	0.23
2001	-0.036***	0.0065	0.21	0.23	2001	-0.022***	0.0044	0.20	0.24
2002	-0.021***	0.0058	0.19	0.21	2002	-0.0035	0.0038	0.20	0.22
2003	0.0031	0.006	0.18	0.2	2003	0.012***	0.0042	0.17	0.20
2004	0.0065	0.0061	0.20	0.23	2004	0.009**	0.0041	0.21	0.23
2005	0.0003	0.0061	0.20	0.23	2005	0.012***	0.0039	0.21	0.24
2006	0.0011	0.006	0.19	0.21	2006	0.012***	0.0038	0.20	0.22
2007	0.0044	0.0052	0.20	0.23	2007	0.013***	0.0041	0.20	0.23
2008	0.0019	0.0052	0.21	0.23	2008	0.014***	0.0041	0.20	0.24
2009	0.0065	0.0057	0.19	0.23	2009	0.016***	0.0042	0.20	0.24
2010	0.0015	0.0055	0.19	0.22	2010	0.013***	0.0038	0.20	0.23
2011	0.0042	0.0056	0.21	0.22	2011	0.016***	0.0037	0.21	0.23
2012	0.0094*	0.0056	0.20	0.23	2012	0.021***	0.0040	0.21	0.24
2013	0.011*	0.0056	0.19	0.21	2013	0.019***	0.0041	0.20	0.22
2014	0.0051	0.0049	0.21	0.21	2014	0.017***	0.0038	0.2	0.23
2015	0.010*	0.0056	0.20	0.22	2015	0.017***	0.0042	0.21	0.23
2016	0.012**	0.0051	0.20	0.22	2016	0.017***	0.0040	0.20	0.23
2017	0.014**	0.0056	0.20	0.23	2017	0.019***	0.0044	0.21	0.24
2018	0.014**	0.0056	0.19	0.2	2018	0.019***	0.0040	0.19	0.21
2019	0.013**	0.0056	0.20	0.22	2019	0.020***	0.0043	0.20	0.23
2020	0.014**	0.0056	0.20	0.22	2020	0.019***	0.0043	0.21	0.23

Notes: ATE estimates as well as standard errors given in Fig. 3 were converted to MgC per ha for ease of interpretation. Since the original values of NPP are expressed in gC per 16×10^4 m^2, Estimates shown here are of this original unit. Due to spacing concerns, Abadie-Imbens Robust standard errors are given to the right of ATE estimates. The indicators for statistical significance are as follows:

*** 1% significance

** 5% significance

* 10% significance

Table A7 — Covariate balance and estimations details of the impact of fires on NPP from 2000 to 2021.

Details and Statistics of Estimations on All Land														
Year of NPP Estimated	Total Raw Obs.	Total Matched Obs.	Treated Raw Obs.	Treated Matched Obs.	Control Raw Obs.	Control Matched Obs.	Easting Std. Diff. Raw	Easting Std. Diff. Matched	Easting Var. Ratio Raw	Easting Var. Ratio Matched	Northing Std. Diff. Raw	Northing Std. Diff. Matched	Northing Var. Ratio Raw	Northing Var. Ratio Matched
2000	208,301	416,602	6,816	208,301	201,485	208,301	0.099	-0.00087	0.71	0.99	0.10	0.0040	0.71	1.042
2001	208,301	416,602	6,816	208,301	201,485	208,301	0.099	-0.00087	0.71	0.99	0.10	0.0040	0.71	1.042
2002	208,301	416,602	6,816	208,301	201,485	208,301	0.099	-0.00087	0.71	0.99	0.10	0.0040	0.71	1.042
2003	208,343	416,686	6,818	208,343	201,525	208,343	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2004	208,343	416,686	6,818	208,343	201,525	208,343	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2005	208,343	416,686	6,818	208,343	201,525	208,343	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2006	208,363	416,726	6,818	208,363	201,545	208,363	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2007	208,363	416,726	6,818	208,363	201,545	208,363	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2008	208,363	416,726	6,818	208,363	201,545	208,363	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2009	208,369	416,738	6,818	208,369	201,551	208,369	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2010	208,369	416,738	6,818	208,369	201,551	208,369	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2011	208,369	416,738	6,818	208,369	201,551	208,369	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2012	208,369	416,738	6,818	208,369	201,551	208,369	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2013	208,369	416,738	6,818	208,369	201,551	208,369	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2014	208,369	416,738	6,818	208,369	201,551	208,369	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2015	208,369	416,738	6,818	208,369	201,551	208,369	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2016	208,369	416,738	6,818	208,369	201,551	208,369	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2017	208,369	416,738	6,818	208,369	201,551	208,369	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2018	208,369	416,738	6,818	208,369	201,551	208,369	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2019	208,369	416,738	6,818	208,369	201,551	208,369	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042
2020	208,369	416,738	6,818	208,369	201,551	208,369	0.099	-0.00088	0.71	0.99	0.10	0.0040	0.71	1.042