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Damages and Costs of Forest Wildfires in New Zealand Using Satellite Data

Elodie Blanc[1] · Ilan Noy[2,3]

Abstract

We estimate wildfire impacts on Aotearoa New Zealand forests, focusing specifically on impacts in terms of vegetation recovery and costs. To this end, we use satellite-derived imagery of fire intensity and a vegetation index to measure burn severity and vegetation recovery. We then calculate profitability costs and post-fire remediation and clearing costs, estimated under various wildfire intensity scenarios, to determine the total cost of wildfires. We conclude, maybe unsurprisingly, that forests subject to high-intensity fires take longer to recover than those suffering medium- and low-intensity fires. The economic cost is also higher for higher-intensity fires, averaging 18,000 NZ$/Ha, but due to the small relative share of high-intensity fires, it is the medium-intensity fires that cause the most economic damages in New Zealand.

Keywords Wildfires · Economic costs · Remote sensing · Vegetation index · New Zealand

JEL Classification Q23 · Q54

Introduction

In Aotearoa New Zealand (NZ), two individual wildfires during the 2018/19 and the 2019/20 summer seasons burnt the largest forest areas recorded during the last 70 years (Scion 2020). Australia, which shares some global climate trends with NZ, has similarly experienced a raft of very devastating fires in the last 15 years; its wildfires were estimated to have a very large adverse wellbeing effect on people exposed to them (Johnston et al 2021). The consensus prediction, as expressed in the 6th Assessment Report by the Intergovernmental Panel on Climate Change is that "[f]ire weather indices are projected to increase in most of Australia (high confidence) and many parts of New Zealand (medium confidence), in particular with respect to extreme fire and induced pyro-convection." (p.

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1809; Seneviratne et al. 2021). *Ceteris paribus,* this increase in fire weather will lead to more fires with higher intensity, resulting in greater damages and impacts on wellbeing.[1]

Generally, three main factors can explain the severity of wildfires: terrain, weather and fuel availability (National Park Services 2024). Wildfires have an immediate impact on vegetation and also soil nutrients (Certini 2005), which in turn affect the recovery of vegetation cover over time. Depending on the time scale considered, different aspects of fires can be investigated. Fire intensity is a measure of instantaneous fire behaviour (i.e., the radiative energy released by a fire as it burns), fire severity relates to the immediate impact on the environment, while burn severity refers to longer term changes in the ecosystem (Rogers et al. 2015). All of these will determine the longer-term recovery trajectory of an affected ecosystem. In this study, we use remote sensing data to focus on burn severity and recovery as well as the cost associated with wildfire events.

To detect these disparate aspects of wildfires, remote sensing imagery has proved to be very useful. It covers a long time-span and wide geographic area and does not require on-the-ground assessment in remote locations. Remote sensing data have been widely used to investigate post-fire vegetation dynamics at the regional level. Several remote sensing studies on post-fire recovery focus on boreal forests. They find that these take between five and 15 years to recover (Amiro et al. 2011; Cuevas-González et al. 2009; Epting & Verbyla 2011; Hicke et al. 2003; Jin et al. 2012; Yang et al. 2017). Mediterranean ecosystems recovery takes longer, from 7 to 20 years (Fernandez-Manso et al. 2016; Hope et al. 2007). Studies for other types of forest find recovery time of three to six years for Eucalyptus forests in Australia (Caccamo et al. 2014), and 6 years for conifer in the US. Recovery rate of forests can depend on the regeneration type (e.g., from seeds for conifers, from resprouting for Eucalyptus) or whether the first is replaced with another ecosystem, such as grassland (Randerson et al. 2006). The burn severity also plays an important role in determining recovery rates (Jin et al. 2012).

Burn severity and vegetation recovery can be measured using either on the ground observations by calculating a field-based Composite Burn Index (CBI) (Key & Benson 2006), or using spectral indices from remote sensing imagery. Amongst spectral indices, the most commonly used are the Normalized Difference Vegetation Index (NDVI) (e.g. Rogers et al. 2015; Díaz-Delgado et al. 2010; Carlson et al. 2017), the Enhanced Vegetation Index (EVI), which is similar to NDVI but has improved sensitivity over high biomass regions (Ba et al. 2022; Caccamo et al. 2014; Jin et al. 2012; Kim et al. 2021), and the Normalized Burn Ratio (NBR) (e.g., Hislop et al. 2020; Bright et al. 2019).

When compared to CBI data from a ponderosa pine forest in South Dakota, Chen et al. (2011) find that differences between pre-and post-fire values of NDVI and EVI were highly correlated with the CBI scores for the first couple of years. Beyond those initial years, EVI showed better correlation, while NBR demonstrated a significant and high correlation through most of the sample. A study by Zheng et al., (2016) also compared CBI and several burn severity indices of five fires across the Western United States. They also devised a new index accounting for both Land surface temperature (LST) and EVI. They find that EVI based indices perform better than other measures in vegetation recovery in post-fire forests. Wu et al. (2015)'s comparison of CBI from east-central Arizona forests also finds that spectral indices, including the EVI, are effective for vegetation burn severity mapping.

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[1] According to the Ministry of Primary Industries, the forestry sector generates an annual gross income of around NZ$6.6 billion (1.6% of New Zealand's Gross Domestic Product) and employs 35,000-40,000 people. More detailed projections about future fire weather are available in Watt et al. (2019).

No study using remote sensing data has focused on NZ wildfires. The goal of this analysis is therefore to estimate wildfire impact on NZ forests in detail, using a much richer data, spatially and temporally, than is usually available in such quantifications elsewhere. We specifically focus on impacts in terms of vegetation recovery and costs.

Data and Methods

The analysis is conducted over the period 2001–2018 for both the North and South Islands of NZ. In order to estimate the impact of wildfires on forestry in NZ, we first extract land use data to distinguish forest types. We then determine if these forest grid cells have been affected by a fire during the study period and extract the associated fire intensity. Of those fire affected grid cells, we distinguish those having suffered a decrease in biomass (i.e. damaged) and estimate the recovery time. Using fire intensity dependent cost estimates, we finally determine the total cost of wildfire on planted forests.
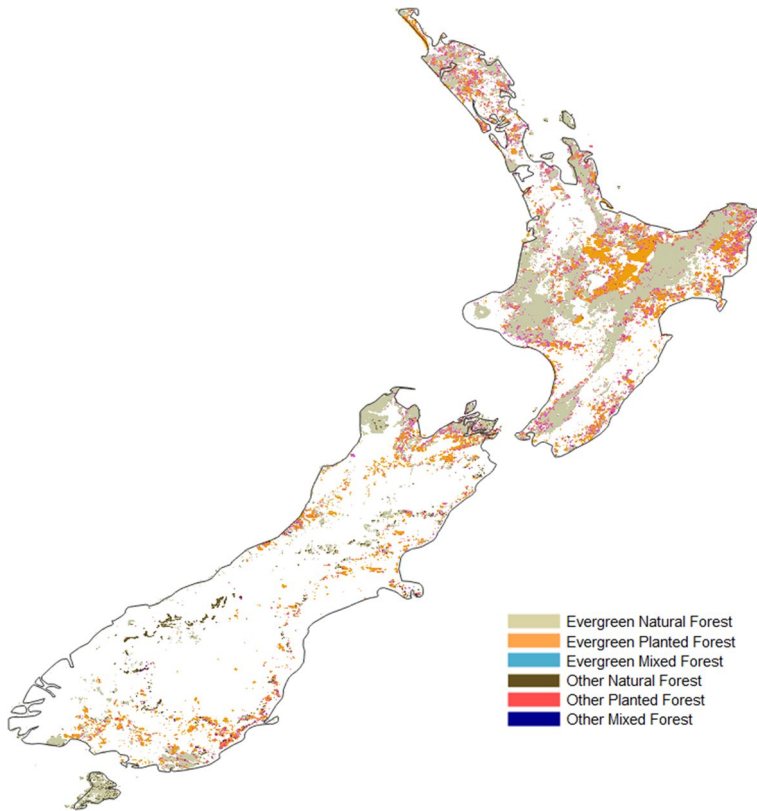
Land Use

To determine land use within each parcel, we used information from the Land Use Carbon Analysis (LUCAS) land use map v008 developed by the New Zealand Ministry for the Environment.[2] The LUCAS land use maps use a range of remote sensing, environmental and land use data sources to distinguish 12 land use classes over NZ, among which are three forest classes (pre-1990 natural forest, pre-1990 planted forest, and post-1989 forest). From these classes, we construct two main categories: 'Planted Forest', consisting of 'Pre-1990 planted forest', and 'Post-1989 forest' and 'Natural forest'. Land use information is available for 1 January 1990, 1 January 2008, 31 December 2012, and 31 December 2016. We consider that for a given year, the land use type corresponds to 2008 land use for the years up to 2010, the 2012 land use for the period from 2011 to 2013, and the 2016 land use for the period 2014 and after. Given our interest in wildfires, we focus on forested land only.

To determine if a forest is evergreen or deciduous, we use land cover classification obtained from the Terra and Aqua combined Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Type data product (MCD12Q1), version 6. It provides yearly land cover types at 500 m resolution. Using the International Geosphere-Biosphere Programme (IGBP) classification scheme, we consider evergreen forests as those represented by the 'Evergreen needleleaf forests' and 'Evergreen broadleaf forests' categories (Sulla-Menashe and Friedl 2018).

Grid cells overlapping non-forest land use types, in full or in part, are excluded from the analysis. Furthermore, grid cells overlapping multiple types of forest are classified as 'Mixed-type Forest'. Each of these types can be classified as evergreen if they encompass evergreen categories. We have therefore created six categories: 'Natural Forest', 'Evergreen Natural Forest', 'Planted Forest', 'Evergreen Planted Forest ', 'Mixed Forests', and

Fig. 1 Forest land use categories

Table 1 Land use area in NZ

Land use	Area (km2)			Share of total NZ land area		
	Evergreen	Other	Total	Evergreen	Other	Total
Mixed forest	7,716.75	240.25	7,957.00	3%	0%	3%
Natural forest	44,832.44	1,161.81	45,994.25	17%	0%	17%
Planted forest	15,895.88	725.81	16,621.69	6%	0%	6%
Total	68,445.06	2,127.88	70,572.94	26%	1%	26%

Total land area in NZ is 268,021 km.2

'Evergreen Mixed Forests'. In cases where forest type changes over time, the grid cell is classified as 'Mixed' over the whole span of the study period.

A map representing those forest categories is provided in Fig. 1. The sample area (in km^2) for each type of forest is reported in the first three columns of Table 1. The last three columns represent those area as a proportion (in percent) of total NZ land

area (268,021 km^2). These figures show that a majority of forests in NZ are evergreen natural.

Forest Fires

Given that forest recovery rates depend on burn severity (Jin et al. 2012), many studies distinguish different burn severity classes (e.g., 'high', 'moderate', or 'low' burn severity) to then measure forest recovery using a vegetation index temporal change (e.g. de Simone et al. 2020; Hao et al. 2022). NBR related measures are commonly used to distinguish burn severity classes. However, class thresholds differ between study regions (Key & Benson 2006; Miller & Thode 2007; Saulino et al. 2020) and can only be used reliably with field data calibration (French et al. 2008). Unfortunately, no class thresholds have been estimated for NZ forests, and it is not possible to determine class threshold values without ground reference data. Instead, we use fire radiative power (FRP) as a proxy for burn severity. FRP has been found to have a significant correlation with NBR in estimating the degree of fire disturbance (Shvetsov 2022) and can be used to predict long-term negative ecological effects of fires (Heward et al. 2013).

We follow Gatebe et al. (2014), Yang et al. (2017), Deng et al. (2021), and Qin et al. (2019) and consider active fires products such as the Thermal Anomalies and Fire 8-Day (MOD14) Version 6[3] (Giglio et al. 2003). The MOD14A1 dataset is available daily at a 1000 m spatial resolution. We account for all fire of nominal confidence and extract the corresponding maximum FRP.

Vegetation Change

To measure burn severity and forest regeneration, we extracted satellite derived imagery to identify the vegetation index for each grid cell across time. We use the Terra MODIS vegetation indices (MOD13Q1) version 6,[4] which is provided every 16 days at a 250 m resolution.[5]

To estimate the damage caused by fires in forest area, we first calculate the difference between vegetation pre- and post-fires:

$$dVI_t = \mathrm{VI}_{t+n} - \mathrm{VI}_{t-n} \qquad (1)$$

where $\mathrm{VI}_{f,t+n}$ is the VI index value of the fire affected grid cell considered for the nth 16-day period following a fire and $\mathrm{VI}_{f,t-n}$ is the VI index value for the nth 16-period preceding a fire.[6]

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[3] Available for download at https://lpdaac.usgs.gov/products/mod14a2v006/.

[4] Available for download at https://lpdaac.usgs.gov/products/mod64a1v006/.

[5] The Enhanced Vegetation Index (VI) is calculated using the near-infrared (*NIR*; 841–876 nm) and red (620–670 nm) spectral bands reflectance ρ, but reduces residual atmospheric contamination and variable soil back-ground reflectance by adjusting the reflectance in the red band as a function of the reflectance in the blue band (459–479 nm): $$VI=2.5\frac{{\rho }_{NIR}-{\rho }_{red}}{{\rho }_{NIR}+{6\rho }_{red}-7.5{\rho }_{blue}+1}$$.

[6] For instance, for a fire taking place in a given pixel between December 27 and January 17, pre-fire VI are obtained for the MOD13Q1 16-day product ending on December 16. Post-fire VI values are obtained from the MOD13Q1 16-day product ending on February 2.

Then, we calculate the same values for the forest grid cells surrounding the fire affected pixel as:

$$dVIs_t = \overline{\mathrm{VIs}}_{t+n} - \overline{\mathrm{VIs}}_{t-n} \tag{2}$$

where $\overline{\mathrm{VIs}}_{t+n}$ is the VI index value for the nth 16-day period following a fire and $\overline{\mathrm{VIs}}_{t-n}$ is the VI index value for the 16-period preceding a fire. In this case, $\overline{\mathrm{VIs}}$ correspond to the mean of VIs over the grid cells located within 5 km from the fire affected grid cell considered, but that are classified as forest and that are not themselves affected by fires (those are also called control pixels of offset areas). The 5 km radius was tested against other distances and showed the highest correlation between pre-fire VI values for the surrounding cells and pre-fire VI for the fire affected cells. We also restrict the surrounding cells to those whose VI values are within 10% of the VI value of the fire affected cell preceding a fire. This restriction is designed to ensure that we are only considering unburned control area that are representative of forest similar in phenology (e.g., Cuevas-González et al. 2009; Leeuwen et al. 2010; Parks et al. 2014).

When data are not available for the closest pre- or post-period n, the next closest period is considered. However, for consistency, the same period n is considered for both dVI_t and its surrounding cells $dVIs_t$. To determine the effect of a forest fire, we then take the delta between the dVI values:

$$\Delta VI_t = dVI_t - dVIs_t \tag{3}$$

Following Parks et al. (2014), we also calculate the relativized value, $R\Delta VI$, calculated as:

$$R\Delta VI_t = \frac{\Delta VI_t}{\sqrt{|\mathrm{VI}_{t-n}|}} \tag{4}$$

Cost Data for Planted Forests

Monge and Dowling (2022) quantified the most vulnerable factors of a forest system to wildfires in NZ. They considered different forest types (based on age classes, size, and slope) and used the following profit function as a reference when mapping various levels of fire intensities to different variables in the profit function:

$$profit_s = \sum_g \left(price_{g,s} * yield_{g,s}\right) - \sum_t^T \left(var_{s,t} + fix_{s,t}\right) - rem_s \tag{5}$$

where the s subscript represents the forest type, g the log grades, and t is time. $price$ is the log of prices and $yield$ is the log of productivity (both for each g and s), var is a measure of variable costs, and fix stands for fixed costs (both for each s, and t), and finally rem is a measure of remediation costs (for each s).

There are several reasons why different intensities of forest fires can affect yields, prices or cost parameters. These include: (1) Wildfires might affect the price of the log product, by affecting its marketable quality or salvage value, with different log grades being impacted by different fire intensities differently. (2) Wildfires most likely affect yields (or productivity) by delaying the time of harvest (i.e., delaying the optimal time to harvest). (3) Wildfires will also affect variable costs (var) by affecting productivity. For example, if the

forest stock is completely lost (*yield* = 0), then the landowner will not have to incur in any additional variable costs. If some of the forest is still salvageable, then some variable costs will need to be incurred but not at the same level as before the wildfire. (4) Wildfires will most likely not affect fixed costs as these still need to be incurred independently of whether the forest suffered any fire damage. (5) Wildfires will affect remediation costs (*rem*). For example, if a forest was completely lost, then the landowner would need to clear the land to replant (a form of remediation).

Based on this profit specification, Monge et al. (2023) used information from Tasman Pine Forests Ltd, following the Pigeon Valley fire near Nelson (NZ) in February 2019 to calibrate their model and analyse the cost of fire under current policy conditions on the forestry business. Post-fire salvage revenues were also quantified based on the Pigeon Valley fire assuming that for 25- and 26-year-old forests, 80% of non-pulp and unpruned log grades could be sold whereas young forests were assumed to need clearing and follow up windrowing. Monge et al. (2023) also developed the following set of scenarios based on how different fire intensities would affect different items in the previous profit function:

Low Intensity Fire (< 100 kW/m)

It was assumed that a low-intensity fire would spare the trees but scorch the undergrowth, possibly causing some damage to the trees. Young trees (0–10 years old) were assumed to perish even in a low-intensity fire. Clearing the land would be necessary to remove them before replanting, but it was assumed that replanting would be straightforward, requiring no additional remediation. For trees of intermediate age (11–20 years), it is conceivable that a low-intensity fire might spare the crop while burning only the low-lying scrub underneath. While the crop would likely sustain damage, evaluating this damage would be challenging if the trees remained alive, so no loss was assumed. For mature trees (20–30 years old), it was similarly assumed that there would be no loss.

Medium Intensity Fire (100–3,000 kW/m)

We assume that a medium-intensity fire results in the death of trees but leaves them intact for salvage operations. For young trees (0–10 years old), the heat from the fire would be sufficient to kill them. We presume that medium-intensity fires incur half the remediation costs of high-intensity ones. Since there is no salvage value for young trees, land clearing would be necessary. The incurred loss includes the value of the tree crop, clearing costs, and half of the remediation costs for fencing and erosion (based on high-intensity fire standards). For trees of intermediate age (11–20 years), they would require removal. The loss encompasses the value of the tree crop, clearing costs, and half of the remediation costs for fencing and erosion. Mature trees (20–30 years old) would also perish but salvaging them might be possible. However, the salvage value would be subject to a 20% reduction in value due to the compromised quality of burned logs. The loss incurred comprises the value of the tree crop and half of the remediation costs (fencing and erosion), adjusted for the salvage value.

High Intensity Fire (> 3,000 kW/m)

We assume that in the event of a high-intensity fire, all the trees are killed, and the quality of the logs is significantly degraded. For young trees (0–10 years old) and intermediate

Table 2 Fire remediation and clearing costs

Item	Cost
Fencing (NZ$/m)	25.00
Erosion for small and medium forests	485.00
Erosion for large forests	40.00
Windrowing for small forests	800.00
Windrowing for medium forests	650.00
Windrowing for large forests	500.00
Felling small forests (NZ$/tonne)	14.85
Felling medium forests (NZ$/tonne)	11.55
Felling large forests (NZ$/tonne)	8.25

Table 3 Forest areas affected by fires in NZ over the period 2001–2018

Land use	Area (km2)			% of forest area		
	Evergreen	Other	Total	Evergreen	Other	Total
Mixed forest	91.56	3.44	95.00	1.19%	1.43%	1.19%
Natural forest	128.88	1.19	130.06	0.29%	0.10%	0.28%
Planted forest	158.88	6.56	165.44	1.00%	0.90%	1.00%
Total	379.31	11.19	390.50	0.55%	0.53%	0.55%

The percentages of forest area are calculated using values from Table 1

age trees (11–20 years old), land clearing would be necessary to remove the crop before replanting, resulting in a loss equivalent to the entire value of the tree crop and the associated remediation costs. Mature trees (20–30 years old) also succumb to the fire but can potentially be salvaged at a 20% reduction in their value. The incurred loss would encompass the value of the tree crop and the remediation costs, adjusted for the salvage value.

The profitability of representative forest types was modified accordingly to include the damages exerted by these wildfire scenarios. The representative forest types differed in size (i.e., small, medium, and large), age classes (i.e., young, intermediate, and mature), and slope (i.e., flat and steep). Although we have estimated the potential fire impacts on a total of six different forest types (3×2), we used the average across these 18 types for each wildfire intensity. Table 2 describes the post-fire remediation and clearing costs that were used under the various wildfire intensity scenarios according to the intensity measured.

Results

Summary Statistics

Forest areas are categorized into six different groups, distinguishing natural, planted and mixed forests and within those, whether they are evergreen forests or of another type (i.e., deciduous or mixed type). Table 3 presents the area of forest having been affected by a fire over the study period, as well as the proportion of NZ forest these

Fig. 2 Fire affected area (in km.²)
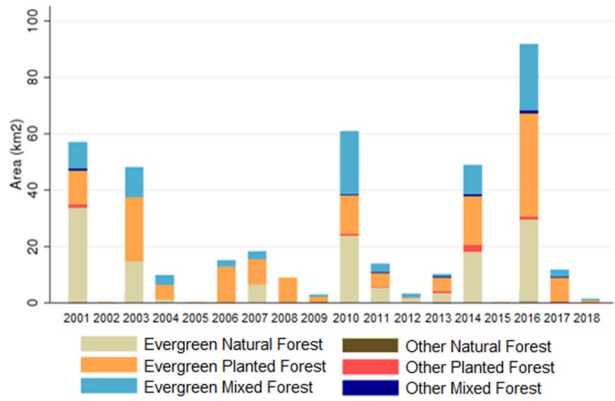
**Fig. 3** Location of fire-damaged forest
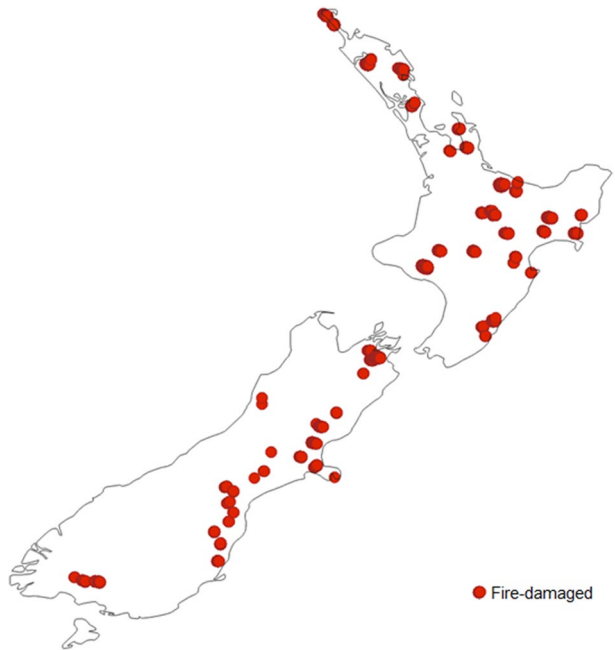
areas represent. These figures show that only a small percentage of forest area have been affected by fire and that most of those are planted and natural evergreen forests.

As presented in Fig. 2, the area having experienced an active fire in NZ vary from year to year across the study period, with peak years in 2010, and 2015. However, for 2002, 2016 and 2018, there were very few fire-affected areas. In the present sample, each grid cell only experienced fire once over the analysis period. Planted forests are usually the most affected by forest fires, except in 2001 when most of the fire affected areas were classified as natural forest. Across the year, the fires are most prevalent in February and March. Natural forest seems to be most prone to fires in February and

Table 4 Forest areas affected and damaged by fires in NZ over the period 2001–2018

Land use	Area (km2)			% of fire affected forest area		
	Evergreen	Other	Total	Evergreen	Other	Total
Mixed forest	46.31	1.75	48.06	50.58%	50.91%	50.59%
Natural forest	73.56	1.00	74.56	57.08%	84.21%	57.33%
Planted forest	70.56	4.63	75.19	44.41%	70.48%	45.45%
Total	190.44	7.38	197.81	50.21%	65.92%	50.66%

The percentages of fire affected forest area are calculated using values from Table 3
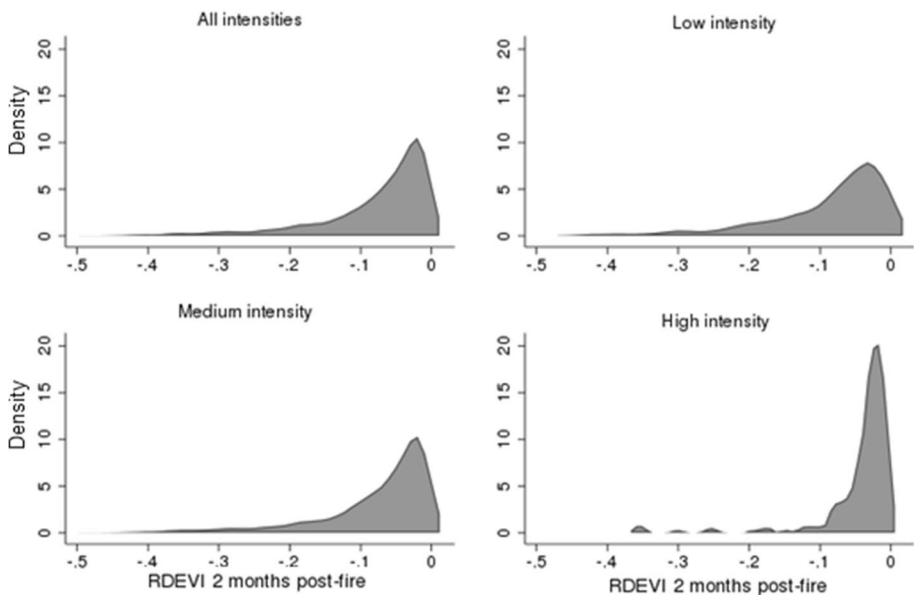
Fig. 4 Density R∆EVI for all fire damaged forests, by fire intensity categories

May. There were few fires during the winter season. As shown in Fig. 3, forest wildfires occur mainly in the central North Island of NZ and in the lower South Island.

Wildfire Damages and Recovery

Not all areas having been affected by a fire show a loss in biomass. Table 4 shows the fire affected forests that experienced a loss in biomass (R∆EVI < 0). For ease of understanding, those cells are henceforth classified as 'damaged'. Amongst those fire affected forests, 50% of the evergreen forests and 66% of 'Other' forests were damaged during the study period. The analysis in this and following section will consider only fire-damaged forest areas.

Figure 4 shows the R∆EVI density for fire-damaged areas calculated 2 months after a fire for all forests. The graphs show that largest share of the density two months post fire is close to 0 R∆EVI, indicating that a majority of the area' vegetation has suffered a

Fig. 5 Forest recovery time from wildfires
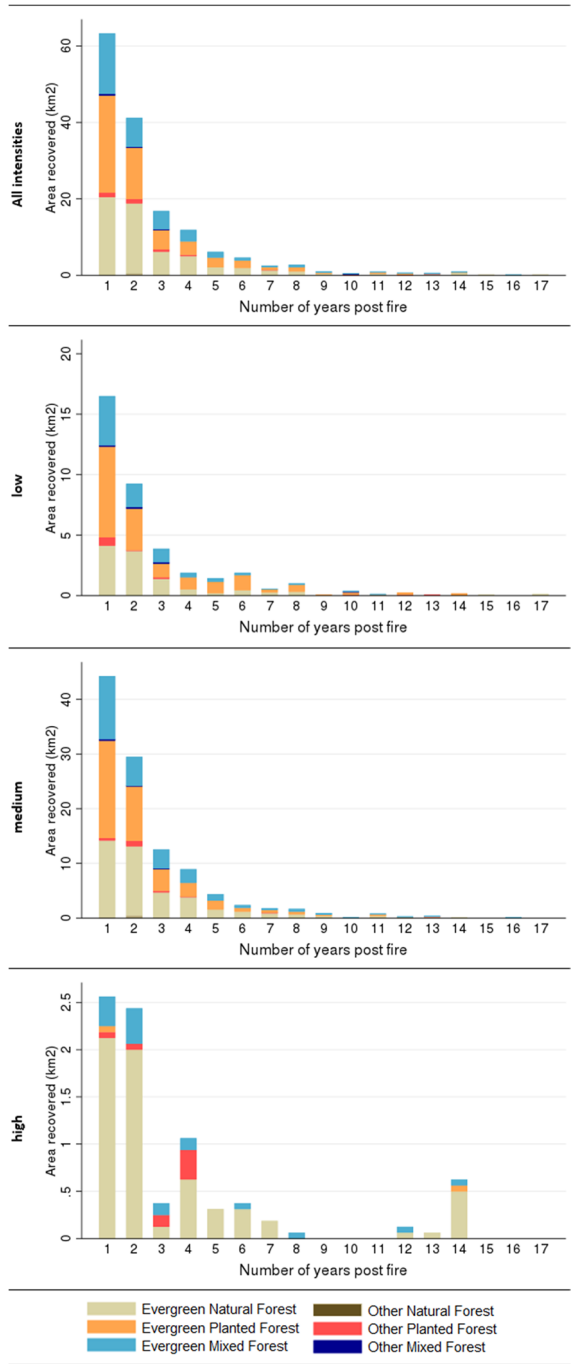
Table 5 Costs for each fire intensity, by type of forest

Forest types	Economic costs ($/km²) for different fire intensities		
	Low	Medium	High
Small-Young-Flat	1,459,300	1,641,700	1,824,000
Small-Young-Steep	1,413,900	1,596,300	1,778,600
Small-Intermediate-Flat	0	2,509,700	2,692,100
Small-Intermediate-Steep	0	2,058,900	2,241,300
Small-Mature-Flat	0	496,700	1,872,800
Small-Mature-Steep	0	745,700	2,322,000
Medium-Young-Flat	1,189,900	1,236,500	1,283,100
Medium-Young-Steep	1,189,200	1,235,800	1,282,400
Medium-Intermediate-Flat	0	2,154,500	2,201,100
Medium-Intermediate-Steep	0	1,824,600	1,871,200
Medium-Mature-Flat	0	361,000	1,601,300
Medium-Mature-Steep	0	608,700	2,066,700
Large-Young-Flat	935,700	939,900	944,200
Large-Young-Steep	1,061,200	1,076,600	1,091,900
Large-Intermediate-Flat	0	1,891,000	1,895,200
Large-Intermediate-Steep	0	1,706,800	1,722,200
Large-Mature-Flat	0	318,600	1,516,500
Large-Mature-Steep	0	576,200	2,015,300
Average ($/ha)	402,700	1,276,600	1,790,100

Size: small (< 10 ha), medium (10–50 ha), large (> 50 ha); Age: young (0–10 yrs), intermediate (11–20 yrs), mature (>20yrs); Slope: flat (≤ 10°), steep (> 10°)

relatively small loss in biomass. The density functions tails to the left, with some grid cells experiencing a sharp decline in vegetation, although one would have expected the density functions to be skewed further to the left as the fire intensity increased.

To determine the recovery time, we calculate the number of years for the RΔEVI to become positive. Figure 5 shows recovery time by grid cell for each forest type. Grid cells not having recovered by the end of the sample, either because data are missing, or because of fires occurring late in the sample period are not represented in this graph. The other bars show that most grid cell take one or two years to recover from a wildfire, but for a few cells, the forest has not recovered after more than a decade after the fire. For high intensity fires, the area not having recovered beyond the first two years is larger than those for the other categories, showing the larger impact of high intensity fire. The results for the evergreen forest sample are very similar in their substance to those for the whole sample, indicating that the whole sample is not influenced by canopy phenology (which was, to some extent, already accounted for by using RΔEVI which compares grid cell to unburnt neighbouring forest grid cell).

Wildfire Costs

Next, in Table 5, we calculate the estimated costs, per hectare, for the three wildfire intensities and for the 18 types of forests we examined. It's worthwhile to note that while
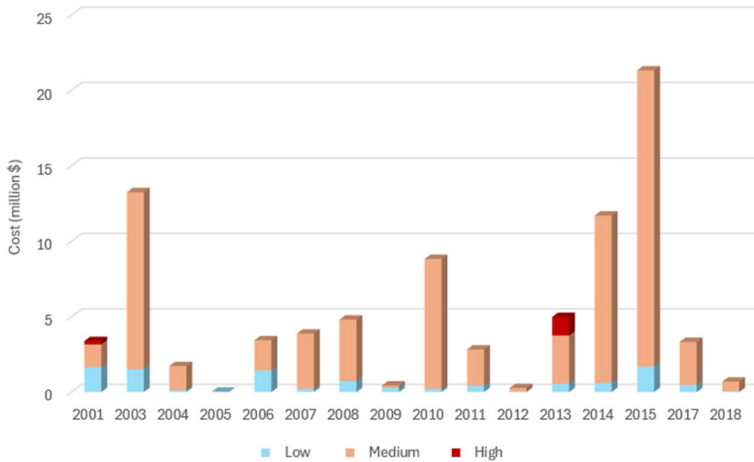
Fig. 6 Overall costs, by year, for each fire intensity

Table 6 Overall costs by forest land use type and intensity

Land use	Low	Medium	High	Total
Evergreen Planted Forest	9.44	69.57	0.22	79.24
Other Planted Forest	0.5	3.83	1.23	5.56
Total	9.94	73.4	1.45	84.8

medium-intensity fires are about three times as costly as low-intensity ones, the difference between medium- and high-intensity fires is much smaller. On average, high-intensity fires are about 40% more costly, but they are also much rarer. For young forests, the differences between the three intensities are very small, and in some cases it is negligible. It is also worth noting that for many types of forest combinations, low-intensity fires are not really damaging; it is only for young trees that the low-intensity fires are damaging.

Lastly, using the average calculated costs in Table 5, we estimate the overall costs of fires in NZ over the past two decades (2001–2018). The time series is not long enough to discern any trends with any statistical confidence, but a few of the worst years have been more recent. The two worst years in our sample were 2010 and 2015; in 2015, our estimates suggest that wildfires cost the owners of the planted forests NZ$17 million and NZ$22 million respectively.

We note that these costs do not include the many other costs associated with wild-fires. These include the costs of operating the emergency services, the costs associated with increased particulate matter (pollution) in the atmosphere, costs of the hedonic amenities provided by the burned areas before the fire, and any spillovers associated with the employment shock the fires may have generated. Another interesting observation is that in those past years in NZ, most of the damage was associated with medium-intensity fires, and not with high-intensity ones (see Fig. 6). That is, of course, because high-intensity fires were much rarer than medium-intensity ones, and medium-intensity fires are much more damaging the low-intensity ones. These results may be a function of random events in those years. With the dryer and windier conditions that are

predicted for both hotspots for fires in the NZ landscape, an increasing probability of high-intensity events may lead to significant changes in these patterns in years to come. Overall, in these years, the estimated costs to owners from the destruction of trees and the other associated costs from wildfires is almost NZ$85 million. As shown in Table 6, the costs are the largest for evergreen natural forests.

Caveats and Conclusions

In this study, we focused on identifying the burn severity and recovery from wildfires in NZ using remote sensing imagery. We also calculated the cost associated with these identified wildfire events. To detect these disparate aspects of wildfires, we used remote sensing imagery given its extensive and intensive spatial and temporal detail and the absence of on-the-ground assessments.

No other study using remote sensing data has focused on NZ, so ours is the first study to provide an aggregate measure of wildfires costs for the NZ case – for the years 2001–2018, we find an aggregate cost of almost NZ$ 150 million, with 2015 showing about NZ$ 35 million worth of damage to the tree crop. We also found that medium-intensity fires, which are much more common than high-intensity ones in the NZ case, are also the most damaging in the aggregate.

The goal of this analysis was to estimate wildfire impacts on New Zealand forests in detail, using a much richer data than is usually available in such quantifications. These impacts, and their costs, are significant; they clearly suggest a need to manage wildfire risk better.

Previous research has shown that the Enhanced Vegetation Index is well calibrated to perform better than other remote sensing indices for measuring vegetation recovery in post-fire forests. We note, however, that recovery may be a function not only of the ability of the forest to regenerate after the damage from a fire, but also may be determined by the actions of the landowner. For example, the landowner may decide to change the use of the land, after the fire, into other uses (e.g., pasture). In that case, we will observe no recovery, but that failure to recover is not a failure of the natural ecosystem to do so. We are unable to determine landowners' intentions, however. We also note that no ground-truthing of the use of EVI in the NZ context is available, which requires us to investigate the robustness of our results further.

Our analysis is also limited to the direct monetized costs associated with wildfires. This analysis does not include aspects that cannot be monetised easily, such as the damage to ecosystems and the services they provide, or to indirect costs associated with increased pollution of particulate matter that can be created by the fire. There are several ways to monetize these kinds of costs; for example in the various non-structural econometric work on pollution impacts, or with willingness-to-pay for environmental services. We leave these issues for future research.

Data Availability All data will be posted publicly once the paper is accepted for publication.

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