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The influence of prescribed burning and wildfire on lidar-estimated forest structure of the New Jersey Pinelands National Reserve

Timothy A. Warner [A,D], *Nicholas S. Skowronski*[B,D] *and Inga La Puma*[C]

[A]Department of Geology and Geography, West Virginia University, Morgantown, WV 26506, USA.
[B]USDA Forest Service, Northern Research Station, Morgantown, WV 26505, USA.
[C]Center for Remote Sensing and Spatial Analysis, Rutgers University, New Brunswick, NJ 08901-8551, USA.
[D]Corresponding authors. Email: Tim.Warner@mail.wvu.edu; nicholas.s.skowronski@usda.gov

Abstract. Prescribed burning is a common land management tool used to reduce fuels, emulate the effects of wildfire and increase heterogeneity in fire-prone ecosystems. However, the forest structure created by prescribed burning is likely to be dissimilar to that produced by wildfire. We used three-dimensional estimates of canopy bulk density (CBD) from lidar data to explore the relationship between fire type, number of burns and fuel structure/forest structure in the New Jersey Pinelands National Preserve, USA. We found that in areas of previous prescribed fires, as the number of fires increased, the understorey (1–2 m) exhibited a slight decrease in CBD, while the upper canopy (15–23 m) had higher values of CBD for ≥4 fires, though these differences were not statistically significant. However, an increasing number of wildfires was associated with a statistically significant increase in CBD in the mid-storey (3–7 m) and a decrease in CBD in the canopy (≥8 m). These results have important implications for forest resource managers because they indicate that prescribed burning reduces ladder fuels that lead to torching and crown fires, but it does not replicate the structure created by wildfire.

Additional keywords: airborne laser scanning (ALS), burn frequency, canopy height profile, forest structure, lidar, prescribed fire, wildland fire.

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Introduction

Many forest ecosystems are adapted to periodic fire (Pausas and Keeley 2009) and exclusion of fire from such areas has often proven to be counterproductive, resulting in changes in forest composition and structure, and more intense fires, when fires inevitably return (Stephens and Ruth 2005). The latter is of considerable concern in the wildland–urban interface, where property and lives are at risk (Clark *et al.* 2009). Forest resource managers therefore use prescribed fires to gain, in a more controlled environment, some of the benefits of wildfire, including reduced forest fuels, ecologically preferred outcomes such as the maintenance of fire-adapted communities, creating wildlife habitat, encouraging rare species and restoration of the stand- to landscape-scale structural complexity, as well as global climate benefits, such as stabilising forest carbon (Fernandes and Botelho 2003; Ryan *et al.* 2013; Addington *et al.* 2015; Clark *et al.* 2015; Hurteau *et al.* 2019). However, prescribed fires are by design usually less intense than wildfires. Therefore, in forests that are historically prone to crown fire, prescribed burning, and even repeated prescribed burning, is unlikely to produce a forest structure similar to that produced by wildfires. For forest resource managers focused on habitat creation or emulating historical conditions, this raises key concerns about whether prescribed burning regimes are achieving the desired forest attributes (Welch *et al.* 2000) and if so, how to quantitatively show these objectives are being met.

Using a case study in the New Jersey Pinelands National Reserve (PNR), in New Jersey, USA, we quantified how pine forests vary in their vertical structure as a function of fire, comparing forests burned one or more times by prescribed fires, wildfire or both. Prior work by Boerner (1981) established that in these forests, wildfires reduce canopy fuels and increase understorey fuels, whereas prescribed fires cause temporary decreases in understorey fuels and have little effect on canopy fuels. Boerner's (1981) findings are consistent with a general model for fire-adapted ecological communities where high-intensity wildfires result in substantial crown mortality and low-intensity prescribed fires that predominantly burn understorey fuels and have less effect on the canopy (Agee and Skinner 2005). Boerner's (1981) study was based on just five sites within a small area of the Pinelands and his study quantified field observations in terms of broad measures such as above ground biomass or numbers of stems in different height classes.

In this work, we applied the lidar-canopy bulk density (CBD) methods proposed by Skowronski *et al.* (2011) to quantify a theoretical land management objective in which prescribed fires are designed to match the structural effects of wildfire. We hypothesised that in PNR's predominantly pine forests, areas with a history of prescribed fire will have reduced ladder fuels but increased canopy fuels in comparison to areas with a history of wildfire. We also hypothesised that because prescribed fires are expected to reduce the intensity of wildfires (Agee and Skinner 2005), areas that have experienced both wildfires and prescribed fires in recent years will have a structure more similar to that of areas with a history of prescribed fire than of wildfire.

We quantified fuel loads in terms of vertical arrangement of the CBD (with units of kg m^{-3}), a measure of biomass, including combustible foliage and woody material, per unit volume (Botequim *et al.* 2019). CBD is useful metric for characterising the structural effects of disturbance, including fire, and is also a key input in fire behaviour models such as FARSITE (Finney 1998) and firebehavioR (Ziegler *et al.* 2019). CBD has been traditionally measured using destructive methods, but can also be modelled using non-destructive methods such as those based on allometric equations, most notably in the Fire and Fuels Extension to the Forest Vegetation Simulator (FFE-FVS) (Scott and Reinhardt 2001; Reinhardt *et al.* 2006). As an alternative to these approaches, airborne lidar (also known as airborne laser scanner (ALS) data) can be used to produce maps of the variation of CBD with height above the forest floor (Skowronski *et al.* 2011; Hoe *et al.* 2018). One particular strength of utilising lidar-based CBD maps is the provision of detailed, spatially explicit information covering the entire study area. Many studies have evaluated the effect of prescribed fires and wildfires on fuels with field methods (e.g. Boerner 1981; Little 1998) and lidar (e.g. Loudermilk *et al.* 2012; Hudak *et al.* 2016; Botequim *et al.* 2019; Huesca *et al.* 2019), but the strength of this study is the detailed characterisation of the canopy CBD profile in 1-m increments, the comprehensive archive of maps of historic fires extending back more than 80 years and the broad spatial scale covered, which encompassed a major portion of the PNR. The database includes areas that have been burned many times over many years, allowing an assessment of variation in forest fuels at the fire regime level rather than at the scale of a single event. To our knowledge, this is the first study to do so over a broad extent using lidar.

Study area

The PNR is a 445 000-ha forested region and UNESCO World Heritage Site, located between New York City and Philadelphia (Pinelands Commission 2015). The PNR region is a mixture of undeveloped forest and small, isolated rural settlements. Our study area was 150 000 ha within the PNR, comprising the south-eastern portions of Burlington and Camden counties, New Jersey. The boundaries of the study area were determined by the availability of the lidar dataset used, as discussed in the following section.

The dominant upland forest species are pitch pine, *Pinus rigida* Mill., and a variety of oaks, including *Quercus alba* L., *Q. velutina* Lam., *Q. coccinea* Muenchh. and *Q. prinus* Willd. (Boerner *et al.* 1988; Little 1998). The proportion of pine varies from pure pine to pure oak (McCormick and Jones 1973). The major forest communities are pine-oak, pine-scrub oak and the so-called pine plains, a distinctive short-statured (< 2 m) community. The understorey is generally dense, with *Gaylussacia* spp. and *Vacccinium* spp. common throughout the area and *Q. ilicifolia* Wangenh., *Q. marilandica* Muenchh. and *Q. prinoides* Willd. principally in the pine-scrub oak community (Boerner *et al.* 1988; Landis *et al.* 2005).

The PNR is a fire-adapted landscape (La Puma *et al.* 2013; Warner *et al.* 2017; Skowronski *et al.* 2020), as indicated by the many fire-adapted traits found here, such as epicormic sprouting and serotinous cones (Givnish 1981). Although there is limited information on the pre-European settlement fire frequency, it was likely greater than today (Forman and Boerner 1981). Human settlement, especially the introduction of charcoal production in the 1800s and the development of railroads, likely initiated a period of increased fire frequency and larger fires. Forman and Boerner (1981) estimated a 20-year fire return interval for upland forests in the PNR in the early 20th century, changing to ~65 years following the introduction of periodic prescribed burning in the late 1930s. In a more recent forest landscape simulation study, Scheller *et al.* (2008) assumed a pre-colonial 32-year return interval for wildfire, and 186-year return interval for the current landscape. La Puma *et al.* (2013) found a return interval of 76–113 years for the wildfire-only regime between 1963 and 2007 in upland pine-dominated systems. In the dwarf pine plains, fires have been considerably more frequent than in the rest of the uplands. Buchholz and Zampella (1987) calculated a 28-year fire return interval between 1953 and 1982 in the dwarf pine plains and La Puma *et al.* (2013) calculated a 35–47-year wildfire return interval between 1963 and 2007.

Most prescribed fires are implemented during the dormant season and within the study area averaged ~2450 ha $year^{-1}$ over the previous 60 years (1956–2015). Wildfires over the same period burned 2100 ha $year^{-1}$ on average, though the annual value is currently decreasing; over the last 5 years of that interval (2010–15) only 724 ha $year^{-1}$ within the study area were burned. An added complexity is that occasional wildfires grow much larger in size (Mueller *et al.* 2017). Most wildfires have an anthropogenic origin, with only 1% of wildfires caused by lightning (La Puma *et al.* 2013).

Data

Lidar data

The lidar data of the study area were acquired in April 2015, during the leaf-off period, by Quantum Spatial Inc., under contract to the United States Geological Survey (USGS) (Quantum Spatial Inc. 2015). A Leica sensor, able to record up to four returns per pulse, was flown at ~1580 m above the ground, with a maximum scan angle of 36°, resulting in an average of 8 points m^{-2}. The data were post-processed by Quantum Spatial Inc., including classification of the point cloud into ground and canopy classes. A bare earth digital elevation model from these points was found to have a vertical root mean square error (RMSE) of 0.041 m (Quantum Spatial Inc. 2015).

Burn area maps

Vector data of historical burn areas were obtained from a geodatabase compiled by La Puma *et al.* (2013), who digitised fire perimeters from hardcopy fire records maintained by the New Jersey Forest Fire Service (NJFFS). Perimeters were located and updated by La Puma *et al.* (2013) using a 1930s aerial photography mosaic (exact date not known), digital mosaics of USGS topographic maps, which ranged in dates from 1954 to 1997, and more recent aerial photography, which included 1995–97 and 2006 digital orthophotos. Fires after 2007 were archived digitally and added to the geodatabase by the NJFFS. The database contains 347 wildfires and 940 prescribed fires before the lidar acquisition date in the study area. The earliest wildfires in the database for the study area occurred in 1930 and the earliest prescribed fires occurred in 1956. One limitation to the data is that the ability to verify prescribed fires before 2007 was limited. Older prescribed fires were digitised from paper maps obtained from the NJFFS' Division B headquarters on which the date of burning was typically indicated. In some cases, it was clear that burns were planned using the paper maps, but an actual burn date was not recorded on the map; however, shading in of burn blocks or confirmation from local fire wardens was interpreted to mean that burns did take place during the planned year.

Vegetation map

To identify pine forests, we used the 2012 New Jersey land use/land cover (LULC) map, produced by the New Jersey Department of Environmental Protection (2012). The vector map was generated through visual interpretation of satellite and aerial imagery and is part of a series of LULC maps of New Jersey that has been produced since 1986. The minimum mapping unit is 1 acre (0.4 ha). An earlier version of the map, from 2001, had an estimated overall map accuracy of 91% (Lathrop and Kaplan 2004). The map uses a modified Anderson *et al.* (1976) level III–IV classification scheme. We used classes 4210 and 4220 (coniferous forest, with crown closure of respectively 10–50% and > 50%), as well as classes 4311 and 4312 (dominantly coniferous, with mixed deciduous forest, and crown closure of respectively 10–50% and > 50%). These classes correspond to the pine-dominated forest communities of pine-oak and pine-scrub oak discussed above; the pine plains corresponding specifically to class 4210.

Methods

The lidar processing generally followed the procedures developed by Skowronski *et al.* (2011), in which the lidar point cloud is rasterised into a three-dimensional set of voxels that characterise the vertical distribution of biomass, termed the canopy height profile (CHP). We used only the lidar first returns, to be consistent with Skowronski *et al.* (2011). The voxel approach assumes that the proportion of lidar returns, p_{bin}, from any one level (bin) in the canopy is an indication of the distribution of biomass in that level. One complexity is that, as the energy from the lidar pulses is progressively reflected away by interactions with the upper canopy, there is less energy remaining for potential interaction with lower layers. Therefore, the analysis is performed sequentially from the top layer (23 m in our study) to the lowest. Thus, p_n, for a voxel in the top level of a voxel stack of n levels, is calculated as:

$$p_n = \frac{R_n}{R_{\text{total}}} \tag{1}$$

where R_n represents the number of lidar returns in the voxel of height n, and R_{total} represents the total number of returns summed over all height levels (1 to n). The subsequent, lower levels are calculated using:

$$p_{n-x} = \frac{R_{n-x}}{R_{\text{total}} - \sum_{y=0}^{y=x-1} R_{n-y}} \tag{2}$$

where x is a value from 1 to (n – 1) (Skowronski *et al.* 2011).

We used the Toolbox for Lidar Data Filtering and Forest Studies (Tiffs; Chen 2007) to produce voxels that are 30 × 30 m in the horizontal, × 1 m in the vertical. These CHP values were calibrated to CBD (Botequim *et al.* 2019) using the 'all height bins' equation developed within the study area by Skowronski *et al.* (2011). The CBD model was developed with data from 19 plots × 20 height bins for a total of 380 data points for the equation. The calibration had an RMSE of 0.015 kg m^{-3} and an overall regression coefficient between the lidar and field data of 0.82. The regression coefficient between the lidar and field data for the individual CBD 1-m layers varied as a function of height: it increased from 0.0 at 1 m to 0.8 at 7 m, decreased to 0.4 at 9 m, then increased again to almost 1.0 at 12 m, before decreasing again to 0.9 at 17 m. The 'all height bins' equation estimates CBD from Eqn 3 below (originally from table 4 in Skowronski *et al.* 2011):

$$\text{CBD}_{\text{bin}} = 0.182 p_{\text{bin}} + 0.005 \tag{3}$$

where CBD_{bin} is the estimated CBD for the voxel of height bin, and p_{bin} is the lidar proportion value from Eqns 1 and 2.

Summary data on the canopy profile were produced by averaging the CBD voxels for the understorey (1–2 m), midstorey (3–7 m), lower canopy (8–14 m) and upper canopy (15–23 m). The thresholds separating the three vegetation strata were chosen empirically, after examining summary CHP graphs.

The lidar CBD data were then compared with the fire frequency analysis data, after masking all areas not dominated by pine, as indicated from our vegetation classes. Fire frequency was mapped separately for areas that since 1930 had experienced only prescribed fires, only wildfires or both. The maximum number of prescribed fires recorded at any one location was 15, the maximum number of wildfires was 6 and for areas that had experienced both prescribed and wildfires, the maximum number was 19 fires. However, the areas experiencing such frequent fires were very small (< 100 ha) and we therefore combined all pixels with ≥ 5 prescribed burns or wildfires in the categories of ≥ 5 prescribed fires or ≥ 5 wildfires respectively, and similarly areas with ≥ 10 combined prescribed and wildfires were grouped in a single category of ≥ 10 combined fires.

We calculated the least-squares linear relationship in the average CBD as the number of fires increased, for each of the 23 1-m voxels for both wildfires and prescribed fires (Skowronski

2011). The significance of the relationship between the number of fires and CBD was determined from an F-test (Illowsky and Dean 2012). To address the multiple comparisons problem, we applied the Benjamini-Hochberg procedure to control the false discovery rate (incorrect rejections of the null hypothesis) at a critical value of 0.05 (Benjamini and Hochberg 1995). The Kolmogorov–Smirnov two-sample test was used to evaluate the differences in the distributions for mean CBD with various numbers of prescribed fires, wildfires and both prescribed fire and wildfire. We used the R ks.test function in the dgof package (v1.2) (Arnold *et al.* 2016).

Results

Areas burned by only wildfires in the previous 85 years covered the largest area within the study site, 26 912 ha (Table 1, Fig. 1). Areas burned by only prescribed fires covered 4962 ha and areas that experienced both wildfires and prescribed fires covered an additional 9427 ha.

The pattern of variation in CBD values with increasing numbers of fires generally showed the largest differences in CBD for wildfire, intermediate differences for wild and prescribed fire and the smallest differences for prescribed fires (Fig. 2). Wildfire exhibited a strongly positive relationship (i.e. increased biomass as the number of previous fires increased) for 2–7 m and then a strongly negative relationship above 7 m, peaking at 12 m. These relationships were statistically significant from 4 m to 6 m and from 9 m to 18 m. Prescribed fires were related to negative differences in CBD below 15 m, with a small peak at 2 m and a slightly larger peak at 11 m. Above 15 m, the relationship was positive. However, none of these relationships were statistically significant. The combination of both prescribed fires and wildfires had a negative relationship with the number of fires below 11 m and positive values above that threshold. The coefficient of determination of the linear relationships for this combination class was generally low for the upper two-thirds of the canopy profile (8–22 m), with only 1–6 m and 23 m having statistical significance (Fig. 2).

Table 1. Area of pine-dominated forest within the study burned by fire type and number of fires

No. of fires	Area burned (ha): Both wildfire and prescribed fire	Wildfire only	Prescribed fire only
1		11 626	1662
2	1850	10 597	1074
3	2106	3175	993
4	1965	1350	799
5	1230	163[B]	433[C]
6	1023		
7	498		
8	471		
9	124		
10	159[A]		
Sum (ha)	9427	26 912	4962

[A]Areas with ≥ 10 combined wildfires and prescribed fires.
[B]Areas with ≥ 5 wildfires.
[C]Areas with ≥ 5 prescribed fires.

Fig. 3 explores these relationships by plotting the distribution of CBD within the selected strata as a function of the number of fires. Areas that experienced wildfires generally had a wider range of CBD values than prescribed fires, with the exception of the upper canopy, where wildfires were mostly associated with very low densities. The number of prescribed fires did not appear to have a strong influence on CBD values, with the exception of the upper canopy, where densities were higher in areas with ≥ 4 previous fires. Table 2, which summarises the Kolmogorov–Smirnov two-sample test for equality of continuous distributions, indicates that relationships between number of fires and mean CBD were generally significantly different for wildfires versus prescribed fires and for wildfires versus both wildfires and prescribed fires, with the exception of the lower canopy, where no relationships were significantly different. However, for prescribed fires versus both wildfires and prescribed fires, the distributions were not significantly different, except for the upper canopy.

Discussion

Prescribed fire is used by some land managers as an attempt to mimic the effects of wildland fire (Kolden 2019) and by others to reduce fire hazard (Fernandes and Botelho 2003), as well as the likelihood of wildfires (Addington *et al.* 2015). The objective of this study was to evaluate the contrasts in forest structural response that result from wild and prescribed fires. We found significant relationships between fire frequency and fuel loading at most heights within the canopy for wildland fire, but the relationships were not significant for prescribed fire (Fig. 2). The slope of these relationships was opposite for the two fire types for all heights within the canopy, except 8–14 m. For instance, areas with higher wildfire frequency had a lower density of fuel at the top of the canopy, whereas increased frequency of prescribed fire had more fuels at the same height, although the effect was only apparent after ≥ 4 burns. In contrast, increased wildfire frequency correlated with increased fuel loading in the understorey and mid-storey, with prescribed fire showing the opposite relationship.

Following Boerner (1981), we hypothesised that, because prescribed fires are often low-intensity fires, the greatest effect of prescribed fire in removing fuels would be near the surface and in the lowermost section of the canopy. Not surprisingly, our results, as shown in Fig. 2, were consistent with this hypothesis, because increasing fire frequency correlated with a loss of fuels from the understorey and lower canopy (1–14 m). However, Fig. 3 indicates that this relationship, as with the pattern in the upper canopy, was apparent only after ≥ 4 fires. There may be several reasons for this result. First, a forest parcel that has been unburned for an extensive period will likely have a high initial fuel loading. To mitigate risk, the firing operations during the first several entries into the parcel will likely be very conservative and result in very low fire intensity (NJFFS, pers. comm.). Second, much of the loss in fuel loading is likely due to subsequent understorey stem mortality and not consumption during the prescribed fires; repeated burns present a higher probability of previous injury, which can lead to mortality (Alexander *et al.* 2008).

In contrast to prescribed fires, wildfires are often more intense, leading to crown fires that consume canopy fuels and in many cases cause overstorey stem mortality. For example, Boerner (1981) found almost one-quarter of pine stems were dead 3 years following wildfires. Consequently, even a single wildfire can have a major effect on the canopy, with a strong relationship of decreasing CBD in both the upper and lower canopy and a marked increase in CBD at the mid-storey level with an increasing number of wildfires. Boerner (1981) described a dense canopy above 1 m following severe wildfires in the PNR. In this forest system, the most likely cause of this pattern is recruitment and resprouting following the fire. A wildfire could result in a range of different conditions, depending on its severity. In the case of a low-severity fire in pitch pine stands, epicormic resprouting from the bole and branches is common. In a more severe fire, the upper bole and branches die and the tree resprouts at the base (Pausas and Keeley 2017). In the case of the most severe fires, mineral soil may be exposed, with regeneration subsequently occurring from seeds released from serotinous cones (Landis *et al.* 2005) or the development of an alternate stable community dominated by lichens and mosses (Sedia and Ehrenfeld 2003). However, these latter circumstances are rare in the PNR, as pitch pine is very successful in surviving even very intense fires. Because of their relatively lower frequency, these wildfires may self-perpetuate because they open the canopy, allowing additional growth in the understorey and mid-storey. Although fire exclusion over an extended period of time leads to more oak species, Boerner (1981) notes that adaptations to frequent fire have resulted in a species assemblage that minimises species turnover in both the overstorey and understorey following wildfires.

The canopy response to the combined effects of wildfire and prescribed fire is perhaps our most interesting finding. The overall patterns of variation in CBD values with increasing numbers of fires in these areas were more like those of the prescribed fire areas than the wildfire areas, although there are small differences, such as in the upper canopy, where average CBD is lower for the combined wildfire and prescribed fire class than for prescribed fire alone. This overall pattern could indicate that, on average, the prescribed fires in these areas have been successful in limiting the severity of wildfires. Additionally, the recent history of severe and infrequent wildfires is not representative of the natural fire regime, but is instead a consequence of fire suppression (Forman and Boerner 1981). In this scenario, wildfires before fire suppression may have been more frequent and of lower intensity, similar to prescribed fires. This may be supported by the similarity in the resulting CBD patterns between prescribed fire alone areas and regions that have experienced both wildfires and prescribed fires.

These results provide insight for forest resource managers in the PNR as they consider whether their prescribed burning

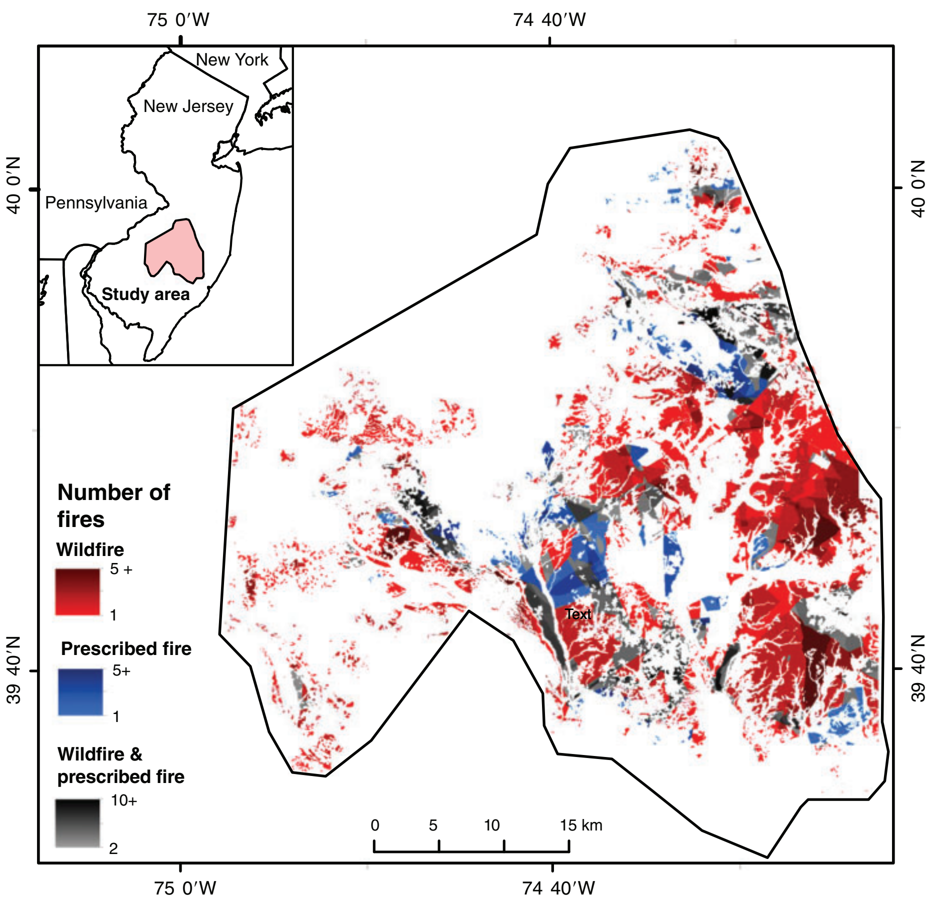

Fig. 1. Study site map showing the location of the New Jersey Pinelands National Reserve in NJ, USA, and the number of fires by fire type, masked to include only areas dominated by pine.

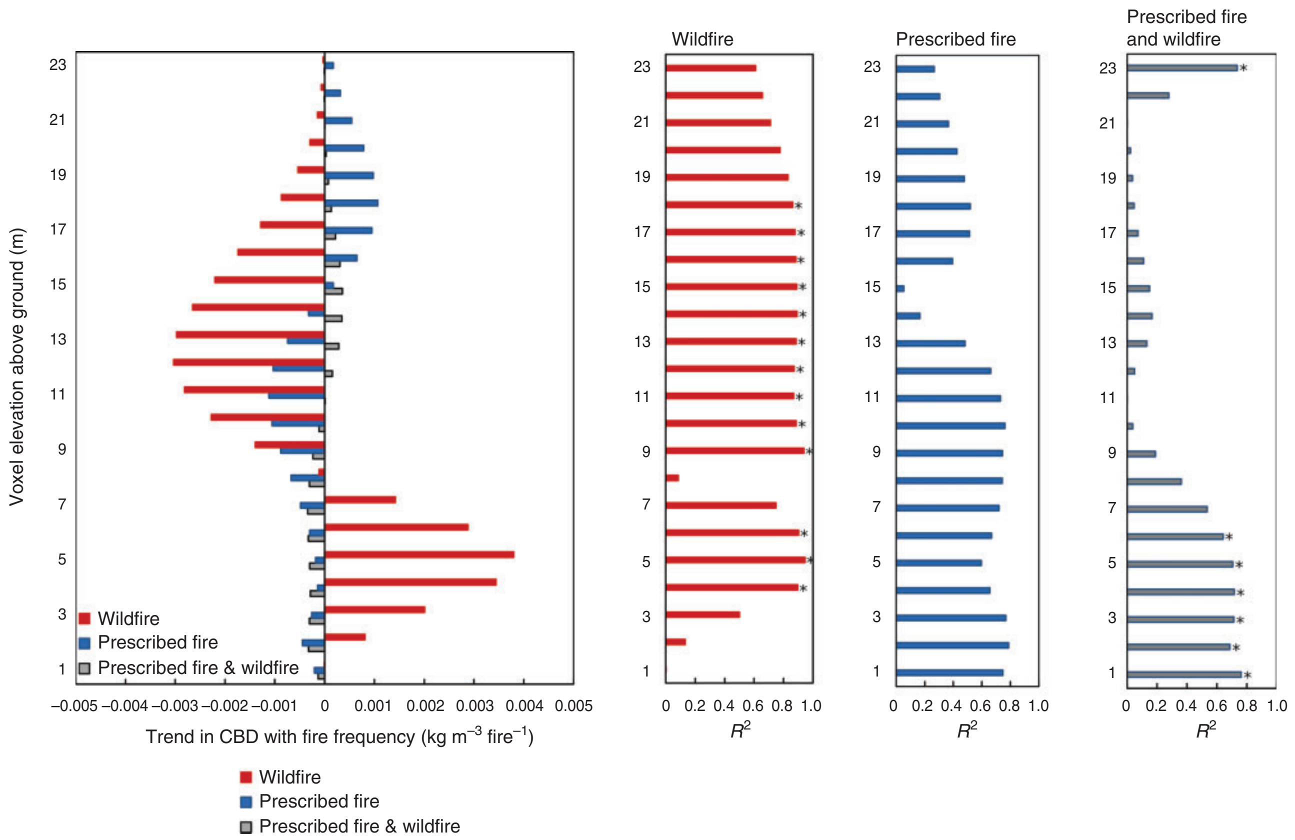

Fig. 2. Average canopy bulk density (CBD) and prior burn history, together with associated coefficient of determination. The length and direction of the bars in the lefthand graph indicate the least-squares linear relationship in CBD values as the number of fires increases. In the three graphs to the right, asterisks (*) indicate relationships that are significant based on the Benjamini and Hochberg (1995) procedure, controlling the false-positive rate at a critical value of 0.05.

programs will achieve the outcomes in forest canopy fuels that they desire. (For descriptions of New Jersey and PNR prescribed burning programs and their goals over the past 70 years, see Little *et al.* 1948; Cumming 1969; Clark *et al.* 2015; BillTrack50 2018). In considering the effectiveness of prescribed burning programs, it is important to start from clearly identified, *a priori* objectives, as there is a potential tension between avoiding devastating fires at the wildland–urban interface on the one hand and having fires sufficiently intense to mimic historical fire effects on the other hand. Furthermore, we found that the areas of prescribed fires are characterised by denser canopy fuels compared with areas of previous wildfires and therefore are potentially at greater risk for active crown fires if surface fires reach the canopy during extreme conditions. For example, Duveneck and Patterson (2007) found that the wind speed necessary to sustain an active crown fire for pitch pine forests in Massachusetts was substantially lower in stands that had not been thinned compared with stands that had been thinned.

One potential interpretation of our results is that, if a more open stand structure similar to that produced by current wildland fire is desired, occasional, more intense fires could be introduced into the burning regime, if conditions allow. However, Fig. 3 also suggests that the historical record of mixing wildfires and prescribed fires has resulted in a structure more like that of prescribed fires than wildfires. A possible mechanism for this is that prescribed fires tend to remove ladder fuels and thus when wildfires do occur, the likelihood of passive crown fire is reduced. Therefore, adapting prescribed burns to produce a landscape more like that produced by wildfires may not be simple. One possible solution might be to use silviculture to remove the canopy and then use prescribed fire to maintain the structure.

The methods used in this study hold potential for assessment of other prescribed fire objectives. For example, maps of CBD, supplemented with appropriate geographic information systems (GIS) layers, could be useful for avoiding prescribed burning in old-growth or for evaluating the outcome of forest management activities such as improving wildlife habitat. Preliminary cellular tracking evidence suggests that a species of greatest conservation need in New Jersey, the golden eagle, may prefer the closed canopy and open understorey habitat created by repeated prescribed fires (Trish Miller, unpubl. data).

It is important to note that this study did not include the confounding variables of time since fire, the severity of the fire at each location or how fire effects on fuel structure varied within the study area. One or all of these variables may explain the anomalous increase in CBD in the understorey in areas that have experienced three wildfire burns (Fig. 3). Furthermore, as

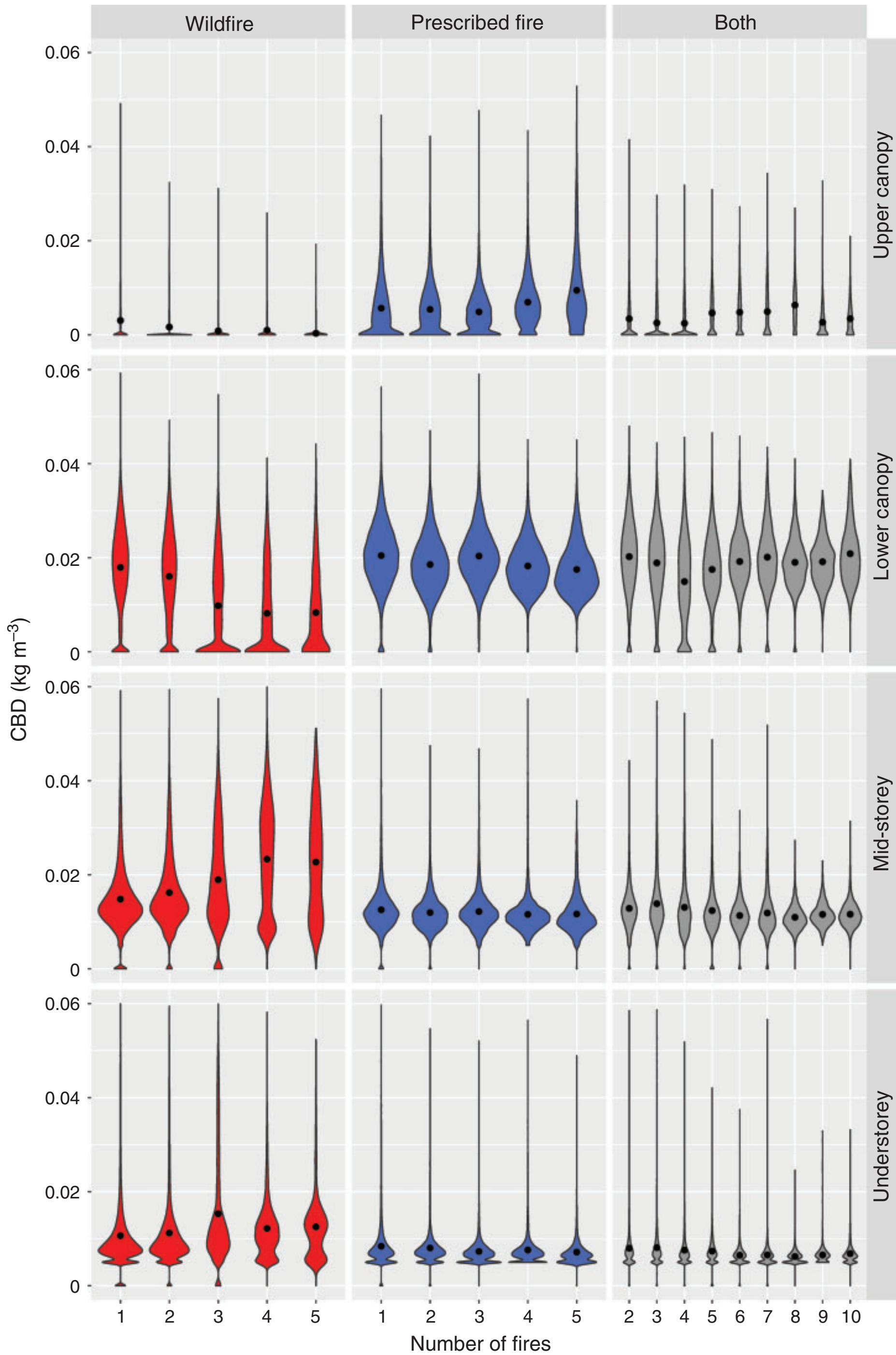

Fig. 3. Violin plots of the distribution of canopy bulk density (CBD) values for various numbers of wildfires, prescribed fires and both (i.e. wildfires and prescribed fires). The width of each plot is proportional to the relative frequency of CBD observations at that value. The black dot represents the mean CBD for the specified number of fires. The understorey is defined as 1–2 m, the mid-storey as 3–7 m, the lower canopy as 8–14 m and the upper canopy as 15–23 m.

already described, there is greater uncertainty in the prescribed fire boundaries before 2007. Despite these limitations, the results are generally consistent with our original hypotheses. In addition, it is worth emphasising that due to the wall-to-wall coverage of the remotely sensed data, and a corresponding extensive fire history, we summarised relationships in not just a small test sample, but within the entire region encompassing over 41 000 ha of pine forest that have experienced a wide range

Table 2. Results of the Kolmogorov–Smirnov two-sample test of the equality of continuous distributions for the means of wildfires, prescribed fires, and both (i.e. wildfires and prescribed fires) as a function of the number of wildfires (*significant at the 0.05 level)

	Distributions compared					
	Wildfires *v.* prescribed fires		Wildfires *v.* both		Prescribed fires *v.* both	
Structural layer	*D*	*P*	*D*	*P*	*D*	*P*
Upper canopy	1.00	<0.01*	0.80	0.01*	0.78	0.03*
Lower canopy	0.80	0.08	0.78	0.03*	0.38	0.63
Mid-storey	1.00	<0.01*	1.00	<0.01*	0.33	0.79
Understorey	1.00	<0.01*	1.00	<0.01*	0.56	0.23

of fire histories, including stands that have been burned only once, to those that have burned more than 10 times.

Conclusions

Wildfire is a natural part of many ecosystems. Forest resource managers use prescribed burns to gain the benefits of fire, while minimising the risks of wildfire. Our study utilised lidar data of the New Jersey PNR to characterise the forest structure associated with wildfire and prescribed burns. Our results indicate that areas with a history of repeated prescribed burns have a very different forest structure than areas that have experienced repeated wildfire.

Average CBD generally showed only limited variation with the number of prescribed fires. The greatest observed differences in CBD are in the understorey and lowermost part of the canopy, where a larger number of recorded prescribed fires correlated with a slight decline in CBD. This result suggests future research should investigate how frequently managers need to burn to achieve the desired fuel structure for reduced fire hazard. Prescribed fires may also have a weak fertilising effect on the upper canopy, as indicated by a small positive relationship associated with $\geq$ 4 fires, a finding that is in agreement with Boerner *et al.* (1988). In contrast, increasing numbers of prior wildfires correlated with higher CBD in the mid-storey. In the upper and lower canopy, the relationship was the opposite, with notably lower CBD as the number of wildfires increased.

These results have important implications for forest resource managers. The differences in the relationships between burning regime and forest structure that are documented here will likely result in long-term changes to the forest ecosystem. If there is a desire to revert to a system that emulates forest structure resulting from wildfire, in areas where the risk of wildfires is of less concern, the prescribed burn regime of the PNR may need to be adapted to allow for more occasional high-intensity fires that more closely mimic wildfires.

Conflicts of interest

The authors declare no conflicts of interest.

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