

Global satellite forest loss mapping conflates transient canopy disturbance with forest destruction

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Global satellite forest loss mapping conflates transient canopy disturbance with forest destruction

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Abstract

Satellite-derived global forest loss products are widely used in Earth System Science to understand global and regional changes in forest cover dynamics, carbon balance, and wildfire impacts. Such remotely sensed estimates of "forest loss", however, are not necessarily equivalent to ecological forest loss, leading to potentially spurious inferences about planetary health. Here we examine the widely used Hansen Global Forest Change product (GFC) to test whether forest loss mapped following the Australian 2019–2020 Black Summer fires represents persistent ecological forest loss or severe fire-induced canopy and structural disturbance. The Blue Mountains provide an informative study system because forest clearance is limited and the region is dominated by highly fire-adapted eucalypt forests, with some areas burned at maximal intensities. We compared GFC fire-related forest loss with Fire Extent and Severity Mapping (FESM) derived from machine learning classification of Sentinel-2 imagery, Sentinel-2 spectral responses and spaceborne lidar measurements of forest structure, supported by airborne lidar and field observations. GWFL_L mapped closely with high fire severity, with a concordance of 6.0% in low-severity areas to 81.8% in extreme-severity

areas. Five years after fire, however, most areas classified as GWFI_L had regained at least 80% of their pre-fire NBR2 values. Remote sensing estimates of canopy cover, foliage height diversity and aboveground biomass density also show the recovery of areas mapped as suffering forest loss. Further, field measurements showed GWFI_L areas had low proportions of tree death (17.3% fire-killed stems and 14.7% basal area). Collectively, these analyses show that GWFI_L in fire-adapted eucalypt forests primarily corresponds with severe fires that cause forest structural damage rather than permanent ecological forest loss. Therefore, care must be taken in applying the GFC product to Australian eucalypt forest, and likely other fire-adapted forests, to map the loss of forest cover.

Keywords: Global Forest Change; fire severity; eucalypt forests; post-fire recovery

Introduction

Forest loss is a major issue in contemporary global environmental change because forests store large amounts of terrestrial carbon, support biodiversity and maintain key ecosystem functions^{1–3}. The spatial distribution, drivers and ecological consequences of global forest loss are not uniform^{4–8}. Permanent forest conversion is closely linked to agricultural expansion^{5,9}, while forestry and shifting agriculture cause more transitory forest loss^{5,10,11}. Wildfire has complex and ecosystem specific effects. In some ecosystems, like rainforests that are poorly adapted to fire, burning can cause substantial forest degradation with repeated fires causing permanent land cover type conversion^{12–15}. However, many forest types are fire-adapted, such that wildfire can cause substantial canopy and structural disturbance without necessarily resulting in permanent forest loss, albeit substantial departures from ecosystem specific fire regimes can cause ecological harm and potentially drive system state change or collapse^{16–20}. Because of these differences, care is required when interpreting wildfire-related forest loss as permanent ecological forest loss.

The Hansen Global Forest Change (GFC) dataset is one of the most influential global forest loss products, with its strength being its global coverage, spatial consistency and annual comparability. It uses Landsat observations at 30 m resolution to detect abrupt tree-cover loss associated with stand-replacing disturbance or canopy removal^{6,12}. Using year-2000 tree cover as its baseline, it provides annual global forest loss data from 2001 onwards⁶. GFC has been used for a wide range of global and regional applications²¹, including mapping forest cover change, assessing disturbance dynamics and carbon losses, and attributing forest loss to drivers such as commodity agriculture, forestry, wildfire, shifting agriculture and

urbanisation^{5,6,10}. Such mapped forest losses are also used in downstream assessments of biodiversity, carbon and climate impacts, where distinguishing transient canopy disturbance from persistent forest-state change is critical^{4,7,22}. More recently, Tyukavina et al.¹² combined forest loss mapped by the GFC product⁶ with associated wildfire events to identify wildfire-related forest impacts. We refer to this classification as the Global Wildfire Forest Impact (GWFI), distinguishing areas where there is mapped loss GWFI_L (Loss) compared to areas with stable forest cover (GWFI_s).

Given the entrenched use of GFC in Earth System Science and global geospatial analyses, it is striking that the product has received limited scrutiny or evaluation, despite evidence that it is unable to distinguish transitory structural damage from long-term shifts in forest type^{6,12,23,24}. This issue is particularly important in the context of wildfire, because abrupt spectral change associated with burning does not necessarily indicate ecological collapse or permanent conversion to non-forest^{17,25,26}. This transitory change in spectral signature is used to assess the biological impact or ‘severity’ of wildfires²⁷. This distinction is particularly important in Australian forests, which are dominated by eucalypt species that have famously well-developed post-fire recovery strategies, noting these vary among fire intensities^{28,29}. Following low to medium intensity fires, many eucalypt forests retain some or all their crowns. Following higher intensity fires that cause complete canopy scorch or consumption, the majority of eucalypt species recover through either epicormic resprouting, resprouting from basal buds (lignotubers), or a combination of both^{29,30}. In most eucalypt forests, severe crown damage can also trigger prolific seedling recruitment from aerial seed banks stored in woody fruits^{25,31}. These different regeneration pathways can produce post-fire vegetation structures ranging from relatively minor canopy disturbance to stand-replacing fire followed by regeneration, meaning that severe canopy disturbance is unlikely to represent permanent forest loss^{26,31,32}.

The widespread and frequently severe 2019–2020 Black Summer fires provide an ideal model system for examining the validity of GWFI_L in highly fire-adapted eucalypt forests. Extreme drought, severe fire weather and abundant fuel made the 2019–2020 fire season one of the most significant in modern Australian history^{33–35}, with around 7.2 Mha burned, comprising some 42.6% of the total Australian coverage of temperate broadleaf and eucalypt forests^{36,37}. Previous studies have shown substantial landscape-scale variation in fire severity patterns following these fires that burned areas little affected by forestry or land clearing^{28,37}.

Here we combine fire severity mapping, Sentinel-2 NBR2 spectral responses and spaceborne lidar structural metrics, validated against airborne lidar and field observations, to test whether GWFI_L in fire-adapted eucalypt forests represents persistent ecological forest loss, or instead reflects severe fire-induced canopy and structural disturbance. Specifically, we test whether areas mapped as GWFI_L (1) are associated with higher severity, canopy damaging fires; (2) retain substantial spectral and structural values five years after fire relative to their pre-fire condition; and (3) show widespread tree mortality and basal-area loss expected under permanent forest loss.

Results

GWFI_L was concentrated in areas burned by high-severity fire

In the footprint of the 2019–2020 fires, most GWFI_s areas were burned at low and medium fire severities, as classified by Fire Extent and Severity Mapping (FESM) (Fig. 1). The area mapped as high and extreme severity fire by FESM was nearly identical to the area classified as GWFI_L (470,100 ha vs. 439,700 ha; Fig. 1c). The small discrepancy is likely related to spatial mismatch in the fire boundary, non-fire canopy disturbance, or the spectral signature being influenced by regional drought, rather than being caused directly by fire. The proportion of each fire-severity class classified as GWFI_L increased markedly with fire severity, from 6.0% in low severity areas to 23.5% in medium severity areas, 59.2% in high severity areas, and 81.8% in extreme severity areas (Fig. 1d).

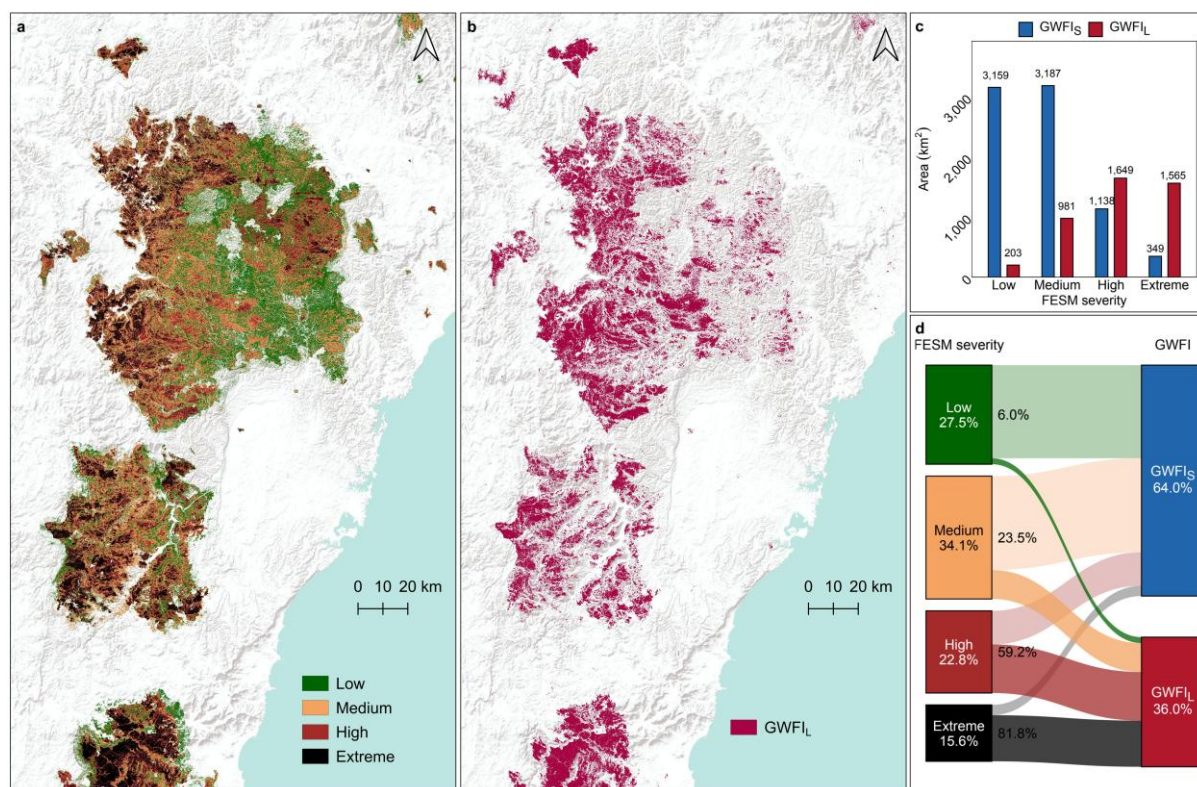


Figure 1. Spatial distribution of FESM fire severity and GWFI_L within the Greater Blue Mountains study area. a, Distribution of 2019–2020 FESM fire severity across four classes: low, medium, high and extreme. b, Spatial distribution of GWFI_L within the study area. c, Area (km²) of GWFI_L and GWFI_S pixels across FESM fire severity classes. d, Proportional Sankey diagram showing the flow from FESM fire severity to GWFI classification (GWFI_L / GWFI_S). Block heights represent the area share of each severity class; percentages on the flows indicate the proportion of each severity class mapped as GWFI_L.

Spectral disturbance and recovery in GWFI_L areas

Immediately after fire, NBR2 values were consistently lower in GWFI_L compared to GWFI_S areas, and the decline was greater with increasing fire severity (Fig. 2). Five years after fire, NBR2 had shown recovery for both GWFI_L and GWFI_S areas, with about half of the area burned at low and medium severity recovering to or above the pre-fire baseline, while most high and extreme severity GWFI_L pixels recovered to 80–110% of baseline. Overall, the marked post-fire difference in NBR2 between GWFI_L and GWFI_S areas had substantially narrowed after five years.

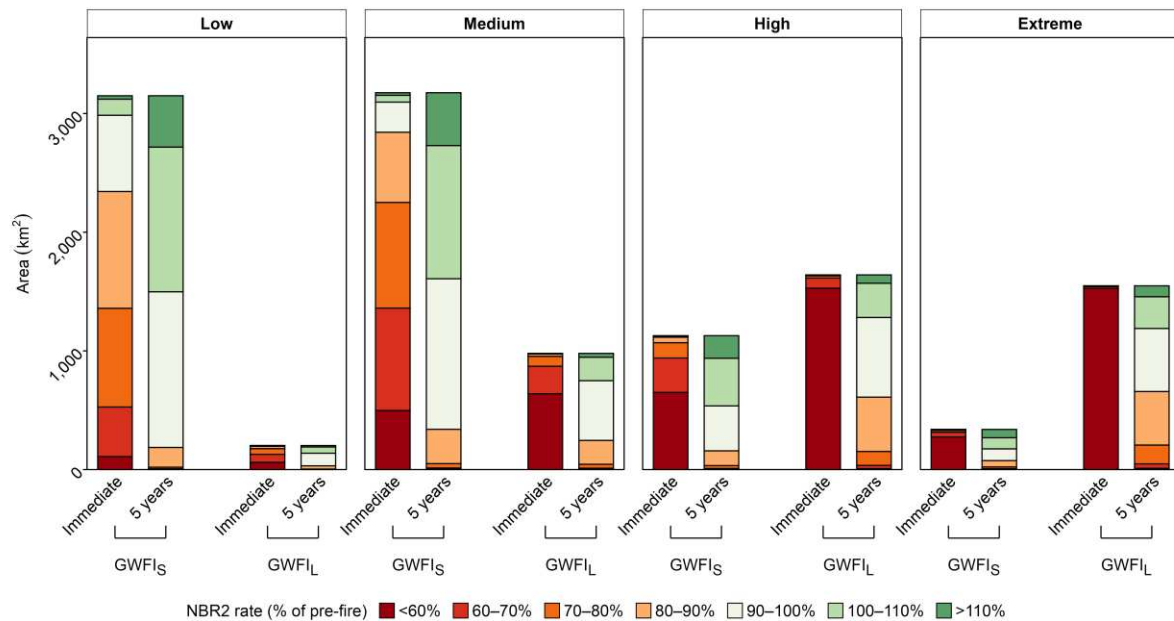


Figure 2. Immediate and five-year post-fire NBR2 responses in GWFI_L and GWFI_S areas across FESM fire severity classes. Bars show the total area (km²) of GWFI_L and GWFI_S pixels within each severity class, with immediate and five-year post-fire conditions shown side by side. NBR2 values are expressed as a percentage of the pre-fire baseline, and stacked segments show the area within seven response classes: <60%, 60–<70%, 70–<80%, 80–<90%, 90–<100%, 100–110%, and >110%.

Structural disturbance and recovery in GWFI_L areas

GWFI_L areas had greater evidence of forest structural change than GWFI_S areas. The three measures of forest structure (canopy cover, structural profile, and aboveground biomass density (AGBD)) all showed increasing impacts in proportion to fire severity just after the fire, with clear evidence of recovery five years after the fire (Fig. 3). For instance, in comparison to pre-fire values, AGBD showed large reductions; in GWFI_L areas burned by extreme-severity fire, AGBD declined to 37% of the pre-fire baseline immediately after fire and recovered to 62% after five years.

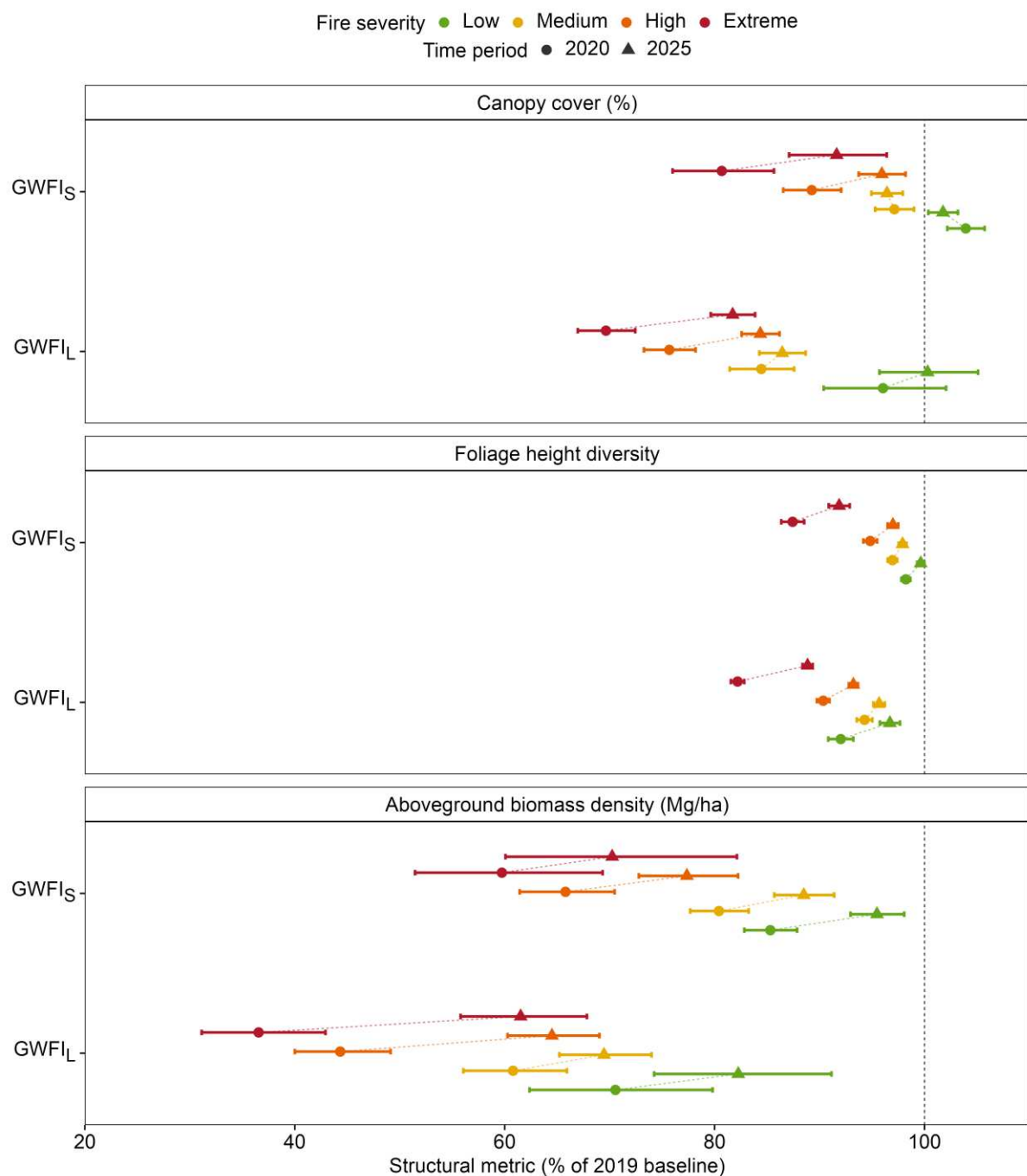


Figure 3. Immediate and five-year post-fire forest structural change in GWFI_L and GWFI_S areas across fire severity classes. Three GEDI forest structural metrics are shown as percentages of their 2019 pre-fire levels: canopy cover, foliage height diversity (FHD) and aboveground biomass density (AGBD). Colours indicate FESM fire severity classes (low, medium, high and extreme), while circles and triangles represent 2020 and 2025, respectively. Points show estimated mean values and horizontal error bars indicate 95% confidence intervals. Dotted lines connect the 2020 and 2025 estimates within each GWFI class and fire severity class to indicate structural change over time. The dashed vertical line indicates the 2019 pre-fire level (100%).

Field measured tree mortality in GWFI_L areas

These post-fire vegetation and structural changes inferred from remote sensing metrics were also supported by ground observations of tree mortality in high and extreme severity areas where the greatest impacts would be expected (Fig. 4). Across GWFI_L plots, mean dead stems were 17.3% (median 12.1%) and mean dead basal area was 14.7% (median 9.4%). Mortality was generally higher and more variable in extreme than high severity plots, particularly for dead basal area. The two samples from GWFI_S sites burned by fire with extreme severity spanned the same range as the GWFI_L sites. Again, these data demonstrate fire damage rather than complete forest loss.

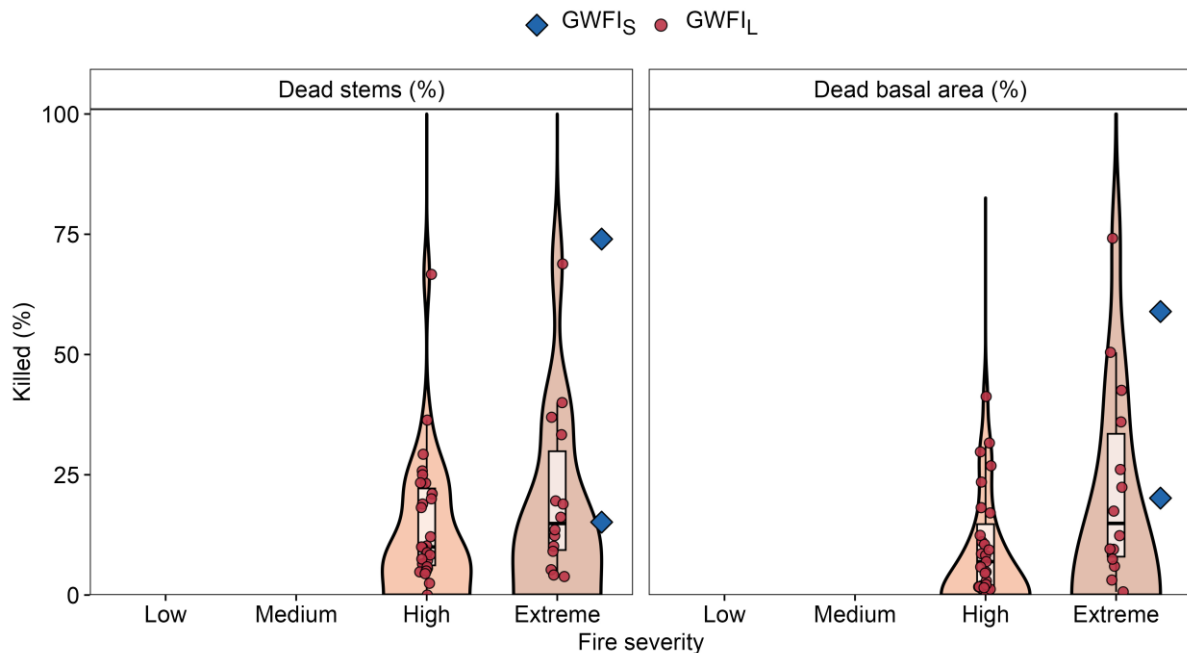


Figure 4. Field measured tree mortality in GWFI_L plots across fire severity classes. The left panel shows the proportion of dead stems (%), defined as the number of dead trees with DBH $\geq$ 5 cm relative to the total number of stems in each plot. The right panel shows the proportion of dead basal area (%), defined as the basal area of dead trees relative to total plot basal area. Violin plots, boxplots and points show the distributions of GWFI_L sites, while blue diamonds indicate GWFI_S sites. Field sites occurred only within high and extreme severity areas; no sites were available in low or medium severity areas.

Discussion

GWFI_L mapping was not associated with forest collapse; rather it was strongly associated with areas burned by high and extreme fire severity. Instead of mapping forest loss in burned eucalypt forests, this metric behaves as a threshold-like disturbance detector, selectively identifying areas where canopy damage is sufficient to produce an abrupt and substantial

Landsat spectral change^{6,12}. While the canopy disturbance detected by GFC is real, interpreting this disturbance as permanent ecological forest loss in eucalypt forests is erroneous^{5,23}. Therefore, this product cannot reliably map annual loss in these fire-adapted eucalypt forests and likely other fire-adapted vegetation types, although this requires testing^{5,6,12,23}. Distinguishing recoverable disturbance from persistent ecological forest loss can therefore benefit from complementary evidence of post-fire recovery from multiyear spectral and structural observations^{23,24,32}.

Eucalypt forests, which burned under some of the worst drought-driven fire weather in recent history, experienced substantial impacts, with large areas mapped as severely burned^{33–37}. The severity mapping closely corresponded to remote sensing estimates of damage to foliage in the canopy and subcanopy strata and total aboveground biomass. Despite substantial damage, forests rapidly attained pre-fire conditions in all but severely burned areas, reflecting the extraordinary capacity to vegetatively recover after fire^{29,30}. Nonetheless, it is well understood that repeated severe fires at short intervals can exhaust eucalypt regenerative capacity causing population collapse of both obligate seeder and resprouter forests^{14,15,19,20,25,38}.

Given that approximately 38% of global forest loss is associated with fire³⁹, distinguishing recoverable disturbance from persistent forest loss is important for global forest and carbon assessments. Therefore, we suggest our study highlights the need to carefully validate and assess uncertainties in global datasets such as the GWFI and GFC that can be used to shape policy and decision-making concerning forest fire management and effects of wildfire on national carbon budgets²⁴.

Methods

Study Area

This study focuses on eucalypt-dominated landscapes affected by the 2019–2020 Black Summer fires in and around the Greater Blue Mountains World Heritage Area in eastern New South Wales, Australia. The study area contains approximately 68,013 km² of mapped land area, encompassing the Greater Blue Mountains and surrounding fire affected landscapes. Located west of Sydney, the Greater Blue Mountains are a forested region with strong topographic variation, diverse vegetation types and a long-recorded fire history, providing a

suitable case for assessing the ecological meaning of GWFI_L in fire-adapted eucalypt forests⁴⁰.
Land clearing and forestry have had a negligible effect on the forests in this area²⁸.

The study area spans clear topographic, geological and moisture gradients. The elevation ranges from approximately 0 to 1,357 m. The Greater Blue Mountains region is underlain primarily by sandstone and shale, with localised outcrops of volcanic rocks, contributing to variation in soils and drainage conditions. The dissected plateaus, valleys, and uplands in the western and central parts of the region, together with the eastern lowlands, form a complex topographic setting (Fig. 5b). Mean annual precipitation (MAP), derived from WorldClim BIO12⁴¹, ranges from approximately 600 to 1,428 mm (Fig. 5d), with wetter conditions in eastern and windward upland areas and drier conditions towards the inland region. This topographic, geological and moisture heterogeneity may influence fuel moisture, vegetation composition, fire behaviour, and post-fire recovery^{42,43}.

The NSW State Vegetation Type Map (SVTM)⁴⁴ shows that the dominant mapped forest types in the study area are wet and dry sclerophyll forests. Dry sclerophyll forest covers approximately 25,668 km² (37.7%), while wet sclerophyll forest covers approximately 5,867 km² (8.6%). Dry forests are more common on nutrient-poor sandstone substrates, exposed ridges and drier topographic positions, whereas wet forests are generally associated with more productive settings, including comparatively fertile shale and volcanic substrates, moist sheltered pole-facing (southern) slopes, and valley floors. These two forest types were retained as the target eucalypt forest domain for subsequent analyses (Fig. 5c).

During the 2019–2020 Black Summer fires, extensive areas of eucalypt forest in and around the Blue Mountains were burnt. Based on the FESM dataset²⁷, approximately 12,230 km² of the wet and dry sclerophyll forest domain was burnt, representing 38.8% of the target eucalypt forest area.

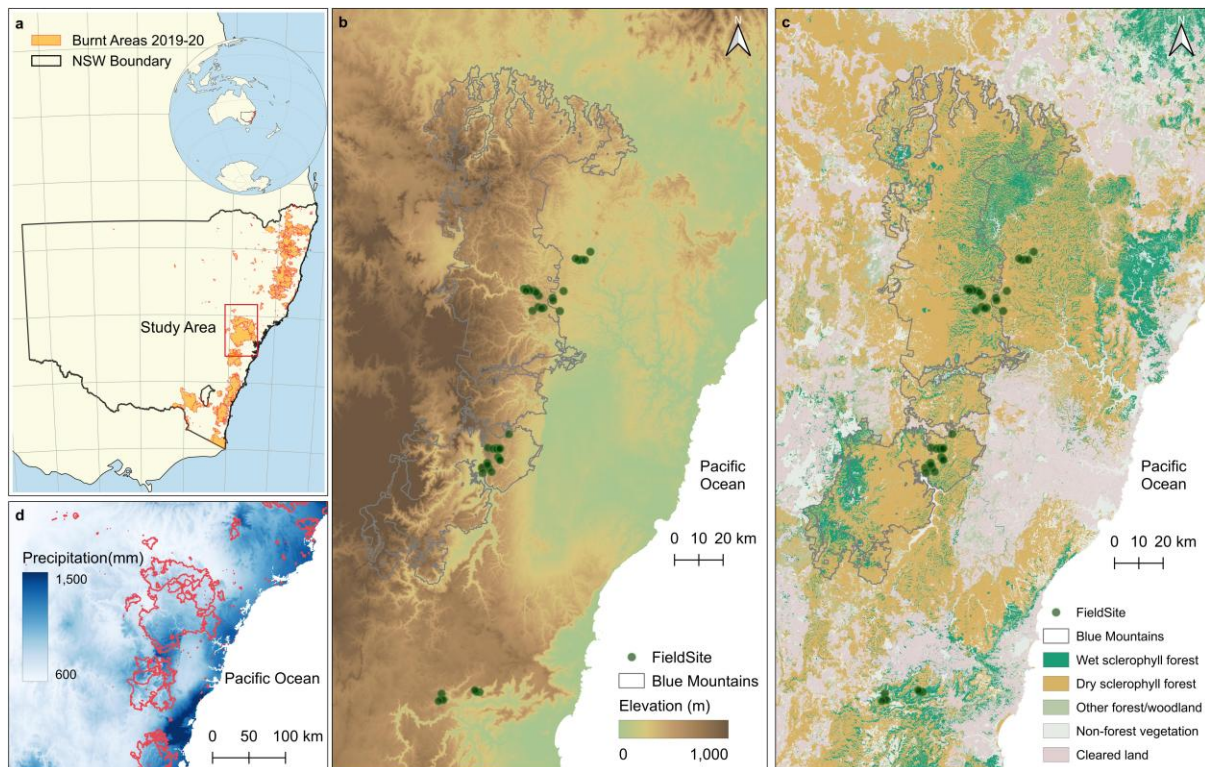


Figure 5. Location and environmental context of the Blue Mountains study area in New South Wales, Australia. a, Location of the study area in relation to the 2019–2020 fire extent in New South Wales, with the inset showing its location in south-eastern Australia. b, Elevation context of the study area, showing the distribution of field plots across the complex terrain of the Blue Mountains. c, Major vegetation and land cover types within and around the study area, including wet sclerophyll forest, dry sclerophyll forest, other forest/woodland, non-forest native vegetation and cleared land. d, Mean annual precipitation (MAP; WorldClim BIO12, mm), showing the regional moisture gradient across the study area and surrounding burnt landscapes.

Field surveys

Field surveys were conducted at 43 sites between September and December 2025. Sites were selected within wet and dry sclerophyll forests subject to high and extreme fire severity that had not had a recent fire prior to the 2019–2020 fire season. Field sampling focused on high and extreme fire severity because these severities are those in which persistent ecological forest loss would be most likely to occur. At each site, a circular plot 30 m in diameter was established, and all trees with a diameter at breast height (DBH) ≥ 5 cm within the plot were assessed. Species, diameter at breast height (DBH) and tree condition were recorded, with DBH measured at 1.3 m above ground. Trees were classified as alive, dead or top-killed, with evidence of post-fire basal resprouting recorded in the field. Trees identified as dead before the 2019–2020 fires were distinguished from subsequent mortality. Five upward-looking canopy photographs were collected at each site for estimation of field canopy cover, with one

taken at the plot centre and four at randomly selected locations toward each cardinal direction, ensuring that canopy was not obscured by understory or midstory vegetation.

Dataset and validation

Based on the SVTM vegetation classification described above, this study retained wet sclerophyll forest and dry sclerophyll forest pixels for analysis. Fire extent and severity were derived from the Fire Extent and Severity Mapping (FESM) dataset²⁷. FESM distinguishes unburnt areas and four levels of fire severity: low, medium, high and extreme. FESM severity was used as the primary measure of fire impact, with high and extreme severity indicating greater canopy scorch, canopy consumption and structural damage. GFC fire-related forest loss data were obtained from the UMD GLAD Global Forest Loss Due to Fire dataset¹², which identifies annual forest loss associated with fire based on the Hansen Global Forest Change product. Because the 2019–2020 Black Summer fire season spanned two calendar years, the target fire season was defined as 1 July 2019 to 30 June 2020. NPWS fire history data were used to exclude 2019 and 2020 GWFI_L pixels associated with fires outside this period. Within the study area, however, the target fires had ended by March 2020, so April–June 2020 was treated as the immediate post-fire period⁴⁵. All GWFI_L / GWFI_s comparisons were restricted to the FESM-burnt forest domain. Within this fire footprint, pixels classified as fire-related forest loss were defined as GWFI_L, while the remaining burnt forest pixels were defined as GWFI_s; unburnt forest outside the FESM fire footprint was excluded. GWFI status was then cross classified with FESM severity to quantify the area and proportion of GWFI_L within each severity class.

This study used Sentinel-2 NBR2 and GEDI spaceborne lidar metrics to represent the spectral condition and three-dimensional structure of post-fire vegetation, respectively. Quarterly Sentinel-2 NBR2 composites were used to characterise pre-fire and post-fire spectral conditions. NBR2 is sensitive to vegetation and soil moisture, charred residues and changes in exposed post-fire surfaces, making it suitable for analysing post-fire surface condition and vegetation recovery⁴⁶. GEDI spaceborne lidar data were used to characterise forest structure. We used footprint-scale canopy cover, foliage height diversity (FHD) and aboveground biomass density (AGBD) to compare post-fire structural conditions between GWFI_L and GWFI_s areas^{47–49}. Together, Sentinel-2 NBR2 and GEDI metrics provided complementary measures of spectral condition and forest structure for evaluating the ecological meaning of GWFI_L.

Before using GEDI structural metrics and Sentinel-2 NBR2 to interpret $GWFI_L$, we evaluated their correspondence with independent airborne and field observations. GEDI structural metrics were compared with pre-fire airborne laser scanning (ALS) data obtained from NSW Government Spatial Services through the ELVIS platform. The ALS data were acquired at multiple locations within the study area between April and September 2017, before the 2019–2020 Black Summer fires⁵⁰. To reduce seasonal differences between the datasets, 2019 GEDI observations acquired during a comparable seasonal period were selected, and 1,000 valid spatially matched GEDI footprints were randomly sampled for comparison with ALS-derived structural metrics. Field canopy photographs were processed using the R package *cover2*, with image-level estimates averaged to obtain site-level canopy cover⁵¹. Field-derived canopy cover was then compared with GEDI canopy cover and Sentinel-2 NBR2 to evaluate whether the satellite metrics reflected variation in canopy condition observed on the ground.

The validation results showed significant positive relationships between GEDI RH98 and ALS RH98 ($R^2 = 0.45$, $p < 0.001$), GEDI AGBD and ALS-derived AGBD ($R^2 = 0.39$, $p < 0.001$), and GEDI FHD and ALS-derived FHD ($R^2 = 0.27$, $p < 0.001$; Fig. 6a–c). GEDI metrics were therefore positively associated with independent ALS estimates of canopy height, biomass, and vertical structural complexity. Field canopy cover was significantly and positively related to Sentinel-2 NBR2 ($R^2 = 0.33$, $p < 0.001$, $n = 41$; Fig. 6d) and post-fire GEDI canopy cover ($R^2 = 0.34$, $p = 0.024$, $n = 15$; Fig. 6e). These comparisons support the use of the spectral and structural metrics in subsequent analyses.

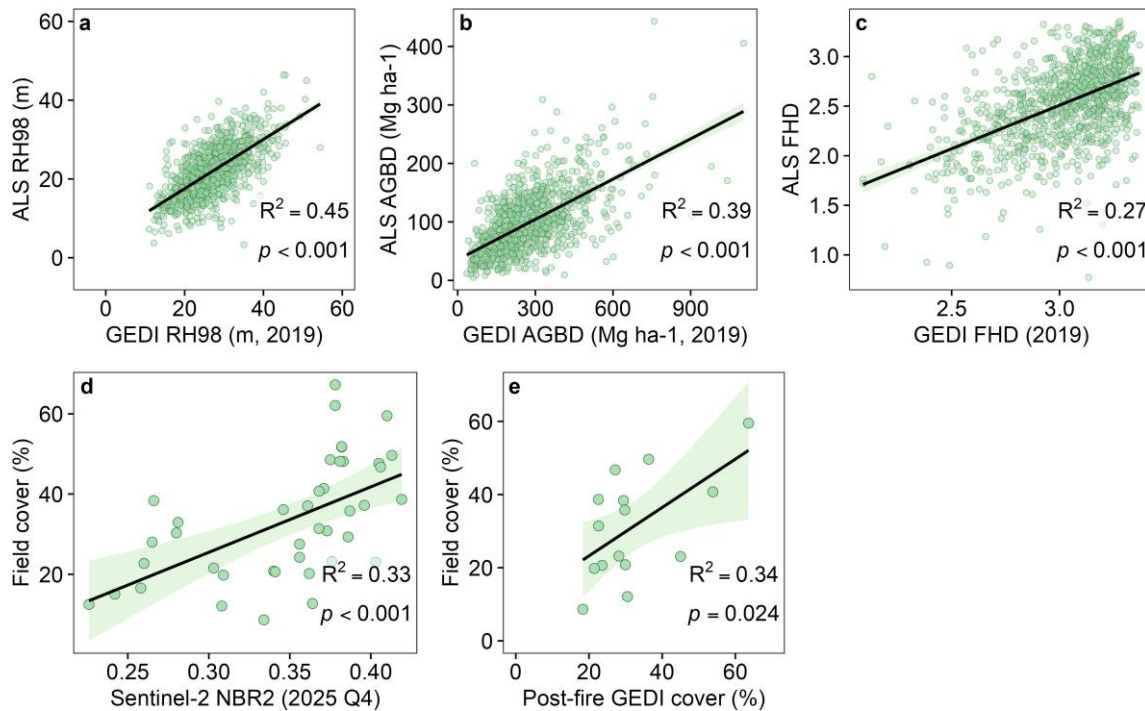


Figure 6. Comparison of remote-sensing metrics with ALS and field observations. a, 2019 GEDI RH98 vs 2017 ALS RH98. b, 2019 GEDI AGBD vs 2017 ALS-derived AGBD. c, 2019 GEDI FHD vs 2017 ALS-derived FHD. d, Sentinel-2 NBR2 (2025 Q4) vs field canopy cover. e, Post-fire GEDI canopy cover vs field canopy cover. Black lines indicate ordinary least-squares regressions and light green bands indicate 95% confidence intervals. Statistics in each panel show R^2 and p values from ordinary least-squares regressions.

Data analysis

Raster datasets were standardised to an approximately 10 m analysis grid and projected to the GDA 1994 NSW Lambert coordinate system (EPSG:3308), ensuring that spatial datasets were compared within a consistent framework. Categorical and continuous data were resampled using methods appropriate to their data types. For GEDI footprint-scale analyses, vegetation type, fire severity and GWFI status were assigned according to the dominant class within each footprint.

To assess post-fire spectral responses in $GWFI_L$ and $GWFI_S$ areas, Sentinel-2 NBR2 data were summarised for three seasonally matched periods: pre-fire (April–June 2019), immediate post-fire (April–June 2020), and five years post-fire (April–June 2025). For each pixel, NBR2 in 2020 and 2025 was expressed as a percentage of its corresponding 2019 pre-fire value. Analyses were stratified by GWFI status and FESM fire severity (low, medium, high and

extreme). NBR2 responses were grouped into seven classes (<60%, 60–<70%, 70–<80%, 80–<90%, 90–<100%, 100–110% and >110% of the pre-fire baseline), and the area within each class was calculated for each GWFI status and fire severity combination.

To quantify post-fire changes in forest structure, GEDI observations were selected from the same seasonally matched periods used for the spectral analysis: pre-fire (April–June 2019), immediate post-fire (April–June 2020), and five years post-fire (April–June 2025). Three structural metrics were analysed: canopy cover, FHD and AGBD. For each metric, separate linear mixed-effects models were fitted to compare 2019 with 2020 and 2019 with 2025⁵²:

$$Y \sim \text{Period} \times \text{GWFI status} \times \text{Severity} + \text{Forest} + (1|\text{Grid})$$

where forest type was included as an additive term and 5 km spatial grids were included as a random intercept to account for spatial clustering. Structural values in 2020 and 2025 were expressed as percentages of their corresponding model-estimated 2019 pre-fire baseline, with 95% confidence intervals.

For the field-based mortality analyses, trees with DBH ≥ 5 cm were included; individuals explicitly recorded as dead before the 2019–2020 fires were excluded, while top-killed trees showing post-fire basal resprouting were classified as live. For each plot, dead stems (%) were calculated as the number of dead trees relative to the total number of live and dead trees. Individual-tree basal area was calculated as $(BA = \pi(DBH/200)^2)$, and dead basal area (%) was calculated as the summed basal area of dead trees relative to total plot basal area. Both metrics were calculated at the plot level, with each plot treated as a single observation. The two mortality metrics were summarised by GWFI status and FESM fire severity.

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Data and code availability

The Fire Extent and Severity Mapping 2019/20 dataset is available at (<https://data.nsw.gov.au/data/dataset/fire-extent-and-severity-mapping-fesm-2019-20>). The NSW State Vegetation Type Map is available at (<https://data.nsw.gov.au/data/dataset/nsw-state-vegetation-type-map>), and NPWS fire history data are available at (<https://data.nsw.gov.au/data/dataset/fire-history-wildfires-and-prescribed-burns-1e8b6>). Airborne laser scanning (ALS) data are publicly available through the Geoscience Australia ELVIS—Elevation and Depth—Foundation Spatial Data platform (<https://elevation.fsdf.org.au/>). Mean annual precipitation data (WorldClim BIO12) are available from WorldClim (<https://www.worldclim.org/data/worldclim21.html>). The Global Forest Loss Due to Fire, Sentinel-2 and GEDI datasets used in this study were accessed through Google Earth Engine (<https://earthengine.google.com/>); the Global Forest Loss Due to Fire dataset is also available from the University of Maryland Global Land Analysis and Discovery laboratory (https://glad.umd.edu/dataset/Fire_GFL/). The field data supporting this study were collected by Rachael Nolan, Vijay Kumar and collaborators as part of a project funded by the Bushfire and Natural Hazards Research Centre and are available from the data owners upon reasonable request. Derived data supporting the findings of this study will be made publicly available in a data repository upon publication.

Author contributions

L.Z.: Conceptualization, Methodology, Software, Formal analysis, Visualization, Project administration, Writing – original draft, Writing – review & editing. D.M.J.S.B.: Conceptualization, Supervision, Project administration, Funding acquisition, Writing – review & editing. R.K.G.: Methodology, Supervision, Writing – review & editing. C.E.G.: Methodology, Writing – review & editing. V.K.: Methodology, Writing – review & editing. R.H.N.: Methodology, Project administration, Writing – review & editing. G.J.W.: Conceptualization, Supervision, Project administration, Funding acquisition, Writing – review & editing.

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