

Fixed-ground multisensor monitoring resolves longitudinal vegetation
condition and fuel-state structure in Southern California chaparral
and oak scenes

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Fixed-ground multisensor monitoring resolves longitudinal vegetation condition and fuel-state structure in Southern California chaparral and oak scenes

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Abstract

Wildfire-relevant vegetation and fuel conditions evolve through interacting changes in vegetation condition, three-dimensional fuel structure, thermal response, and atmospheric drying, yet these dimensions are commonly monitored separately. This study evaluated repeated fixed-ground multisensor monitoring at two fixed vegetation scenes in Placerita Canyon, California. Multispectral imaging, radiometric thermal imaging, light detection and ranging (LiDAR), and local atmospheric measurements were integrated across persistent dense, mixed, and dry vegetation regions during 10 quality-controlled visits at a native-chaparral hillside and 24 visits at an oak/canopy-centered scene. Persistent vegetation regions remained strongly differentiated across sensing domains while also exhibiting longitudinal change. Dense vegetation exceeded dry vegetation in median normalized difference vegetation index (NDVI) by 0.259 and 0.113 at the two sites, showed 4.11 m and 0.56 m greater LiDAR vertical spread, and remained 3.37 °C and 3.88 °C cooler relative to ambient air. Dense chaparral NDVI declined markedly, while dense, mixed, and dry regions at the oak-centered site showed sustained NDVI declines. Corresponding decreases across three additional spectral indices and spatially differentiated oak-canopy changes showed that the temporal signal extended beyond a single spectral index or whole-canopy average. Multisensor analysis of 96 complete visit $\times$ site $\times$ region observations showed vegetation region as the dominant source of multivariate separation (partial $R^2 = 0.491$, $p = 0.0005$). By preserving spatial identity while integrating spectral, structural, thermal, and atmospheric measurements, this fixed-ground framework provides a local longitudinal approach for characterizing evolving vegetation and fuel conditions before ignition.

Keywords: wildland fire; proximal sensing; LiDAR; thermal imaging; spectral indices; semantic regions

Introduction

Wildland fire behavior emerges from the interaction of fuel quantity and arrangement, vegetation condition and moisture, and atmospheric forcing. These components evolve on different temporal scales and are not reducible to a single remotely sensed index or weather variable. Fire-ecology syntheses emphasize that fuel structure, moisture state, and concurrent abiotic conditions jointly shape fire behavior and effects (Kobziar et al., 2024). For pre-ignition monitoring, the resulting measurement problem is therefore multidimensional: the same local vegetation can change physiologically while its three-dimensional structure remains comparatively stable, and thermal response can vary with atmospheric demand even when structural fuel geometry is unchanged.

Remote sensing provides essential regional context for vegetation and fuel condition. Spectral methods have been applied to live fuel moisture and fuel-condition estimation in shrublands, including Southern California chaparral, but the relationship between vegetation indices and live fuel moisture is site dependent and does not make a spectral index equivalent to a direct moisture measurement (Roberts et al., 2006; Qi et al., 2012; Yebra et al., 2013). Broad-area satellite and aerial observations also trade spatial coverage against revisit interval and local structural detail. This creates a methodological opening for proximal measurements that repeatedly observe the same physical fuel areas at much finer temporal and spatial scales.

Repeated near-surface imaging provides a precedent for this approach. Fixed-camera phenology networks have shown that persistent regions of interest can generate robust longitudinal vegetation records when acquisition geometry and processing are controlled (Richardson et al., 2009; Sonnentag et al., 2012; Richardson et al., 2018). The underlying strength is not the camera itself but preservation of spatial identity: the same physical

vegetation is observed repeatedly, making temporal change interpretable against its own prior state rather than against a changing field of view.

Fuel structure requires a different measurement domain. Terrestrial and airborne LiDAR have been used to estimate vegetation height, occupied volume, understory fuel depth, and vertical fuel arrangement (Skowronski et al., 2011; Rowell et al., 2016; Wilson et al., 2021, 2022; Nemens et al., 2026). Recent studies have also demonstrated the value of repeated terrestrial laser scanning for monitoring structural change through time and for complementing spectral assessments (Maxwell et al., 2026). These studies establish three-dimensional structure as a distinct physical axis of fuel characterization rather than a surrogate for spectral condition.

Thermal response provides another distinct axis. Canopy temperature and canopy-air temperature differentials are sensitive to plant water status and energy balance, but their interpretation depends strongly on atmospheric conditions such as vapor pressure deficit (VPD) and radiation (Jackson et al., 1981; Idso et al., 1981; Jones et al., 2009; Neinavaz et al., 2021). For wildland monitoring, this argues for ambient-normalized thermal summaries and concurrent atmospheric context rather than isolated absolute-temperature thresholds.

Multisensor approaches are therefore attractive because spectral, structural, thermal, and atmospheric observations describe different physical aspects of the same vegetation-fuel system. Close-range phenotyping and forestry studies have increasingly combined spectral, thermal, and three-dimensional sensing, while recent reviews distinguish raw-data fusion from feature-level fusion in which independently derived measurements are integrated at a common semantic unit (Liu et al., 2020; Lantin et al., 2023; Balestra et al., 2024).

For complex outdoor scenes, feature-level fusion is particularly relevant because heterogeneous sensing domains characterize different physical properties in distinct native sampling geometries, while persistent semantic regions provide a common spatial unit for integrating those measurements through time.

The present study evaluates a repeated fixed-ground multisensor framework in two Southern California scenes. The central question is whether persistent semantic vegetation regions can remain physically distinguishable across repeated field visits while also expressing longitudinal change, and whether the combined multisensor state retains coherent structure across scenes. The study tests six linked hypotheses: (H1) semantic vegetation regions are separable across shared sensing domains; (H2) spectral vegetation condition changes longitudinally within persistent regions; (H3) three-dimensional fuel structure differentiates regions and provides information distinct from spectral condition; (H4) ambient-normalized thermal response differs among regions and varies with atmospheric dryness; (H5) ecological contrasts exceed short-window technical variability; and (H6) the fused feature representation retains structured multivariate information across site and vegetation region. A spectral extension at an oak/canopy-centered scene further tests whether the longitudinal signal is reproduced across multiple vegetation-condition formulations and localized within the oak canopy.

Materials and methods

Study area and repeated fixed-scene design

Field monitoring was conducted in Placerita Canyon, Los Angeles County, California, within a Mediterranean-climate wildland-urban interface landscape containing native chaparral and oak vegetation. The final study design comprised two fixed scenes monitored repeatedly under a standardized acquisition protocol. Site A was a hillside/native-chaparral transect spanning dense, mixed, and dry vegetation. Site B was an oak/canopy-centered scene containing the same dense, mixed, and dry semantic classes together with inner, outer, and lower oak-canopy regions. The common dense/mixed/dry classes provided the shared cross-scene basis; the canopy regions supported a nested within-Site-B analysis. Each semantic label referred to a fixed, site-specific physical region rather than to an independent population sample.

Ten accepted field visits were available at Site A (30 April–22 May 2026) and 24 at Site B (26 May–17 July 2026), for 34 accepted spectral/structural visits in the analysis set. Thermal and complete shared-core fusion analyses contained 32 accepted visits because of modality-specific completeness requirements. Multiple sensor observations acquired within a field visit were aggregated within the visit-level measurement hierarchy and were not treated as independent ecological replicates. The primary inferential unit was one accepted visit $\times$ site $\times$ semantic region summary per outcome. The study design and inferential roles are summarized in Table 1.

Sensing domains and scientific measurements

The monitoring architecture combined multispectral imaging, radiometric thermal imaging, three-dimensional point-cloud sensing, local atmospheric measurements, and a monochrome imaging channel retained primarily for acquisition-quality assessment.

Multispectral measurements included red, green, and near-infrared responses. The normalized difference vegetation index (NDVI) was calculated as $(\text{NIR} - \text{Red})/(\text{NIR} + \text{Red})$ and served as the shared spectral outcome at both sites. Site B additionally supported the green normalized difference vegetation index, $\text{GNDVI} = (\text{NIR} - \text{Green})/(\text{NIR} + \text{Green})$; the green chlorophyll index, $\text{GCI} = (\text{NIR}/\text{Green}) - 1$; and the ratio vegetation index, $\text{RVI} = \text{NIR}/\text{Red}$. These indices were interpreted as spectral indicators of vegetation condition and moisture-related state. The low-NDVI fraction was the proportion of valid pixels with $\text{NDVI} \leq 0.20$; at Site B, low-GNDVI fraction was defined analogously using $\text{GNDVI} \leq 0.20$.

Three-dimensional structure was summarized from transformed point clouds voxelized at 0.5-m resolution. Primary structural outcomes were vertical spread (90th minus 50th percentile of vertical coordinate), vertical continuity, and an occupancy-derived gap fraction. Vertical continuity was defined as the mean Jaccard overlap of occupied XY cells between adjacent vertical strata (0–0.5 versus 0.5–2 m and 0.5–2 versus 2–10 m). The occupancy-derived gap fraction was one minus the fraction of occupied XY voxel cells within the region point-cloud bounding box. Unique occupied voxels were also counted within the 0–0.5, 0.5–2, and 2–10 m vertical strata. Euclidean range distributions and point support were retained for geometry-sensitive analyses.

Thermal images were converted to radiometric temperature fields and filtered through validity masks. Region-level median and 95th-percentile temperatures were paired to synchronized local air temperature to derive ambient-normalized temperature differences, $\Delta T = T_{\text{region}} - T_{\text{air}}$. Thermal values outside the established reportable domain (-20 to 120 °C), nonfinite pixels, and observations failing thermal quality criteria were excluded before inference. Vapor-pressure deficit (VPD) was derived from measured air temperature (T , °C) and relative humidity (RH, %) as $\text{VPD} = \text{es}(1 - \text{RH}/100)$, where $\text{es} = 0.6108 \exp[17.27T/(T + 237.3)]$ kPa. Particulate and gas-index measurements were retained as environmental context but were not primary endpoints.

The monochrome channel provided brightness, clipping, edge-density, motion, and sharpness/texture measures. These variables were treated as measurement-state diagnostics rather than vegetation-health outcomes. They were retained to identify acquisition failure, motion, exposure instability, or scene-quality changes that could otherwise be mistaken for ecological variation.

Spectral calibration and longitudinal processing

Multispectral processing retained calibration coefficients, reference-target consistency records, valid-pixel masks, exposure/control metadata, and quality flags for each accepted event. Reference-panel acquisitions were collected periodically before and after field sessions as consistency checks on the fixed calibration basis. For the three-band calibration supporting the expanded spectral path, target-fit RMSE across four reflectance targets was 0.0085 for green, 0.0061 for red, and 0.0057 for NIR. Primary longitudinal inference used a spectral harmonization workflow anchored to calibration references and quality-controlled band responses to maintain comparability across repeated field visits. The harmonization applied band-wise affine transformations ($aX + b$) to red, NIR, and green responses before spectral-index calculation. Coefficients were selected from agreement with the calibrated radiometric reference and valid-pixel coverage, with constraint toward the identity transform; semantic-region labels were not involved in parameter estimation. Processing provenance was retained for each accepted event. A separately calibrated radiometric path was retained as a sensitivity reference. Site A publication scope was restricted to NDVI. Site B supported the expanded spectral suite described above.

Semantic regions, registration, and feature-level fusion

Persistent semantic regions were defined to represent the same physical vegetation zones through time. Registration procedures were specific to sensor geometry. Three-dimensional point-cloud measurements were related to the multispectral reference frame through multi-pose rigid extrinsic calibration based on a common geometric target, camera pose estimation, LiDAR target reconstruction, observability testing, and nonlinear

SE(3) refinement. The final LiDAR solution retained 20 accepted calibration poses spanning 2–5 m, with median translational and rotational residuals of 0.142 m and 1.92°, respectively. Thermal and monochrome image channels were registered to the multispectral reference using calibration-target correspondences and fitted image transformations followed by image-domain refinement. The selected thermal target fit had a reprojection RMSE of 3.92 px (median 2.24 px; maximum 7.69 px) before final scene alignment; monochrome registration QA yielded a reprojection RMSE of 4.79 px (median 4.17 px; maximum 9.64 px). Because the image sensors occupied different physical positions, residual depth-dependent parallax across the three-dimensional vegetation scene was addressed during final scene alignment while preserving calibration provenance.

Multisensor integration was then performed at the persistent semantic-region and observation-event level. Each sensing modality contributed measurements describing the same physical vegetation region and visit while retaining its native measurement geometry. This provided a common spatial and temporal basis for combining spectral condition, thermal response, three-dimensional structure, atmospheric context, and acquisition-quality information across repeated observations.

Aggregation, quality control, and missingness

For each modality, accepted technical events were aggregated to visit $\times$ site $\times$ region summaries using fixed processing rules. Analysis records retained the number of contributing events/pixels/points, valid fraction, quality state, relevant exposure/control information, calibration/registration provenance, geometry/support variables, and synchronized atmospheric context. Exclusions were determined from calibration, reportability, and acquisition-quality criteria before outcome significance was inspected. No silent imputation was applied to primary outcomes; the fusion analysis used complete shared-core records.

Statistical analysis

Statistical analyses were designed around the repeated observational hierarchy. Site and semantic region were treated as fixed factors; field visit provided the repeated/blocking structure. Two-sided inference used $\alpha=0.05$ and 95% confidence intervals. Benjamini-Hochberg false-discovery-rate control (Benjamini & Hochberg, 1995) was applied within scientific outcome families, while planned within-model region contrasts and region-specific slopes received local Holm adjustment. Technical quality metrics and exploratory telemetry were not added to confirmatory multiplicity families solely because they were available.

For H1, continuous region-separation outcomes were modeled with visit-blocked mixed models; when random-effects estimation for NDVI was singular, visit-clustered linear estimation was retained. Bounded structural fractions were analyzed with repeated fractional-logit models. Planned dense-mixed, dense-dry, and mixed-dry contrasts were estimated separately for each site.

For H2, the primary NDVI longitudinal model was generalized least squares with a visit-order AR(1) covariance structure and Site $\times$ Region $\times$ Time terms. Region-specific slopes were extracted with local Holm correction. The low-NDVI fraction was analyzed as a repeated fractional response, and NDVI dispersion was retained as a secondary outcome. Site B expanded spectral outcomes were modeled with region-specific repeated-error GLS, using a boundary-safe logit transform for fraction outcomes.

For H3, structural continuous outcomes were modeled with repeated visit structure. Height-band occupancy counts were analyzed using negative-binomial repeated models conditioned on point support and median range. For H4, ambient-normalized median and p95 thermal responses were modeled with site, region, time, and VPD, including selected interactions. H5 quantified technical event/subwindow dispersion and compared the median within-window interquartile range against same-event region contrasts; these ratios were treated as estimation-based signal-to-jitter measures rather than independent hypothesis tests.

For H6, a shared-core fused vector was constructed from NDVI median, low-NDVI fraction, vertical spread, vertical continuity, gap fraction, median ΔT , and VPD. Variables were standardized once across the complete matched dataset. Partial PERMANOVA (Anderson, 2001) was performed in standardized Euclidean feature space with 1,999 restricted permutations: the site term permuted whole-visit blocks, whereas region and site $\times$ region terms were permuted within visits. PERMDISP (Anderson, 2006) was analyzed separately with 1,999 permutations to assess dispersion differences; within each site, region labels were permuted within visit

blocks, and site-level dispersion was evaluated on visit centroids. Primary residual cross-modal associations were evaluated after adjustment for site, region, and time using 999 within-unit circular-shift permutations with multiplicity correction.

Table 1 Study design and inferential roles across the two fixed scenes

Component	Site A	Site B	Role in inference
Accepted visits	10	24	Repeated field observations
Shared semantic regions	Dense, mixed, dry	Dense, mixed, dry	Direct cross-scene comparison
Additional regions	—	Inner, outer, lower oak canopy	Nested Site B localization
Shared spectral outcome	NDVI	NDVI	Longitudinal vegetation condition
Expanded spectral outcomes	—	GNDVI, GCI, RVI, low-GNDVI fraction	Secondary Site B longitudinal depth
Other shared domains	LiDAR structure, thermal response, atmosphere, monochrome QC	Same	Distinct physical-state measurements and QC

Results

Data completeness and analysis set

The final dataset contained 228,534 observations described by 709 variables. After visit-level aggregation and quality gating, the spectral analysis set contained 34 accepted visits: 10 at Site A and 24 at Site B. The shared spectral and structural analyses therefore contained 102 visit $\times$ site $\times$ common-region observations (34 visits $\times$ 3 common regions). Thermal and complete fusion analyses contained 96 common-region observations from 32 visits because two visits lacked the full shared-core modality set. The Site B expanded spectral analysis contained 24 visits $\times$ 6 persistent Site B regions, with the formal dense/mixed/dry family represented by 72 visit $\times$ region observations.

Persistent semantic regions were separable across independent physical domains

NDVI showed strong and ordered separation among dense, mixed, and dry regions at both scenes. At Site A, dense vegetation exceeded mixed vegetation by 0.155 NDVI units (95% CI 0.115 to 0.195) and dry vegetation by 0.259 (0.224 to 0.293); mixed exceeded dry by 0.104 (0.083 to 0.124). At Site B, the corresponding dense-minus-mixed, dense-minus-dry, and mixed-minus-dry contrasts were 0.0619 (0.0544 to 0.0693), 0.1130 (0.1069 to 0.1191), and 0.0512 (0.0483 to 0.0540). All planned NDVI contrasts remained significant after local Holm adjustment.

The same semantic ordering was expressed in three-dimensional structure. Dense vegetation exceeded dry vegetation in vertical spread by 4.11 m at Site A (95% CI 3.74 to 4.48) and by 0.563 m at Site B (0.323 to 0.803). Dense-minus-mixed structural contrasts were 2.41 m at Site A and 0.584 m at Site B. The magnitude difference between sites reflects the distinct scene geometry and vegetation structure rather than a single universal class effect (Fig. 1).

Thermal behavior provided a third independent separation. Relative to synchronized ambient air temperature, dense vegetation was cooler than dry vegetation by 3.37 °C at Site A (95% CI -3.96 to -2.77 for dense-minus-dry) and 3.88 °C at Site B (-4.23 to -3.54). At the 95th thermal percentile, dense-minus-dry differences were -5.62 °C at Site A and -5.71 °C at Site B. Thus, the persistent semantic classes corresponded simultaneously to differences in vegetation reflectance, fuel geometry, and heat response (Fig. 2).

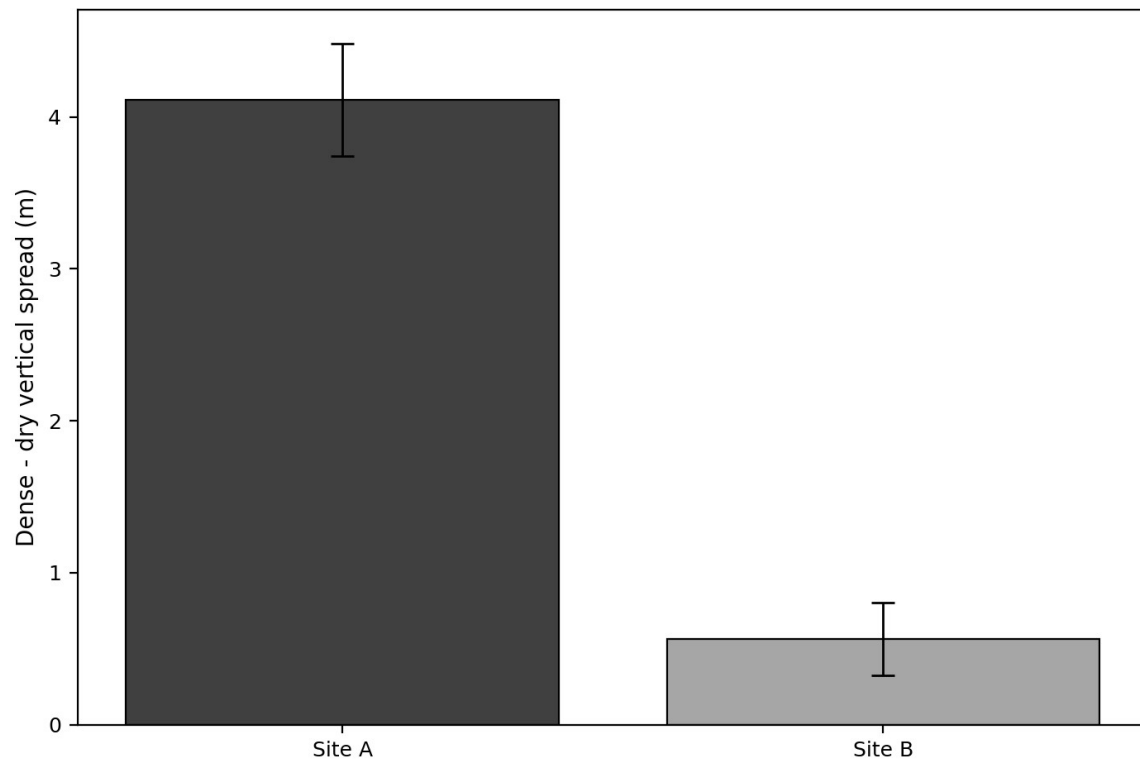


Fig. 1 Dense-minus-dry separation in LiDAR vertical spread. Error bars show 95% confidence intervals from the planned site-specific contrasts

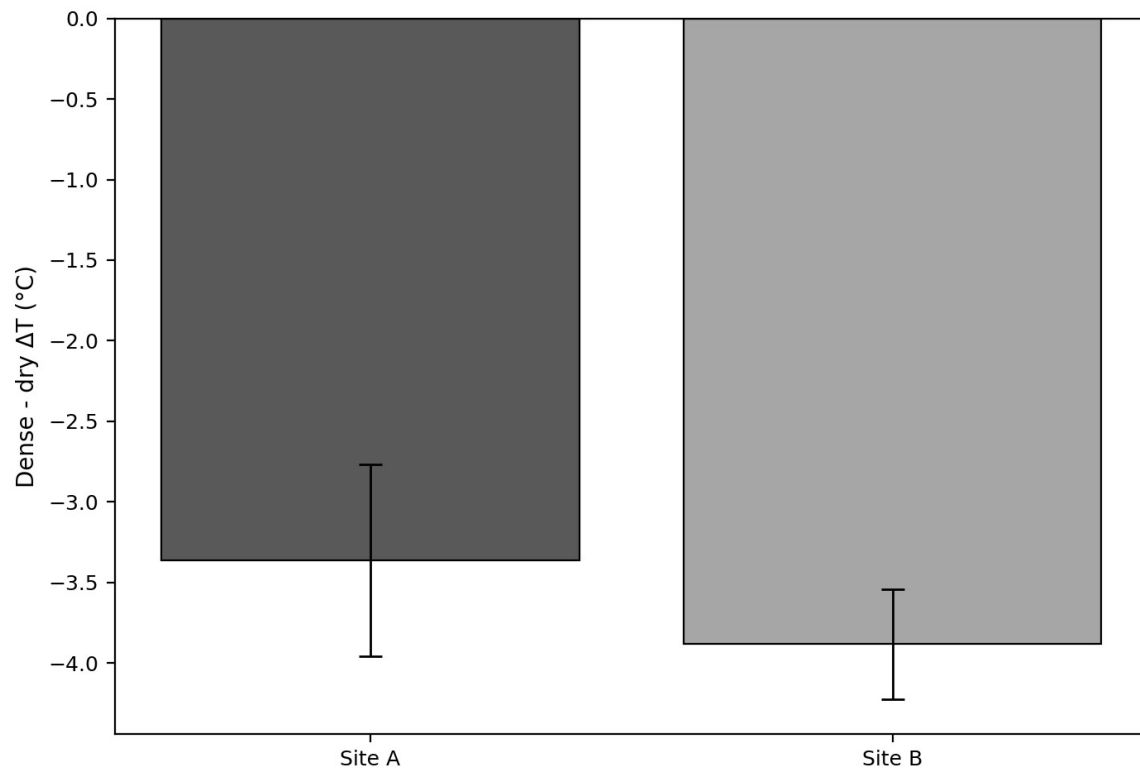


Fig. 2 Dense-minus-dry ambient-normalized median thermal response (ΔT). Negative values indicate that dense vegetation was cooler relative to ambient air than dry vegetation. Error bars show 95% confidence intervals

Longitudinal NDVI trajectories differed by scene and region

At Site A, the dense region exhibited the dominant longitudinal NDVI change over the 22-day monitoring interval. The primary repeated model estimated a slope of $-0.004096 \text{ day}^{-1}$ (95% CI -0.006364 to -0.001828 ; local Holm $p=0.00163$). Mixed and dry slopes were -0.000567 and $-0.000159 \text{ day}^{-1}$, respectively, and were not significant after local correction. The trajectory therefore reflected a pronounced decline concentrated in the initially denser vegetation rather than a uniform scene-wide shift.

Site B showed a slower but broader decline over the longer 52-day record. Dense NDVI decreased at $-0.000874 \text{ day}^{-1}$ (95% CI -0.001171 to -0.000578 ; Holm $p=1.48 \times 10^{-7}$), mixed vegetation at $-0.000259 \text{ day}^{-1}$ (-0.000390 to -0.000128 ; $p=1.67 \times 10^{-4}$), and dry vegetation at $-0.000355 \text{ day}^{-1}$ (-0.000462 to -0.000247 ; $p=1.09 \times 10^{-8}$). The independently calibrated radiometric analysis preserved the same directional pattern across the corresponding region slopes (Fig. 3).

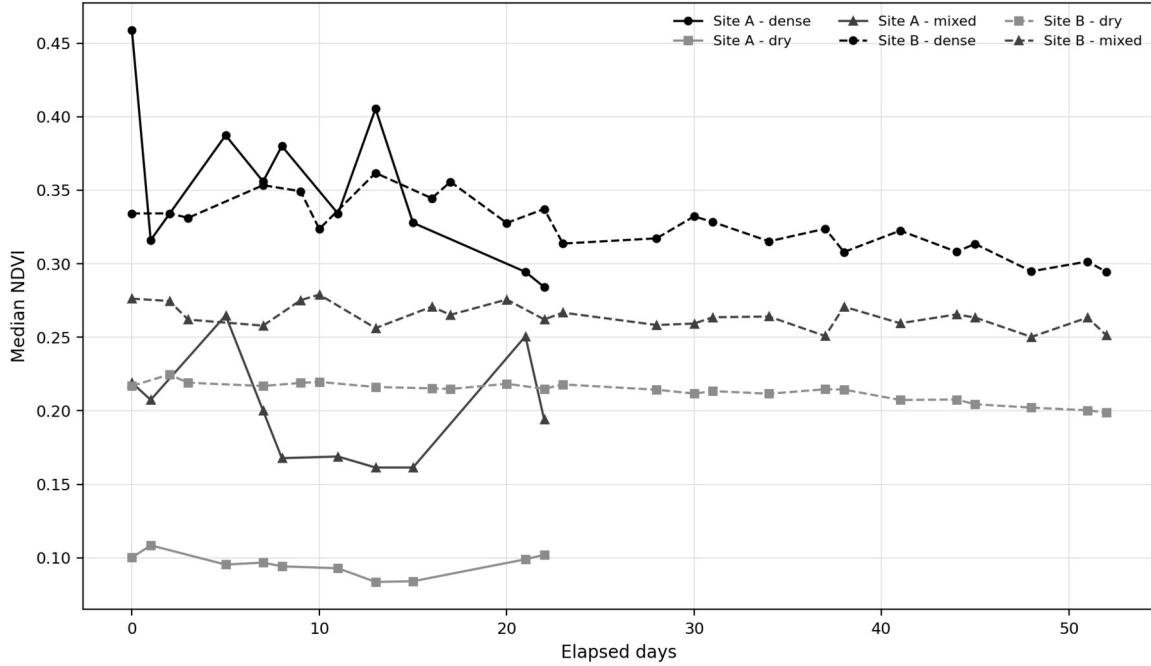


Fig. 3 Longitudinal median NDVI for persistent dense, mixed, and dry regions at both fixed scenes. Each point is one accepted visit $\times$ site $\times$ region summary from the primary spectral harmonization workflow

Site B spectral depth reproduced the dominant dry-down pattern

The Site B expanded spectral analysis tested whether the longitudinal pattern was specific to NDVI or was reproduced by vegetation-condition formulations with different band relationships. GNDVI declined from first to last visit by 11.8% in dense vegetation, 8.8% in mixed vegetation, and 8.2% in dry vegetation. GCI declined by 16.8%, 11.8%, and 10.2%, and RVI declined by 8.5%, 5.2%, and 3.7%, respectively. All nine corresponding region-specific slopes were negative and remained significant after local Holm correction (Fig. 4).

The low-GNDVI fraction increased concurrently, from 0.080 to 0.191 in dense vegetation, 0.301 to 0.366 in mixed vegetation, and 0.405 to 0.490 in dry vegetation. This distributional result complements the median trajectories: the central tendency moved downward while a larger fraction of each persistent region occupied lower GNDVI values. Model-level tests supported both strong average region separation and region-specific temporal behavior for GNDVI, GCI, and RVI after BH-FDR correction.

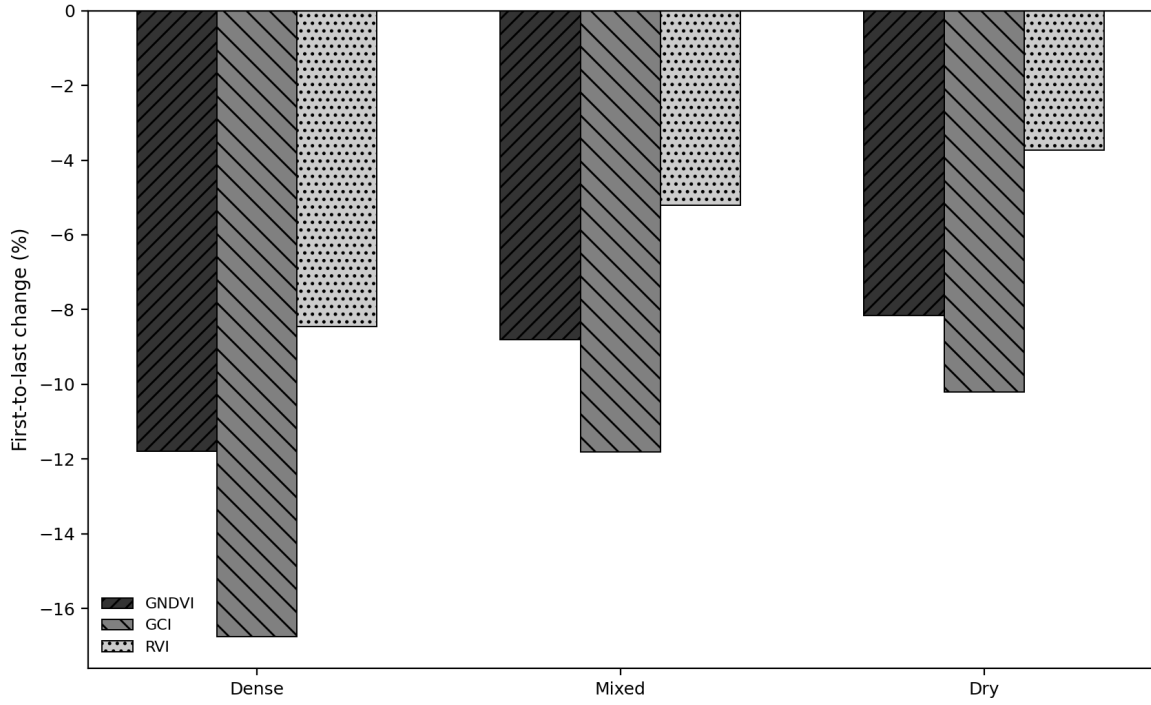


Fig. 4 First-to-last Site B change in retained vegetation-condition indices across persistent dense, mixed, and dry regions. Negative values indicate longitudinal decline

Longitudinal change was spatially localized within the oak canopy

The nested oak-canopy analysis showed that temporal change was not spatially uniform within a single tree structure. Outer-canopy GNDVI, GCI, and RVI slopes were -0.000397 , -0.001906 , and $-0.001901 \text{ day}^{-1}$; lower-canopy slopes were -0.000516 , -0.002536 , and $-0.002504 \text{ day}^{-1}$. All six slopes remained significant after local correction. By contrast, the corresponding inner-canopy slopes were near zero and nonsignificant. NDVI showed the same spatial pattern: outer and lower canopy slopes were negative, whereas the inner canopy slope was indistinguishable from zero. These results demonstrate that persistent within-canopy regions can resolve localized temporal response that would be obscured by a whole-canopy average (Fig. 5).

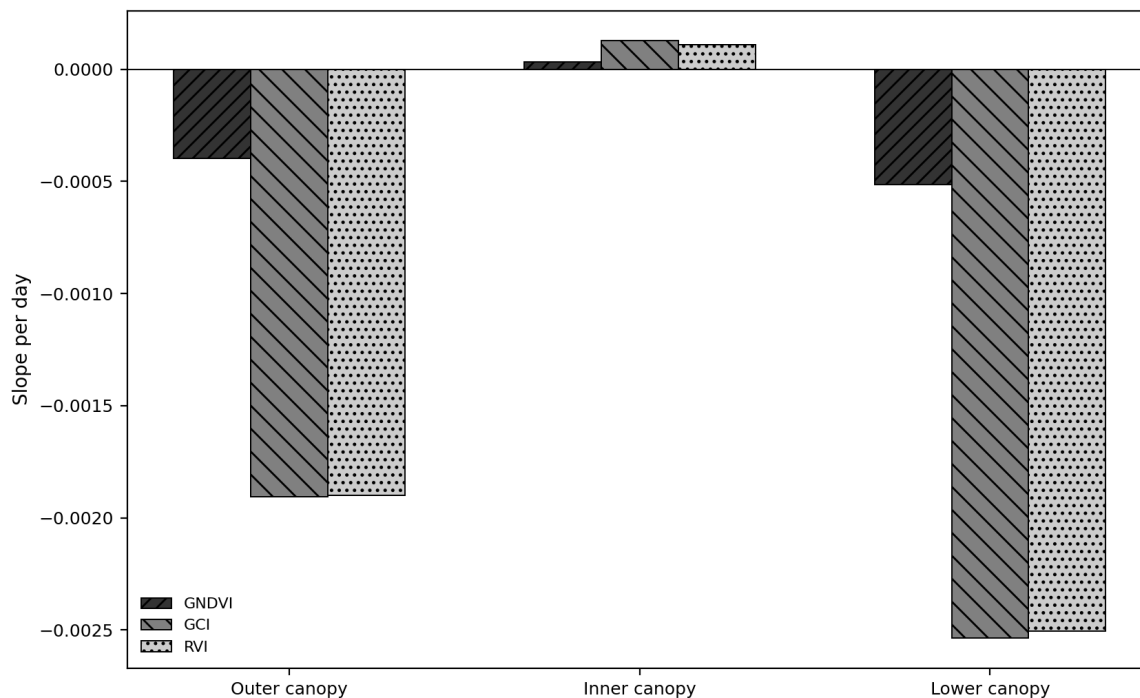


Fig. 5 Site B oak-canopy longitudinal slopes for GNDVI, GCI, and RVI. Decline was concentrated in outer and lower canopy regions, while the inner canopy remained comparatively stable

Structural fuel state was persistent and distinct from spectral condition

LiDAR-derived vertical spread retained strong region separation across repeated visits, whereas layer-occupancy models showed additional geometry-dependent structure. In the 0.5-2 m band, dry vegetation had substantially lower occupancy than dense vegetation at the Site A reference geometry, with strong site $\times$ region modification. In the 2-10 m band, dry and mixed vegetation also differed from dense vegetation after support and range conditioning. No general elapsed-time effect was detected for these occupancy bands after structural-family adjustment, indicating that the dominant short-term structural signal over the study interval was persistent spatial organization rather than a uniform temporal change. Together, the structural and spectral results resolve distinct components of vegetation-fuel state operating on different temporal scales.

Thermal response depended on vegetation region and atmospheric context

Region differences in ambient-normalized thermal response were large and consistent, but thermal trajectories were more environmentally conditioned than the spectral trajectories. In the median- ΔT model, dry vegetation was warmer than the dense reference by 2.56 °C after accounting for site, time, and VPD (thermal-family $q=1.28\times 10^{-9}$). The dense-reference association with VPD was -0.60 °C kPa $^{-1}$ ($q=0.037$), and the dry-region VPD interaction was +0.34 °C kPa $^{-1}$ ($q=0.021$). The corresponding p95 VPD terms did not survive thermal-family adjustment. These results support interpretation of thermal response as a distinct state variable governed jointly by vegetation class and atmospheric forcing.

Ecological contrasts exceeded short-window measurement variability

Short-window repeatability analyses placed the between-region signal against technical variability from repeated measurements within the same acquisition windows. For the dense-versus-dry contrast, the median absolute visit contrast was 71.9 times the median within-window NDVI IQR at Site A and 41.1 times at Site B. The corresponding LiDAR vertical-spread ratios were 76.5 and 20.9. Thermal median- ΔT ratios were lower, as expected for a variable affected directly by short-term atmospheric forcing, but still exceeded unity at 3.25 and 3.21. Across the principal domains, the region effects were therefore substantially larger than the short-window measurement dispersion used to quantify technical jitter.

The fused multisensor state was organized primarily by vegetation region

The complete shared-core fusion matrix contained 96 visit $\times$ site $\times$ region observations. Restricted-permutation partial PERMANOVA found significant structure associated with site (partial $R^2=0.210$, $p=0.0005$), vegetation region (partial $R^2=0.491$, $p=0.0005$), and the site $\times$ region interaction (partial $R^2=0.300$, $p=0.0005$). These are partial effect measures and are not additive variance components. PERMDISP tests did not indicate significant within-site region dispersion differences (Site A $p=0.964$; Site B $p=0.826$), supporting interpretation of the region result as a location/separation effect rather than a simple dispersion artifact (Fig. 6).

The primary residual association analysis identified a strong negative relationship between NDVI and LiDAR gap fraction after adjustment for site, region, and time (Spearman $r=-0.846$, BH-FDR $q=0.018$). Principal cross-domain effects and repeatability contrasts are summarized in Table 2.

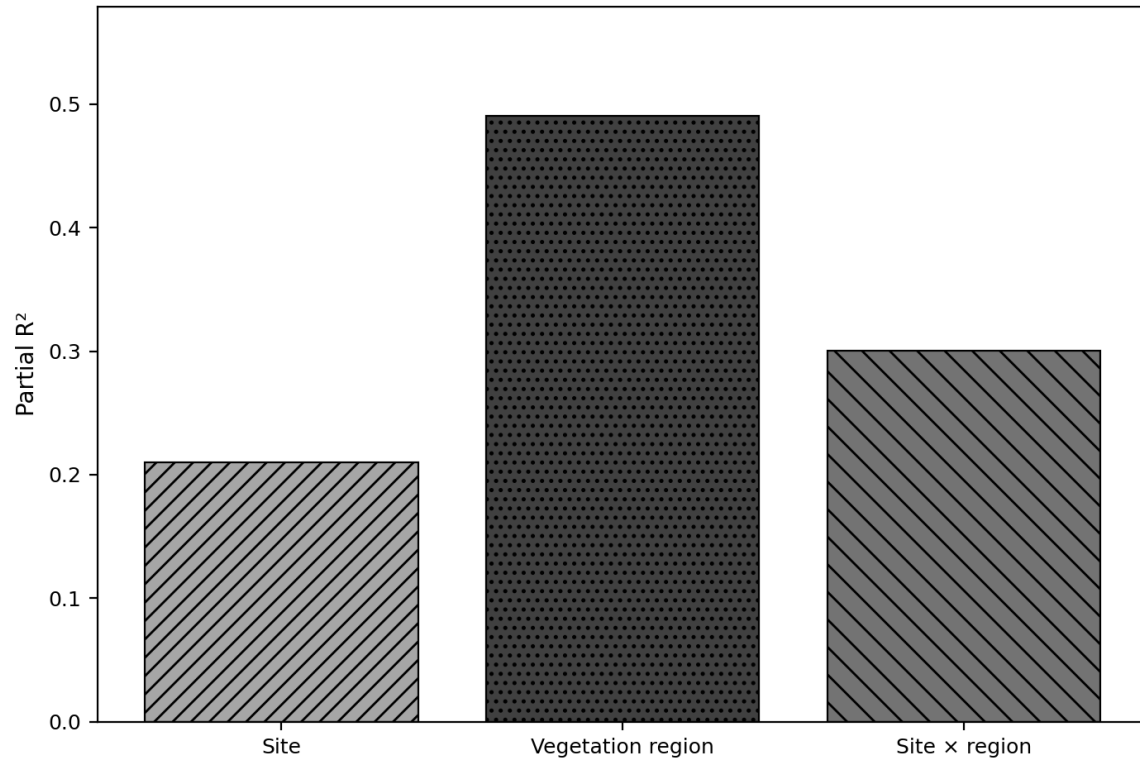


Fig. 6 Partial multivariate effects from restricted-permutation analysis of the shared-core fused state. Vegetation region produced the largest partial effect. Partial R^2 values are effect measures from separate partial tests and are not additive

Table 2 Summary of principal cross-domain evidence from the shared analyses

Evidence domain	Site A	Site B	Interpretation
NDVI dense-dry contrast	0.259 (95% CI 0.224–0.293)	0.113 (0.107–0.119)	Persistent spectral separation
Dense NDVI slope	-0.00410 day ⁻¹	-0.000874 day ⁻¹	Longitudinal condition change
LiDAR dense-dry vertical spread	4.11 m	0.563 m	Persistent 3D structural separation
Dense-dry median ΔT	-3.37 °C	-3.88 °C	Dense vegetation cooler relative to ambient
NDVI dense-dry signal/jitter	71.9×	41.1×	Region contrast exceeds short-window variability
LiDAR dense-dry signal/jitter	76.5×	20.9×	Structural contrast exceeds short-window variability

Discussion

Persistent spatial identity is the foundation of longitudinal local fuel-state monitoring

The most important result is the simultaneous presence of persistence and change. Dense, mixed, and dry semantic regions remained strongly distinguishable across spectral, structural, and thermal measurements, yet their spectral condition changed through time. This combination is essential for longitudinal monitoring: persistent region identity establishes the physical context within which changes and stability across different sensing domains can be interpreted through time. The Placerita data show both properties in the same repeated fixed-scene design.

This result extends the logic of fixed near-surface phenology monitoring. PhenoCam and related repeat-photography studies demonstrated that stable fields of view and persistent regions can resolve seasonal vegetation dynamics at high temporal resolution (Richardson et al., 2009; Sonnentag et al., 2012; Richardson et al., 2018). Here, the same spatial principle is extended beyond visible greenness to vegetation indices, three-dimensional fuel arrangement, ambient-normalized thermal response, and local atmospheric forcing. The scientific contribution is therefore not simply the presence of several sensors; it is the repeated alignment of distinct physical measurements to a persistent semantic unit through time.

Spectral dry-down was reproduced across formulations and localized within canopy structure

The Site B results strengthen the interpretation of longitudinal vegetation-condition change because the dominant trajectory was reproduced by NDVI, GNDVI, GCI, and RVI, which relate red, green, and near-infrared responses in different ways. Their convergence does not constitute four independent biological replications, because several of these indices are mathematically and empirically correlated. It does, however, show that the observed trajectory is not dependent on one specific vegetation-index formulation. The accompanying increase in low-GNDVI fraction adds distributional information: change occurred not only in regional central tendency but also in the share of the region occupying lower-condition values.

The oak-canopy analysis provides a different form of validation. Outer and lower canopy regions declined consistently while the inner canopy remained comparatively stable. Because these regions belong to the same tree structure and experienced the same broad weather regime, their divergence demonstrates that the fixed-region framework can resolve spatially localized change within a canopy rather than simply reproducing a scene-wide temporal trend. This kind of localization is difficult to recover from coarse regional products and is directly relevant to proximal monitoring of heterogeneous vegetation.

Studies in chaparral and other fire-prone vegetation show that spectral indices track aspects of vegetation condition and moisture-related state with site-, species-, and scale-dependent relationships to measured live fuel moisture (Roberts et al., 2006; Qi et al., 2012; Yebra et al., 2013). The present study establishes

longitudinal spectral sensitivity within fixed local regions and demonstrates that this sensitivity is spatially structured across vegetation classes and canopy positions.

Structural persistence and thermal response characterize distinct dimensions of vegetation-fuel state

LiDAR vertical spread strongly separated vegetation regions at both scenes and did so with signal-to-jitter ratios substantially above the corresponding within-window technical variability. The absence of a broad short-term temporal effect in the principal occupancy bands is scientifically informative: vegetation condition changed over weeks while the dominant three-dimensional fuel architecture remained comparatively persistent. This divergence is expected because structural fuel arrangement and physiological condition operate on different time scales. Recent TLS studies similarly emphasize that three-dimensional measurements provide access to height, occupied volume, and understory fuel configuration that spectral measurements cannot directly recover (Wilson et al., 2021, 2022; Nemens et al., 2026; Maxwell et al., 2026).

Thermal response behaved differently again. Dense vegetation was consistently cooler relative to ambient air than dry vegetation, but thermal values were more strongly conditioned by VPD and short-term atmospheric variability. That pattern agrees with plant-thermal literature in which canopy-air temperature differences are meaningful only in environmental context (Jackson et al., 1981; Idso et al., 1981; Jones et al., 2009). Thermal signal-to-jitter ratios were lower than those for NDVI and LiDAR, consistent with a physical variable that responds rapidly to changing atmospheric forcing. Ambient normalization and concurrent VPD measurement make that variability interpretable.

Multisensor fusion is supported most strongly at the joint-state level

The fused analysis showed that vegetation region was the dominant organizing factor in the combined state, with additional site and site $\times$ region structure. This indicates that common semantic classes retained coherent multivariate identity while being expressed differently in a chaparral hillside and an oak-centered scene. The site $\times$ region interaction is particularly important because it prevents an overly simplistic interpretation in which a semantic class is assumed to have one universal numerical signature independent of scene geometry and vegetation form.

The pairwise residual analysis identified a strong negative association between NDVI and gap fraction after adjustment for site, region, and time, linking vegetation condition and structural openness. Together with the restricted-permutation multivariate result, this supports feature-level fusion as integrated characterization of a multidimensional vegetation-fuel state.

This interpretation is consistent with broader fusion literature, in which nonredundant information across sensing domains supports integrated state characterization (Balestra et al., 2024). In practical scientific terms, spectral condition, three-dimensional fuel structure, thermal behavior, and atmospheric demand can move together, remain stable, or diverge. The pattern among those dimensions is itself information about the evolving vegetation-fuel system.

Relation to broad-area remote sensing and repeated terrestrial fuel measurements

The fixed-ground framework occupies a different observational scale from satellite and airborne systems. Broad-area platforms are indispensable for regional mapping, spatial context, and retrospective disturbance assessment, while fixed proximal sensing preserves much finer temporal continuity at selected local areas. Recent repeat-TLS research demonstrates the value of repeated structural measurements for documenting fuel changes through time (Maxwell et al., 2026). The present study extends repeated local observation across spectral, structural, thermal, and atmospheric domains in the same persistent vegetation regions.

The approach also differs from event-detection networks centered on smoke, flame, combustion gases, or acute heat. Those systems address the active-event phase. The present measurements characterize vegetation and fuel state before such combustion signatures exist. That distinction matters scientifically: the target variable is not ignition detection but the evolving pre-ignition physical and physiological condition of local vegetation and fuels.

Registration scale, reproducibility, and inferential scope

Cross-sensor correspondence was established through sensor-specific geometric calibration rather than a common generic registration procedure. LiDAR-to-multispectral registration relied on multi-pose rigid extrinsic calibration with geometric target correspondences, camera pose estimation, LiDAR target reconstruction, quality control, observability testing, and nonlinear SE(3) refinement. Thermal and monochrome channels were registered to the multispectral reference using calibration-target-derived image transformations followed by image-domain refinement. The physically separated image-sensor viewpoints introduce depth-dependent parallax across a three-dimensional vegetation scene; final scene alignment accounted for this geometric effect while retaining the calibrated transformations and quality-assurance provenance. This calibration architecture maintained spatial correspondence between each sensing domain and the persistent vegetation regions throughout repeated observation.

The inferential scope is equally specific. Site A and Site B are two fixed deployed scenes, and site effects therefore describe these monitored scenes over the study period. The two deliberately contrasting scenes provide a cross-scene test of persistent region separation and longitudinal behavior within the intended methodological scope; additional multi-site replication would evaluate transferability across broader vegetation types and environmental settings.

Conclusions

Repeated fixed-ground multisensor monitoring resolved two properties that are central to local pre-ignition state characterization: persistent spatial identity and temporal change. Dense, mixed, and dry vegetation regions remained strongly differentiated in spectral condition, three-dimensional fuel structure, and ambient-normalized thermal response, while spectral trajectories changed through time within the same physical regions. Site B provided the strongest longitudinal replication, with concordant declines across NDVI, GNDVI, GCI, and RVI, expansion of the low-GNDVI fraction, and localized decline in outer and lower oak-canopy regions.

The sensing domains resolved distinct, noninterchangeable components of vegetation-fuel state. LiDAR captured persistent fuel geometry, thermal measurements responded to vegetation class and atmospheric forcing, and spectral indices captured comparatively rapid vegetation-condition change. Their joint representation retained coherent region and scene structure in restricted-permutation analysis.

This supports semantic region/event feature-level fusion as a rigorous approach for integrating spectral, structural, thermal, and atmospheric measurements within persistent physical vegetation regions.

The resulting framework provides a local longitudinal measurement layer that complements regional remote sensing and episodic field campaigns by maintaining repeated observations of the same fuel areas through time. Its value lies in preserving spatial identity while integrating structural, spectral, thermal, and atmospheric measurements within a common monitoring architecture, allowing current observations to be interpreted against the prior state of the same vegetation. The fixed-ground design and persistent semantic regions also support sustained operational monitoring, while additional multi-site replication can further establish transferability across vegetation types and environmental settings.

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Declarations

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Competing interests

The author is affiliated with Graviris Labs, Inc., which owns intellectual property associated with the sensing system and methods described in this study.

Data availability

The data supporting the findings of this study are available from the author upon reasonable request.

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