

UAV data fusion approach to assess vegetation recovery dynamics after pipeline construction

Mattia Balestra^{1,2}, Stefano Chiappini², Bojana Petrovic^{1,3}, Filippo Giusti⁴,
Giacomo Quattrini², Simone Pesaresi², Marco Bonacoscia⁴, Roberto Pierdicca¹

¹ Department of Construction, Civil Engineering and Architecture (DICEA), Marche Polytechnic University, 60131 Ancona, Italy

² Department of Agricultural, Food and Environmental Sciences (D3A), Marche Polytechnic University, 60131 Ancona, Italy

³ Department of Geology and Soil Science, Faculty of Forestry and Wood Technology, Mendel University in Brno, Czech Republic

⁴ Hystrix – Società di ricerca, progettazione e consulenza naturalistica ed ambientale, 61032 Fano, Italy

Keywords: Natural restoration, Linear Pipeline Infrastructure, LiDAR, Multispectral, RGB, Data Fusion

Abstract

Post-construction vegetation monitoring along linear infrastructures is increasingly required to support restoration assessment, yet conventional ground surveys remain spatially sparse and difficult to scale over narrow, heterogeneous corridors. This limitation is critical in recently replanted pipeline clearings, where plant-level restoration outcomes must be inferred under operational constraints and where satellite-based monitoring cannot reliably resolve early post-restoration signals at the scale of individual saplings. This study addresses the problem by developing a UAV data-fusion workflow that integrates UAV laser scanning (ULS), UAV multispectral imagery (UAV-MS), and ultra-high-resolution UAV-RGB observations for sapling-level vitality assessment. The workflow was tested in two restored pipeline corridor sites in the Apennines (Italy), Ponte Baffoni (4.6 ha) and Ca' Romano (1.4 ha), surveyed in May 2025. ULS data were used to detect and geolocate saplings, UAV-MS data were used to extract vegetation-index metrics (NDVI, GNDVI, NDRE), and UAV-RGB imagery supported plot-level expert validation. A PCA-based soft-labelling strategy generated proxy vitality labels, which were then used to train a Random Forest classifier to derive corridor-scale probabilistic maps of sapling vitality, subsequently expressed as *ALIVE*, *DEAD*, and *UNCERTAIN* classes. The proposed workflow detected 5427 saplings in Ponte Baffoni and 801 in Ca' Romano. Random Forest classification achieved balanced accuracies of 0.78 and 0.83, respectively. The resulting corridor-scale maps suggested mortality rates of 48.9% in Ponte Baffoni and 40.0% in Ca' Romano. These results suggest that multi-sensor UAV fusion can provide spatially explicit, sapling-level indicators of restoration performance, complementing field surveys and supporting operational post-construction assessment in restoration corridors.

1. Introduction

Linear infrastructure projects can produce sustained vegetation and land-cover alterations; however, published evidence remains geographically and ecologically heterogeneous, and outcomes depend on local climate, substrate, and restoration practices (Shi et al., 2014; Xiao et al., 2016; McClung and Moran, 2018). Construction phases typically involve vegetation clearing and mechanical soil disturbance. These operations fragment habitats, modifying microsite conditions and delaying spontaneous natural regeneration, particularly where fragile ecosystems show limited resilience (Xiao et al., 2014; Brehm and Culman, 2022). As pipeline networks continue to expand worldwide (Raïter et al., 2018; Wang et al., 2022), environmental policies and stakeholders increasingly require evidence-based restoration performance evaluations, rather than relying on descriptive post-construction monitoring reports.

Despite widespread replanting and restoration efforts, rigorously evaluating their effectiveness remains difficult, particularly when monitoring designs must remain feasible at operational scale (Wortley et al., 2013; Flemming et al., 2023). The problem intensifies in small, fragmented restoration areas, where before–after–control–impact (BACI) designs are rarely applicable due to the lack of comparable untreated reference sites (Smokorowski and Randall, 2017). BACI designs estimate intervention effects by comparing changes through time at an impacted site against contemporaneous changes at an untreated reference site, thereby controlling for background temporal variability. Spectral vegetation index (SVI) time-series monitoring over extended periods can help us detect distur-

ance events and track subsequent restoration trajectories; however, seasonal phenology and inter-annual climate variability can mask these signals by mimicking intervention effects or obscuring them (Gao et al., 2024; England et al., 2021). Satellite-based monitoring further benefits from the growing availability of open multispectral archives, supporting repeated analysis of disturbances at sub-hectare scale under a consistent acquisition strategy Phiri et al. (2020). Satellite imagery time-series approaches can delineate trajectories before and after a defined breakpoint and quantify level and trend changes without randomized experimentation (Linden, 2015). Targeted post-event analyses at finer temporal granularity and higher spatial resolution can then isolate the restoration signal, track recovery progression, and attribute observed changes to specific interventions within the affected area.

Close-range remote sensing technologies provide spatially detailed and temporally consistent observations, and SVIs are widely used to map disturbances and vegetation recovery associated with wildfires, harvesting, and engineered interventions (Monroe et al., 2020; Taddeo, 2022; Lasaponara et al., 2022; Balata et al., 2022). Indices such as the Normalized Difference Vegetation Index (NDVI), the Green Normalized Difference Vegetation Index (GNDVI), and the Normalized Difference Red Edge (NDRE) quantitatively assess crown photosynthetic activity, although they can saturate under high biomass and can remain sensitive to soil background effects in disturbed conditions (Yan et al., 2025). These limitations reinforce the need for high-spatial-resolution observation strategies capable of isolating individual-crown signals from background variability. Unmanned aerial vehicles (UAVs) now play a central role

in environmental surveying (Villarino et al., 2025; Asadzadeh et al., 2022) and, when equipped with passive and active sensors, they provide detailed, plot- to individual-level information on the condition of planted vegetation in operational restoration settings (Noonan et al., 2025). In addition, UAV-based workflows enable semi-automated monitoring of selected areas and complement field surveys, which provide high accuracy but require substantial resources and typically cover only limited representative samples rather than the full restoration extent.

Pipeline corridors pose a distinct evaluation challenge because they seldom include dedicated reference areas. After disturbance, operators also rarely have comparable "parallel" corridors available for comparison, which constrains the applicability of classical counterfactual designs in this setting (Xiao et al., 2014; Smokorowski and Randall, 2017). In this context, UAV-based surveys provide a pragmatic alternative because they allow direct, site-specific observations at plant and plot scale, without requiring spatially matched comparison units (Jayathunga et al., 2023). UAV Laser Scanner (ULS) enables detailed characterization of the tree/crown geometry and its vertical structure, multispectral UAV (UAV-MS) systems allow plot-scale mapping of SVIs describing the vegetation condition around planted saplings, and UAV-based RGB (UAV-RGB) supports expert interpretation for species identification (Pierdicca et al., 2023) and visual assessment of sapling vitality (Liang et al., 2022). By fusing these close-range observed features with systematic sampling and expert validation, researchers can reduce the spatial constraints of field surveys while preserving the monitoring effectiveness (Balestra et al., 2024). This multi-sensor UAV capability is well aligned with post-construction monitoring needs, where operators must verify restoration performance through repeatable, interpretable indicators at the scale of individual planted saplings.

Building on the multi-sensor UAV strategy, this study investigates the potential of an integrated data-fusion workflow combining ULS, UAV-MS, and UAV-RGB to support sapling-level vitality inference and corridor-scale assessment of restoration performance in recently replanted pipeline clearings. Within this framework: (i) UAV-RGB imagery provides plot-level reference counts of *ALIVE* and *DEAD* saplings through expert interpretation; (ii) ULS data enable the detection, delineation, and geolocation of planted saplings along the restored corridor; and (iii) UAV-MS orthomosaics provide vegetation-index metrics linked to each LiDAR-derived individual. Together, these complementary data sources support the inference of proxy sapling vitality classes from structural and spectral indicators and provide spatially explicit, operationally relevant information for post-construction monitoring in narrow restoration corridors.

2. Materials and Methods

2.1 Study areas

The study sites are located along a natural gas pipeline corridor in the hilly landscape of the central Apennines (Province of Rimini, Italy), where vegetation restoration followed construction-related disturbance. Ponte Baffoni (municipality of Novafeltria; 43.87° N, 12.28° E) covers approximately 4.6 ha, whereas Ca' Romano (municipality of Pennabilli; 43.78° N, 12.24° E) covers approximately 1.4 ha. The corridor underwent complete vegetation removal during pipeline installation. Pre-disturbance vegetation consisted of mixed riparian and broadleaf forest communities. Replanting interventions

were implemented in March 2023 using native species, approximately two years prior to the UAV survey campaign conducted in May 2025.

2.2 UAV data collection

We adopted a multi-sensor UAV strategy based on three complementary acquisitions. For ULS, a DJI Matrice 350 RTK carried a DJI Zenmuse L2 integrating a LiDAR unit, a high-precision IMU, and an RGB mapping camera. For UAV-MS, a MicaSense Altum sensor mounted on the DJI Matrice 350 RTK produced five-band products (blue, green, red, red edge, near-infrared), which supported the computation of SVIs (e.g., NDVI, GNDVI, NDRE) describing the vegetation condition of and around planted saplings. For UAV-RGB, a dedicated acquisition employed a DJI Matrice 30 equipped with a 16× optical zoom camera, a laser rangefinder, and RTK positioning. During UAV-RGB operations, the platform was positioned above the centroid of each selected plot using RTK-assisted navigation and maintained in stable hover while high-resolution RGB images were acquired through optical zoom by sequentially framing the shelters located within the plot.

Before data acquisition, four Ground Control Points (GCPs) per site were deployed and surveyed with RTK-GNSS, distributing targets to provide robust geometric coverage. The workflow ensured GCP visibility along planned trajectories and stable RTK connectivity during observations to achieve centimetre-level horizontal and vertical accuracy. All GCPs were referenced to WGS84/UTM Zone 33N. RGB plots were selected using a stratified sampling approach to ensure spatially representative coverage of the restored corridor (Corona et al., 2019). Flight planning for ULS and UAV-MS was carried out in DJI Pilot 2, with acquisition parameters defined according to site extent and target spatial resolution (Table 1).

2.3 UAV data processing

2.3.1 UAV ultra-high-resolution RGB imagery The UAV-RGB dataset used as plot-level reference information was obtained through targeted drone inspections using a DJI Matrice 30 equipped with a 16× optical zoom camera, laser rangefinder, and RTK positioning. The detection workflow was adapted from (Quattrini et al., 2025) and adjusted to the structural characteristics of recently replanted saplings. The drone was manually piloted with RTK-assisted positioning and placed above the centroid of each circular sampling plot (radius 4 m), maintaining a stable hover at approximately 15 m above ground level. From this position, the camera was sequentially oriented towards each shelter located within the plot, acquiring ultra-high-resolution RGB images through optical zoom. The combination of low flight altitude and 16× optical zoom produced very high spatial resolution imagery suitable for detailed visual inspection of individual saplings and surrounding vegetation. The acquired images were subsequently analysed through expert visual interpretation. For each visible shelter, the high-resolution imagery was inspected to identify the species present and determine whether the observed individual corresponded to one of the planted species or to spontaneous vegetation. Only after species identification was the vitality status of the planted sapling assessed (*ALIVE/DEAD*). Because not all saplings within each plot were clearly visible from the UAV-RGB imagery, the resulting reference dataset does not represent a full census of all individuals present in the plot, but rather the subset that could be reliably interpreted from the aerial images.

Table 1. Acquisition parameters for the ULS and UAV-MS surveys at the two study sites.

Parameter	Zenmuse L2		MicaSense Altum	
	Ca' Romano	Ponte Baffoni	Ca' Romano	Ponte Baffoni
Flight speed	3.5 m/s	3.5 m/s	4.00 m/s	4.00 m/s
Flight altitude	44.00 m	44.00 m	50.00 m	50.00 m
Flight duration	8 m 15 s	12 m 25 s	8 m 13 s	17 m 42 s
Field of view (FOV)	70° × 3°	70° × 3°	57°	57°
Flight mode	Linear	Linear	Linear	Linear
Point-cloud density	424 points/m ²	382 points/m ²	/	/
Ground sampling distance	1.45 cm/px	1.35 cm/px	2.00 cm/px	2.16 cm/px

The observations were therefore organised as a plot-level dataset reporting, for each plot, the number of visible living and dead planted saplings and the corresponding mortality proportion. These plot-level counts were finally exported as a georeferenced shapefile and used as plot-level reference information in the UAV data-fusion workflow.

2.3.2 UAV laser scanner point cloud The ULS point cloud was processed in PDAL to separate terrain and above-ground returns. Ground points were classified using the Cloth Simulation Filter (CSF) and exported as a classified LAS product, which was subsequently split into ground and non-ground subsets for downstream processing. Elevations were then normalised to derive height-above-ground metrics. Local ground elevation was estimated with the k -nearest-neighbour height-above-ground filter, which interpolates the terrain surface from points labelled as ground while preserving small-scale topographic variability.

Candidate planted-sapling locations were delineated by extracting local maxima from a canopy height model (CHM) derived from the normalised ULS products and exporting the detections as a georeferenced point layer. A local-maximum detector was applied to the CHM to identify candidate canopy peaks associated with individual saplings, and spurious detections were constrained using a minimum height threshold (0.05 m) and a low-value floor to suppress micro-relief artefacts and low-amplitude noise. Spatial uniqueness was enforced through metric non-maximum suppression with a minimum Euclidean separation in map coordinates, consistent with regular plantation spacing, retaining the highest peak within each neighborhood. Retained peak coordinates were converted to point geometries and attributed with the corresponding CHM-derived height. The final individual sapling detections were exported as an ESRI Shapefile to support subsequent spatial joins and object-based analyses.

2.3.3 UAV multispectral imagery UAV-MS imagery was processed in Agisoft Metashape. Radiometric calibration used the MicaSense Altum reflectance panel and the system-integrated downwelling light sensor to compensate for illumination variability during flight and to ensure consistent reflectance values across acquisitions. The photogrammetric workflow included image alignment, dense point cloud reconstruction, digital surface model (DSM) generation, and multispectral orthomosaic production. The resulting orthomosaics retained the acquired spectral bands and achieved a ground sampling distance (GSD) of 2.5 cm. The orthomosaics were then imported into a GIS environment to compute SVIs, specifically NDVI, GNDVI, and NDRE, as follows:

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R}, \quad (1)$$

$$GNDVI = \frac{\rho_{NIR} - \rho_G}{\rho_{NIR} + \rho_G}, \quad (2)$$

$$NDRE = \frac{\rho_{NIR} - \rho_{RE}}{\rho_{NIR} + \rho_{RE}}, \quad (3)$$

where ρ_{NIR} , ρ_R , ρ_G , and ρ_{RE} denote the reflectance in the near-infrared, red, green, and red-edge bands, respectively.

2.4 Proxy-based sapling vitality inference and mapping

2.4.1 Plot-Based SVI Metrics for ULS saplings Starting from the ULS sapling-detection point layer, a circular buffer of 0.15 m radius was generated around each detection point to approximate a local crown-centred area associated with each detected sapling. This radius was selected as an operational compromise intended to capture the spectral signal associated with the sapling and its immediate surroundings while limiting contamination from adjacent soil, shadow, and protective shelters. Although a formal sensitivity analysis of buffer size was beyond the scope of this study, the selected radius was considered appropriate for the dimensions of the detected saplings and the spatial resolution of the multispectral orthomosaics. Sapling-associated SVIs were then computed through zonal statistics in a GIS environment by overlaying the buffered polygons on the SVI rasters. The median NDVI, GNDVI, and NDRE were extracted for each buffered object. The median was preferred over the mean to reduce the influence of outliers caused by radiometric noise, shadowing effects, and reflectance artefacts from protective shelters installed around individual saplings. The sapling objects were subsequently clipped to the 22 UAV-RGB plots in Ponte Baffoni and the 13 UAV-RGB plots in Ca' Romano (Figure 1), thereby establishing correspondence between plot-level expert validation from ultra-high-resolution RGB imagery and the SVI metrics extracted for LiDAR-detected saplings within the same spatial sampling units.



Figure 1. UAV-RGB image-acquisition procedure. Left: the UAV hovers above the plot centroid during image capture. Right: a 16× optical-zoom RGB frame showing an *ALIVE* sapling within an individual protective shelter.

2.4.2 PCA and soft classification We performed a plot-level Principal Component Analysis (PCA) on sapling-level median NDVI, GNDVI, and NDRE values. Prior to PCA, the indices were standardised, and principal components were derived from the covariance matrix. The first principal component (PC1) represents a standardised linear combination of NDVI, GNDVI, and NDRE and condenses their shared variability into a single synthetic indicator of vegetation vigour. A direct one-to-one correspondence could not be established between ULS-detected saplings and the individuals visually interpreted in the UAV-RGB imagery within each plot; therefore, only plot-level counts of *ALIVE* and *DEAD* saplings were retained from the RGB inspection. These counts referred exclusively to individuals that were clearly visible in the images and therefore did not necessarily represent the full sapling population present within each plot.

To enable individual-level labelling under this constraint, we adopted a soft classification strategy based on the relative distribution of PC1 values within each plot. Specifically, ULS-detected saplings were ranked according to their PC1 scores, interpreted as a proxy of local vegetation vigour associated with the detected saplings, and labels were assigned so that the number of *ALIVE* and *DEAD* saplings matched the corresponding plot-level counts derived from the UAV-RGB interpretation. Under this assumption, saplings with higher PC1 values were preferentially associated with the *ALIVE* class, whereas lower PC1 values were associated with the *DEAD* class. By integrating ULS-derived structural detections with UAV-MS spectral information, this procedure produced plot-specific, sapling-level proxy vitality labels suitable for subsequent supervised classification.

2.4.3 Machine learning-based inference of sapling vitality Plot-level, proxy-derived sapling labels were used to train a Random Forest (RF) classifier and to extrapolate sapling vitality probabilities to the full population of ULS-detected saplings outside the UAV-RGB plots. The predictor set included one structural variable derived from ULS (sapling height) and three spectral summaries extracted from UAV-MS data (median NDVI, median GNDVI, and median NDRE). RF modelling was implemented in Python using the `scikit-learn` library, with `RandomForestClassifier`. The final model was parameterised with `n_estimators = 500`, `max_depth = 8`, `min_samples_leaf = 6`, `max_features = "sqrt"`, `class_weight = "balanced"` and `random_state = 42`.

Model generalisation was evaluated through cross-validation at plot level in order to avoid information leakage among correlated samples belonging to the same UAV-RGB plot. A grouped *k*-fold strategy (`GroupKFold`) was applied, with the number of folds set to the minimum between five and the number of unique groups. Performance was summarised using a pooled confusion matrix and balanced accuracy. After validation, the classifier was retrained on the labelled dataset and applied to an independent inventory containing all ULS-detected saplings across the study areas, including individuals located outside the UAV-RGB plots. For each sapling with complete predictor values, the posterior probability of belonging to the *ALIVE* class (p_{alive}) was obtained through the RF probabilistic output. A categorical vitality class was then assigned using asymmetric decision thresholds, with *DEAD* for $p_{\text{alive}} \leq 0.45$, *ALIVE* for $p_{\text{alive}} \geq 0.55$, and *UNCERTAIN* otherwise. These thresholds were introduced to define a narrow uncertainty band around the

decision boundary ($p = 0.5$) (Table 2), thereby reducing over-confident assignments for saplings with weak class separability and keeping the *UNCERTAIN* class restricted to low-confidence cases. These predictions should be interpreted as probabilistic indicators of sapling vitality inferred from structural and spectral attributes.

Table 2. Probability thresholds used for sapling vitality classification.

Condition on p_{alive}	Assigned class
$p_{\text{alive}} \leq 0.45$	<i>DEAD</i>
$0.45 < p_{\text{alive}} < 0.55$	<i>UNCERTAIN</i>
$p_{\text{alive}} \geq 0.55$	<i>ALIVE</i>

3. Results

Using the ULS workflow described in Section 2.3.2, we detected a total of $n = 5427$ saplings in Ponte Baffoni and $n = 801$ saplings in Ca' Romano (Figure 2). We used these ULS-derived detections as the spatial backbone for all subsequent analyses. We then restricted the inventory to saplings falling within the UAV-RGB plot boundaries, obtaining $n = 397$ saplings in Ponte Baffoni and $n = 164$ saplings in Ca' Romano (Figure 3).



Figure 2. ULS-derived sapling detections along the two study areas. White points indicate the positions of detected saplings; totals are $n = 5427$ at Ponte Baffoni and $n = 801$ at Ca' Romano.

We further compared plot-level UAV-RGB observations against ULS-derived sapling counts within the same sampling units (Figures 4–5). Ponte Baffoni exhibited larger absolute errors and weaker linear agreement between plot-observed and ULS-detected counts ($R^2 = 0.29$, RMSE = 4.96, Bias = 0.45, Rel. Bias = 11.6%), consistent with the higher planting density and greater potential for occlusion and peak merging. Ca' Romano showed a stronger linear relationship and lower absolute error ($R^2 = 0.41$, RMSE = 2.50, Bias = 1.46), but also a higher relative bias (15.1%). This indicates that, although ULS detections tracked plot-to-plot variability more consistently in Ca' Romano, the average deviation represented a larger fraction of the observed counts, likely because of the smaller sapling counts per plot.

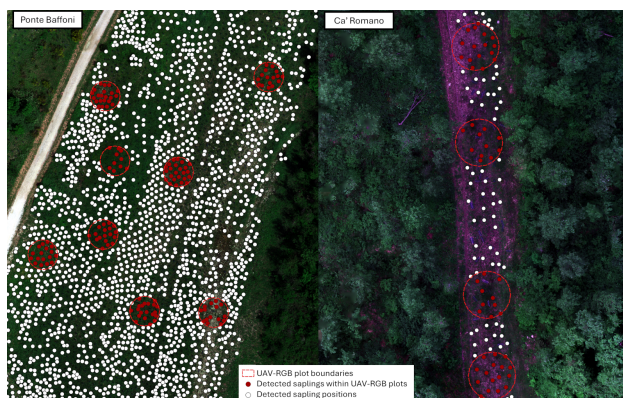


Figure 3. ULS-derived sapling detections with a zoom on UAV-RGB plots at Ponte Baffoni and Ca' Romano. White points denote ULS-detected sapling positions, while red points indicate detections falling within UAV-RGB plot boundaries.

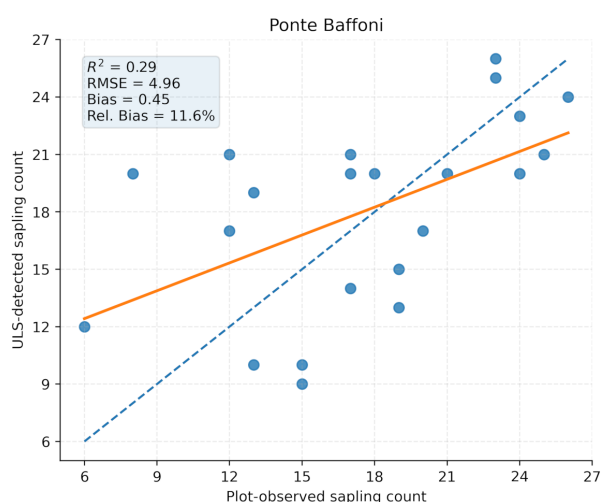


Figure 4. Comparison between plot-observed and ULS-detected sapling counts at Ponte Baffoni. Each point represents one UAV-RGB plot. The solid line shows the fitted linear regression, while the dashed line denotes the 1:1 agreement line. The inset reports R^2 , RMSE, bias, and relative bias.

Following the PCA-based soft-labelling procedure described in Section 2.4.2, we computed PC1 as a synthetic proxy of vegetation vigour derived from the joint variability of NDVI, GNDVI, and NDRE, and we evaluated its consistency against the input SVIs. In both study sites, PC1 showed the strongest linear association with NDRE (Pearson $r = 0.946$ in Ponte Baffoni and $r = 0.951$ in Ca' Romano), as illustrated in Figures 6 and 7. By combining plot-level UAV-RGB validation with the PC1-based soft classification, we assigned proxy vitality labels based on spectral indicators to a subset of ULS-detected saplings, resulting in $n = 161$ labelled saplings in Ponte Baffoni and $n = 114$ labelled saplings in Ca' Romano. These labelled samples were then used to train the RF classifier described in Section 2.4.3, and vitality predictions were subsequently extrapolated to the full ULS-derived sapling inventories. The RF achieved a balanced accuracy of 0.78 in Ponte Baffoni and 0.83 in Ca' Romano (Figures 8 and 9).

We generated corridor-scale probabilistic maps of sapling vitality classes for both study areas by assigning each ULS-detected

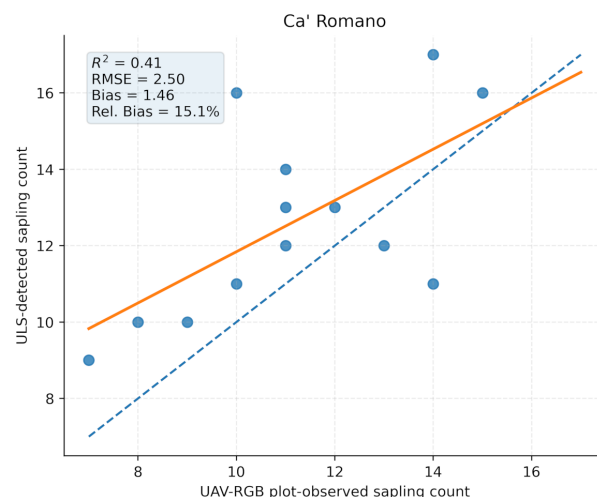


Figure 5. Comparison between plot-observed and ULS-detected sapling counts at Ca' Romano. Each point represents one UAV-RGB plot. The solid line shows the fitted linear regression, while the dashed line denotes the 1:1 agreement line. The inset reports R^2 , RMSE, bias, and relative bias.

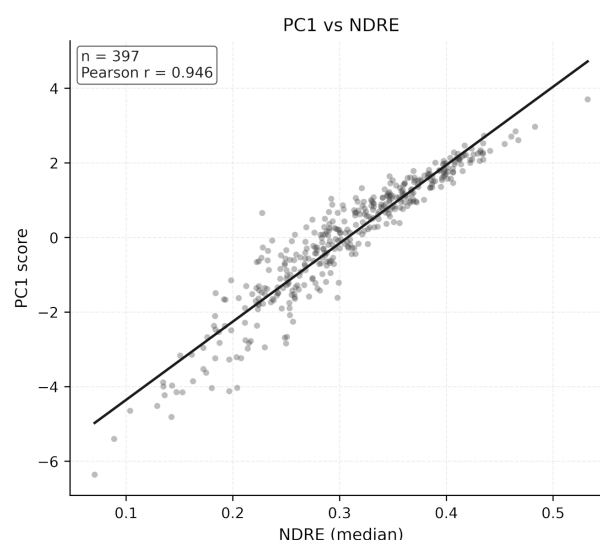


Figure 6. PC1 score as a function of sapling-level median NDRE in Ponte Baffoni. NDRE is reported here as a representative example of the relationship between PC1 and the input SVIs, as it showed a strong linear association with the PCA-derived component. Points represent individual saplings ($n = 397$). The Pearson correlation coefficient ($r = 0.946$) indicates strong agreement between PC1 and NDRE.

sapling to one of three classes (*ALIVE*, *DEAD*, *UNCERTAIN*) based on the RF posterior probability thresholds (Table 2). Figure 10 shows the spatial distribution of predicted vitality classes along the restored pipeline corridors in Ponte Baffoni and Ca' Romano. The resulting class counts were: Ponte Baffoni (*ALIVE*: $n = 2208$, *DEAD*: $n = 2652$, *UNCERTAIN*: $n = 567$) and Ca' Romano (*ALIVE*: $n = 431$, *DEAD*: $n = 320$, *UNCERTAIN*: $n = 50$). The proportion of *UNCERTAIN* predictions was markedly higher in Ponte Baffoni (10.4% of all ULS-detected saplings) than in Ca' Romano (6.2%), suggesting lower class separability in the former site. Corridor-scale

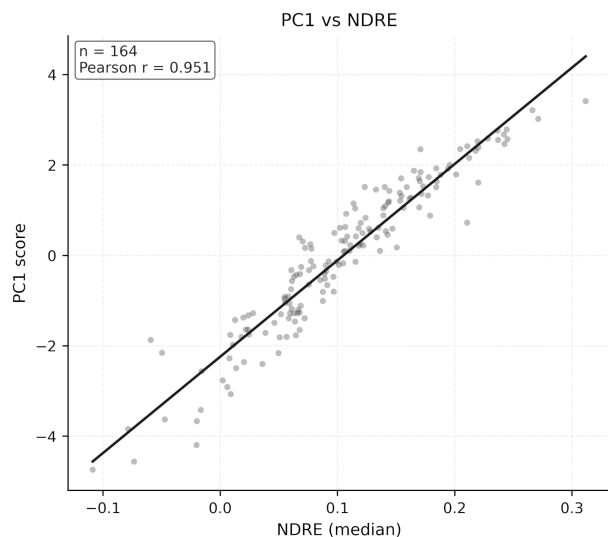


Figure 7. PC1 score as a function of sapling-level median NDRE in Ca' Romano. NDRE is reported here as a representative example of the relationship between PC1 and the input SVIs, as it showed a strong linear association with the PCA-derived component. Points represent individual saplings ($n = 164$). The Pearson correlation coefficient ($r = 0.951$) indicates strong agreement between PC1 and NDRE.

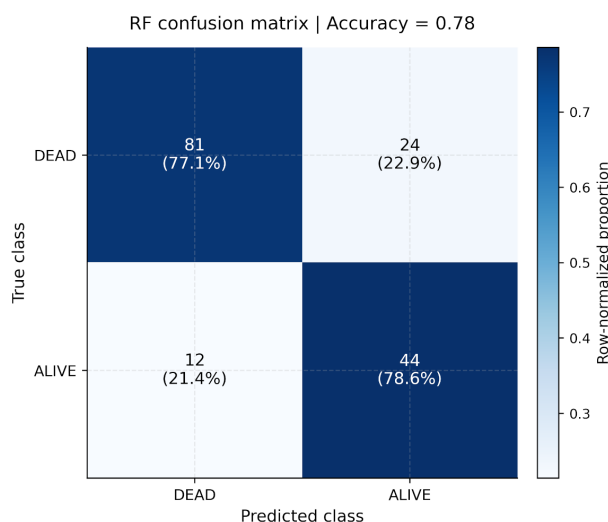


Figure 8. Confusion matrix comparing true and predicted *ALIVE/DEAD* classes in Ponte Baffoni ($n = 161$), each cell reports the corresponding proportion and number of saplings.

mortality rate was computed as the proportion of saplings classified as *DEAD* over the total number of ULS-detected saplings in each study area, yielding estimated sapling mortality rates of 48.9% in Ponte Baffoni and 40.0% in Ca' Romano. These corridor-scale estimates can be compared with the mean mortality rates derived from UAV-RGB plot inspections, which were 66.5% for Ponte Baffoni and 39.6% for Ca' Romano.

4. Discussion

Our results suggest that integrating ULS-based individual detection with UAV-MS spectral metrics describing local veget-

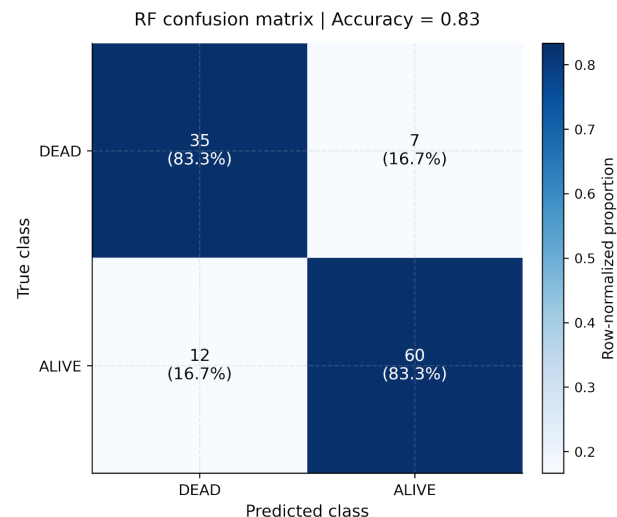


Figure 9. Confusion matrix comparing true and predicted *ALIVE/DEAD* classes in Ca' Romano ($n = 114$), each cell reports the corresponding proportion and number of saplings.

ation conditions supports corridor-scale probabilistic mapping of sapling vitality in restored pipeline clearings. We used ULS to generate a spatially explicit sapling inventory that anchored all subsequent analyses ($n = 5427$ saplings in Ponte Baffoni; $n = 801$ in Ca' Romano), thereby overcoming the intrinsic spatial sparsity of ground-based surveys, which remain highly reliable but typically cover only limited areas. By coupling this individual inventory with UAV-MS vegetation-index metrics, we achieved a spatial granularity suitable for inferring outcomes at the plant level and for propagating plot-based expert validation into corridor-scale vitality maps. This workflow supports spatially continuous post-construction monitoring assessment in narrow restoration units, where satellite-only monitoring and plot-based field checks cannot resolve individual outcomes (Galdelli et al., 2025; Petrovic et al., 2026). In this framework, spectral indices should be interpreted as indicators of local vegetation conditions associated with each sapling rather than direct measurements of individual vitality.

UAV data fusion remains essential because neither structural ULS products nor multispectral metrics alone are likely to provide equally robust corridor-scale vitality inference (Samadzadegan et al., 2025; Balestra et al., 2024). The comparison between UAV-RGB plot observations and ULS-derived sapling counts shows that stand structure and planting configuration strongly modulate detectability and counting accuracy. Ponte Baffoni exhibited larger discrepancies between plot-observed and ULS-detected counts ($R^2 = 0.29$, RMSE = 4.96), consistent with higher planting density and increased occlusion, as well as peak merging in CHM-based local-maximum detection. In contrast, Ca' Romano showed lower errors and a clearer linear trend ($R^2 = 0.41$, RMSE = 2.50), indicating that lower-density conditions improve individual delineation and reduce downstream propagation of detection errors into spectral attribution. The higher proportion of *UNCERTAIN* saplings in Ponte Baffoni suggests lower separability between vitality classes under denser planting conditions. Greater local crowding, increased shadowing, and more frequent interaction between vegetation and protective shelters likely reduced the distinctiveness of both structural and spectral predictors, thereby increasing the number of saplings fall-

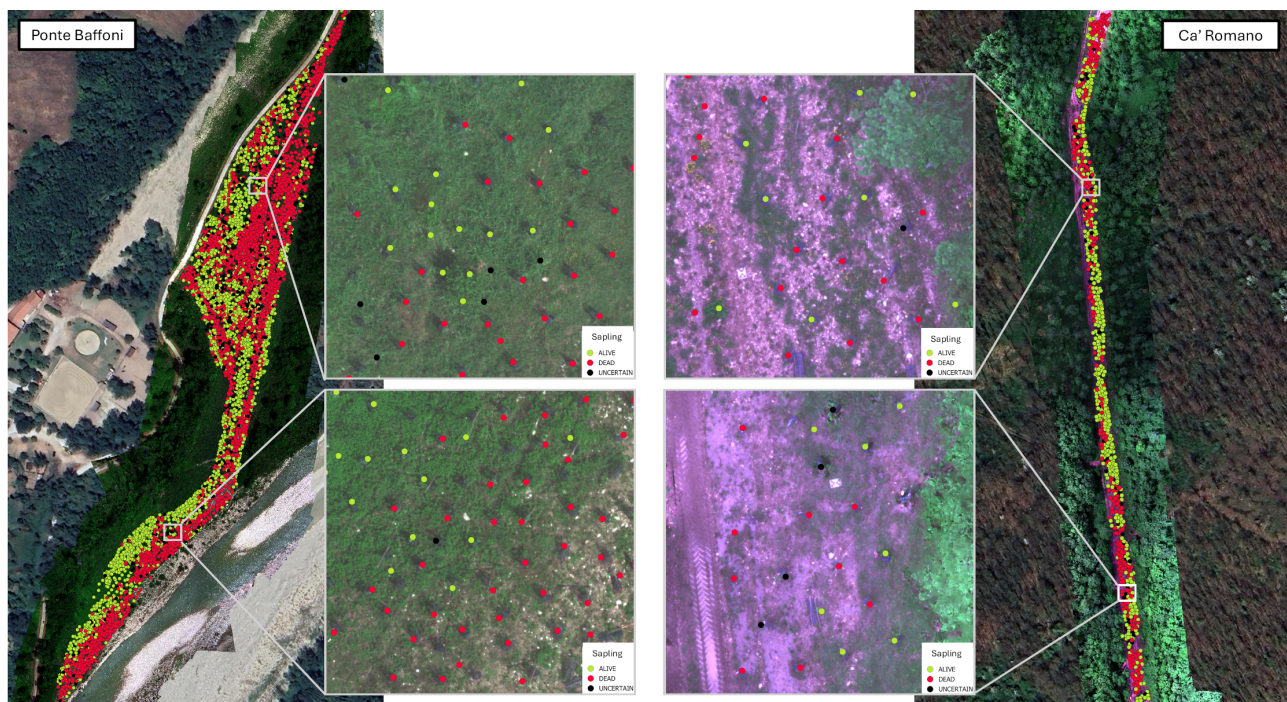


Figure 10. ULS-detected saplings mapped along the restored pipeline corridors at Ponte Baffoni and Ca' Romano and assigned to probabilistic vitality classes. The resulting classes should be interpreted as probabilistic indicators of sapling vitality inferred from structural and spectral attributes. The four zoomed panels highlight contrasting local sapling densities and the spatial pattern of predicted *ALIVE*, *DEAD*, and *UNCERTAIN* classes.

ing near the RF decision boundary.

A key constraint is that UAV-RGB inspections provide plot-level *ALIVE/DEAD* counts rather than unambiguous one-to-one labels for individual ULS detections. We therefore adopted a proxy-labelling strategy that compresses redundant spectral information into PC1 and then propagates plot-level validation into sapling-level labels through soft classification. This approach does not claim individual-level ground truth; instead, it provides a pragmatic mechanism to train a supervised classifier under operational monitoring constraints while enabling extrapolation beyond the UAV-RGB sampling units. We then used the proxy-labelled samples to train a RF model and estimate sapling vitality probability for the full ULS-derived inventories. We explicitly represented low-confidence predictions by introducing an *UNCERTAIN* class near the decision boundary, which supports uncertainty-aware mapping and targeted follow-up. At the corridor scale, the RF-based maps suggest class-based mortality estimates of 48.9% in Ponte Baffoni and 40.0% in Ca' Romano, which we compared with mean plot-based UAV-RGB mortality estimates (66.5% and 39.6%, respectively). These map products should therefore be interpreted as probabilistic, proxy-based representations of sapling vitality rather than as direct field observations of individual condition.

5. Conclusions

The closer agreement in Ca' Romano, together with its stronger ULS–plot consistency, suggests that planting density and local visibility conditions drive both detection uncertainty and apparent mortality discrepancies, reinforcing the need for spatially continuous, uncertainty-aware products in heterogeneous corridor environments. From an operational perspective, the mapped distribution of *DEAD* and *UNCERTAIN* saplings can support targeted post-construction inspections and prioritisation

of replanting or maintenance actions, especially in corridor sections where local density, shelter effects, or microsite heterogeneity appear to reduce establishment success.

References

- Asadzadeh, S., de Oliveira, W. J., de Souza Filho, C. R., 2022. UAV-based remote sensing for the petroleum industry and environmental monitoring: State-of-the-art and perspectives. *Journal of Petroleum Science and Engineering*, 208, 109633.
- Balata, D., Gama, I., Domingos, T., Proença, V., 2022. Using satellite NDVI time-series to monitor grazing effects on vegetation productivity and phenology in heterogeneous Mediterranean forests. *Remote Sensing*, 14(10), 2322.
- Balestra, M., Marselis, S., Sankey, T. T., Cabo, C., Liang, X., Mokroš, M., Peng, X., Singh, A., Stereńczak, K., Vega, C. et al., 2024. LiDAR data fusion to improve forest attribute estimates: A review. *Current Forestry Reports*, 10(4), 281–297.
- Brehm, T., Culman, S., 2022. Pipeline installation effects on soils and plants: A review and quantitative synthesis. *Agrosystems, Geosciences & Environment*, 5(4), e20312.
- Corona, P., Fattorini, L., Franceschi, S., Marcheselli, M., Pisani, C., Chiavetta, U., Puletti, N., 2019. Estimating tree diversity in forest ecosystems by two-phase inventories. *Environmetrics*, 30(2), e2502. <https://onlinelibrary.wiley.com/doi/abs/10.1002/env.2502>. e2502 env.2502.
- England, J., Angelopoulos, N., Cooksley, S., Dodd, J., Gill, A., Gilvear, D., Johnson, M., Naura, M., O'hare, M., Tree, A. et al., 2021. Best practices for monitoring and assessing the ecological response to river restoration. *Water*, 13(23), 3352.

- Flemming, B. H., Futoransky, V., Pruett, W., 2023. Quantifying restoration success via natural recovery in forested areas following pipeline construction. *Restoration Ecology*, 31(3), e13749.
- Galdelli, A., Pesaresi, S., Quattrini, G., Pierdicca, R., Benson, T. A., Mancini, A., 2025. VegRecoverAI: A deep learning-based system for automated vegetation recovery assessment and prediction with demonstration case study on gas pipeline construction. *Environmental Modelling & Software*, 106601.
- Gao, X., Zhuo, W., Gonsamo, A., 2024. Humid, warm and treed ecosystems show longer time-lag of vegetation response to climate. *Geophysical Research Letters*, 51(18), e2024GL111737.
- Jayathunga, S., Pearse, G. D., Watt, M. S., 2023. Unsupervised Methodology for Large-Scale Tree Seedling Mapping in Diverse Forestry Settings Using UAV-Based RGB Imagery. *Remote Sensing*, 15(22). <https://www.mdpi.com/2072-4292/15/22/5276>.
- Lasaponara, R., Abate, N., Fattore, C., Aromando, A., Cardetini, G., Di Fonzo, M., 2022. On the use of Sentinel-2 NDVI time series and Google Earth Engine to detect land-use/land-cover changes in fire-affected areas. *Remote Sensing*, 14(19), 4723.
- Liang, X., Kukko, A., Balenović, I., Saarinen, N., Junttila, S., Kankare, V., Holopainen, M., Mokroš, M., Surov, P., Kaartinen, H. et al., 2022. Close-range remote sensing of forests: The state of the art, challenges, and opportunities for systems and data acquisitions. *IEEE geoscience and remote sensing magazine*, 10(3), 32–71.
- Linden, A., 2015. Conducting interrupted time-series analysis for single-and multiple-group comparisons. *The Stata Journal*, 15(2), 480–500.
- McClung, M. R., Moran, M. D., 2018. Understanding and mitigating impacts of unconventional oil and gas development on land-use and ecosystem services in the U.S. *Current Opinion in Environmental Science Health*, 3, 19–26. Environmental and Health Risks of Hydraulic Fracturing.
- Monroe, A. P., Aldridge, C. L., O'Donnell, M. S., Manier, D. J., Homer, C. G., Anderson, P. J., 2020. Using remote sensing products to predict recovery of vegetation across space and time following energy development. *Ecological Indicators*, 110, 105872.
- Noonan, M., He, Y., Nelson, D., Ge, H., Siu, R., Duval, T. P., 2025. Estimating seasonal fractional green and dead vegetation cover in rehabilitated ecosystems using drone remote sensing. *Ecological Informatics*, 103456.
- Petrovic, B., Balestra, M., Mikita, T., Chiappini, S., Pierdicca, R., 2026. Climate-adjusted time-series analysis of vegetation dynamics following pipeline disturbance and restoration: A proof-of-concept framework. *Ecological Indicators*, 183, 114670.
- Phiri, D., Simwanda, M., Salekin, S., Nyirenda, V. R., Murayama, Y., Ranagalage, M., 2020. Sentinel-2 data for land cover/use mapping: A review. *Remote sensing*, 12(14), 2291.
- Pierdicca, R., Nepi, L., Mancini, A., Malinverni, E., Balestra, M., 2023. UAV4TREE: Deep learning-based system for automatic classification of tree species using RGB optical images obtained by an unmanned aerial vehicle. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 10, 1089–1096.
- Quattrini, G., Pesaresi, S., Lucchetti, L., Hofmann, N., Saiter, F., Mancini, A., Casavecchia, S., 2025. Standardised Drone Procedures for Phytosociological Data Collection. *Applied Vegetation Science*, 28(2), e70032. <https://onlinelibrary.wiley.com/doi/abs/10.1111/avsc.70032>. e70032 AVS-RES-03527.
- Raiter, K. G., Prober, S. M., Possingham, H. P., Westcott, F., Hobbs, R. J., 2018. Linear infrastructure impacts on landscape hydrology. *Journal of Environmental Management*, 206, 446–457.
- Samadzadegan, F., Toosi, A., Dadrass Javan, F., 2025. A critical review on multi-sensor and multi-platform remote sensing data fusion approaches: current status and prospects. *International journal of remote sensing*, 46(3), 1327–1402.
- Shi, P., Xiao, J., Wang, Y.-F., Chen, L.-D., 2014. The effects of pipeline construction disturbance on soil properties and restoration cycle. *Environmental Monitoring and Assessment*, 186(3), 1825–1835.
- Smokorowski, K., Randall, R., 2017. Cautions on using the Before-After-Control-Impact design in environmental effects monitoring programs. *Facets*, 2(1), 212–232.
- Taddeo, S., 2022. Leveraging time series of satellite and aerial images to promote the long-term monitoring of restored plant communities. *Applied Vegetation Science*, 25(2), e12664.
- Villarino, A., Valenzuela, H., Antón, N., Domínguez, M., Méndez Cubillos, X. C., 2025. UAV Applications for Monitoring and Management of Civil Infrastructures. *Infrastructures*, 10(5), 106.
- Wang, G., Cheng, Q., Zhao, W., Liao, Q., Zhang, H., 2022. Review on the transport capacity management of oil and gas pipeline network: Challenges and opportunities of future pipeline transport. *Energy Strategy Reviews*, 43, 100933.
- Wortley, L., Hero, J.-M., Howes, M., 2013. Evaluating ecological restoration success: a review of the literature. *Restoration ecology*, 21(5), 537–543.
- Xiao, J., Shi, P., Wang, Y., Yang, L., 2016. The vegetation recovery pattern and affecting factors after pipeline disturbance in northwest China. *Journal for nature conservation*, 29, 114–122.
- Xiao, J., Wang, Y.-F., Shi, P., Yang, L., Chen, L.-D., 2014. Potential effects of large linear pipeline construction on soil and vegetation in ecologically fragile regions. *Environmental monitoring and assessment*, 186(11), 8037–8048.
- Yan, K., Gao, S., Yan, G., Ma, X., Chen, X., Zhu, P., Li, J., Gao, S., Gastellu-Etchegorry, J.-P., Myneni, R. B. et al., 2025. A global systematic review of the remote sensing vegetation indices. *International Journal of Applied Earth Observation and Geoinformation*, 139, 104560.