

Supporting Information

Article title: Reduced BVOC emissions from birch forest understory during coupled insect outbreak and microclimatic forcing

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The following Supporting Information is available for this article:

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Figure S2: Seasonal dynamics of microclimatic variables across the 2021–2023 growing seasons

Figure S3: Relationships between above-canopy forcing and understory microclimatic conditions

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Figure S8: Classification of understory and birch canopy and the co-registered thermal image.

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Supporting Data SD2: Plant species composition within sampling plots in 2022 and 2023

Supporting Data SD3: Estimated marginal means (EMMs) and pairwise year contrasts for microclimatic variables from generalized least squares models with a continuous-time first-order autoregressive correlation structure (GLS–CAR(1)).

Supporting Data SD4: Estimated marginal means (EMMs) of total BVOC emission rates from linear mixed-effects models and pairwise year contrasts within each plot-dominant species.

Supporting Data SD5: Results from ANOVA evaluating the effects of covariates on Total BVOC emission rates for each plot dominant species.

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Supporting Data SD8: Estimated marginal means (EMMs) of selected compound emission rates from linear mixed-effects models and pairwise year contrasts within each plot-dominant species.

Supporting Data SD9: Estimated marginal trends of environmental drivers from linear mixed-effects models of total BVOC emission rates within each plot-dominant species.

Supporting Data SD10: Estimated marginal trends of environmental drivers from linear mixed-effects models of BVOC Group emission rates within each plot-dominant species.

Supporting Data SD11: Results from ANOVA evaluating the effects of covariates on Group BVOC emission rates for each plot dominant species.

Supporting Data SD12: Backward model selection results for species-specific models of total BVOC emission rates

Supporting Data SD13: Backward model selection results for species-specific models of Group BVOC emission rates

91 **Supporting Data SD14:** Backward model selection results for species-specific
92 models of HIPVs emission rates

93 **Supporting Data SD15:** Overview of variables measured during the study, their
94 spatial scale, timing relative to BVOC sampling, and inclusion in the linear mixed-
95 effects models (LMMs)

96 **Supporting Data SD16:** Results from ANOVA evaluating the effects of covariates
97 on HIPVs BVOC emission rates for each plot dominant species.

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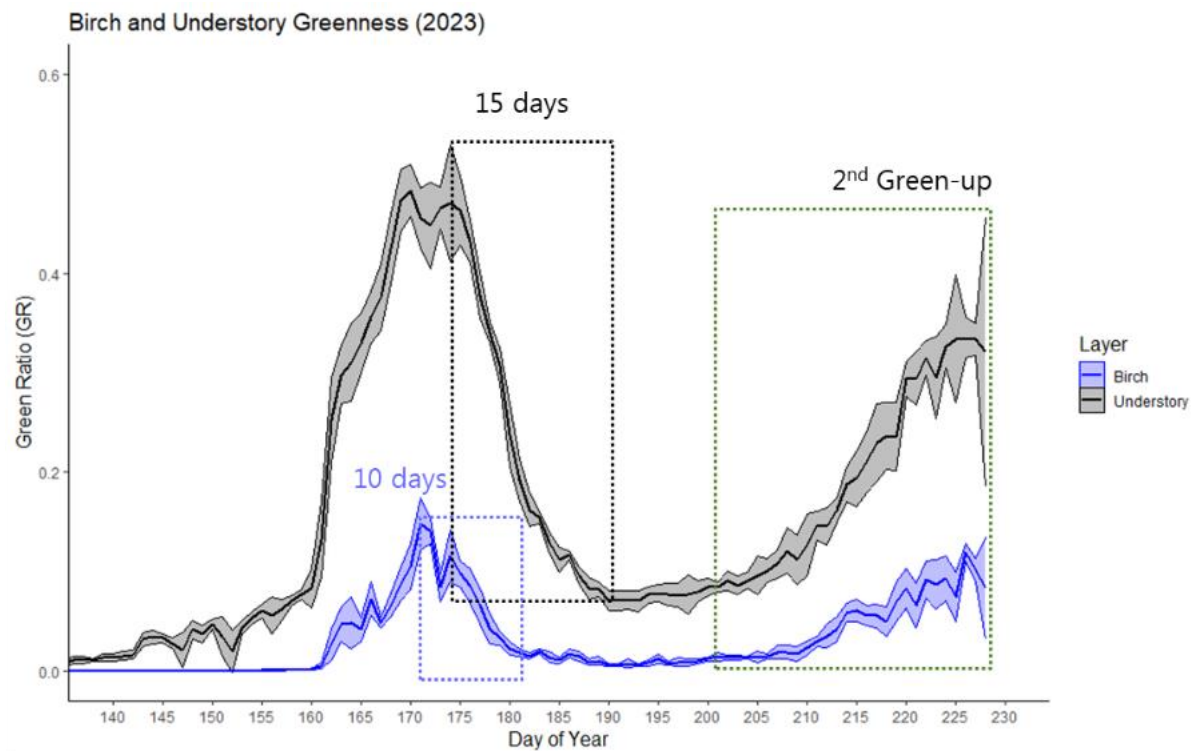


Figure S1: Seasonal dynamics of birch canopy and understory GreenRatio in 2023. Lines show raw daytime mean $\pm$ 1 SD. The dashed boxes highlight the rapid defoliation period of the birch canopy (15 days) and understory (10 days), and the green box marks the secondary green-up later in the season.

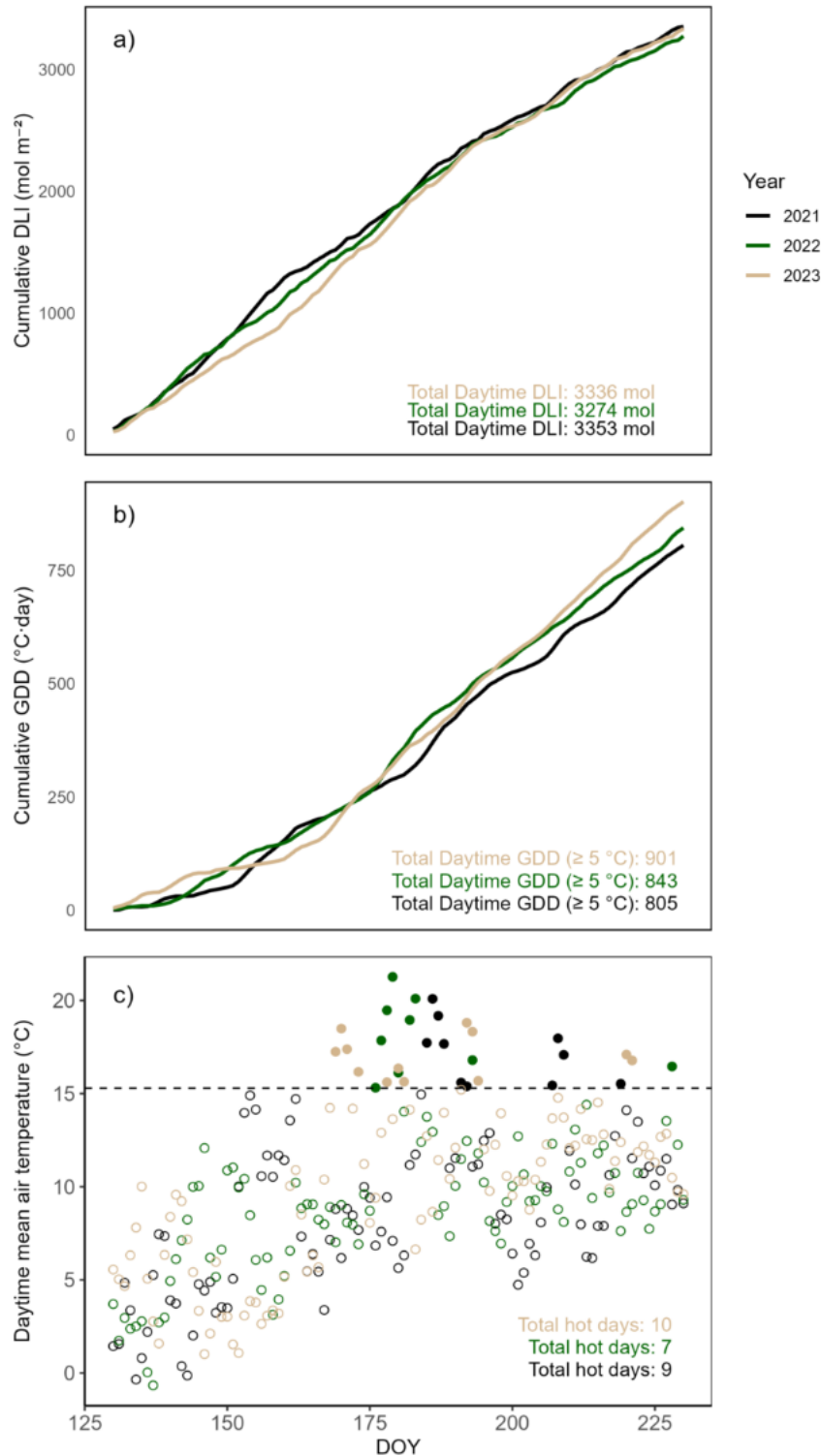


Figure S2. Seasonal development of a) cumulative daytime light availability (DLI), b) cumulative growing degree days (GDD; ≥ 5 °C), and c) hot days defined as mean daytime air temperature ≥ 90 th percentile. Data is presented for the period mid-May (DOY 130) to mid-August (DOY 230) across the three growing seasons (2021-2023). DLI, GDD and warm days were calculated from the above-canopy meteorological data (MET-tower, Fig. 1) using daytime readings only (solar elevation $\geq 5^\circ$). Text within each panel reports total accumulated DLI, GDD, and the number of hot days.

Air temperature and PAR monitored above the birch canopy were comparable among growing seasons (DOY 120-230; 2022-2023; Fig. S5). Mean daytime air temperature was 8.1 ± 1.1 °C in 2022, and 8.8 ± 1.1 °C in 2023 (GLS-CAR(1); EMM contrast, $p = 0.67$, Supporting Data (SD) SD3), corresponding to cumulative daytime GDD_5 °C (Weijers et al., 2013) of 763, and 811 °C day, respectively (Fig. S5a). Mean daytime PAR was 500 ± 24 $\mu\text{mol m}^{-2} \text{s}^{-1}$ in 2022 and 507 ± 24 $\mu\text{mol m}^{-2} \text{s}^{-1}$ in 2023 (GLS-CAR(1); EMM contrast, $p = 0.84$; SD3), corresponding to total daytime light integral of 2543 mol m^{-2} and 2716 mol m^{-2} , respectively (Fig. S5b). Warm-day events (mean daytime air temperature ≥ 90 th percentile) were more frequent in 2023 ($n = 10$) than in 2022 ($n = 7$) (Fig. S5c).

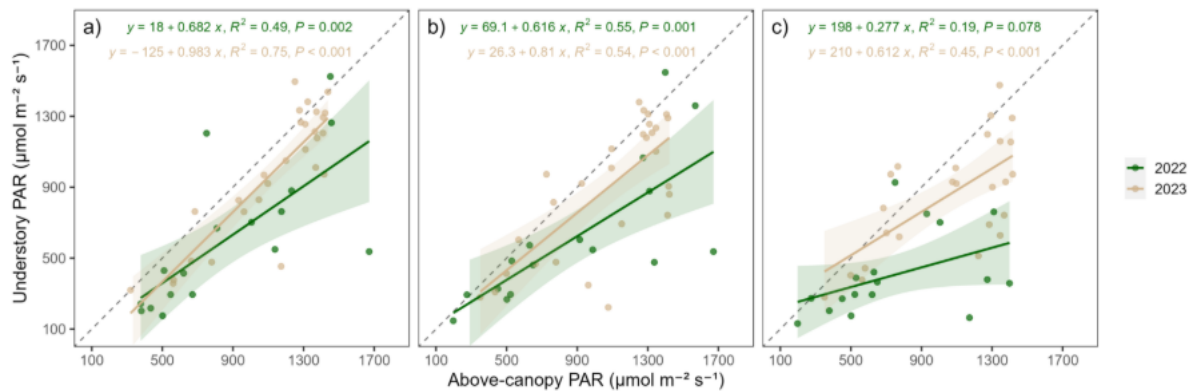


Figure S3: Linear regressions between above-canopy and understory PAR for the three plot-dominant understory species in 2022 and 2023. Each point represents a single BVOC sampling, and solid lines depict species- and year-specific linear regressions with 95% confidence intervals. The dashed black line indicates the 1:1 reference. Panels show a) *E. nigrum*, b) graminoid and c) *V. myrtillus* plots. Slopes and model statistics from the linear regressions are shown within each panel.

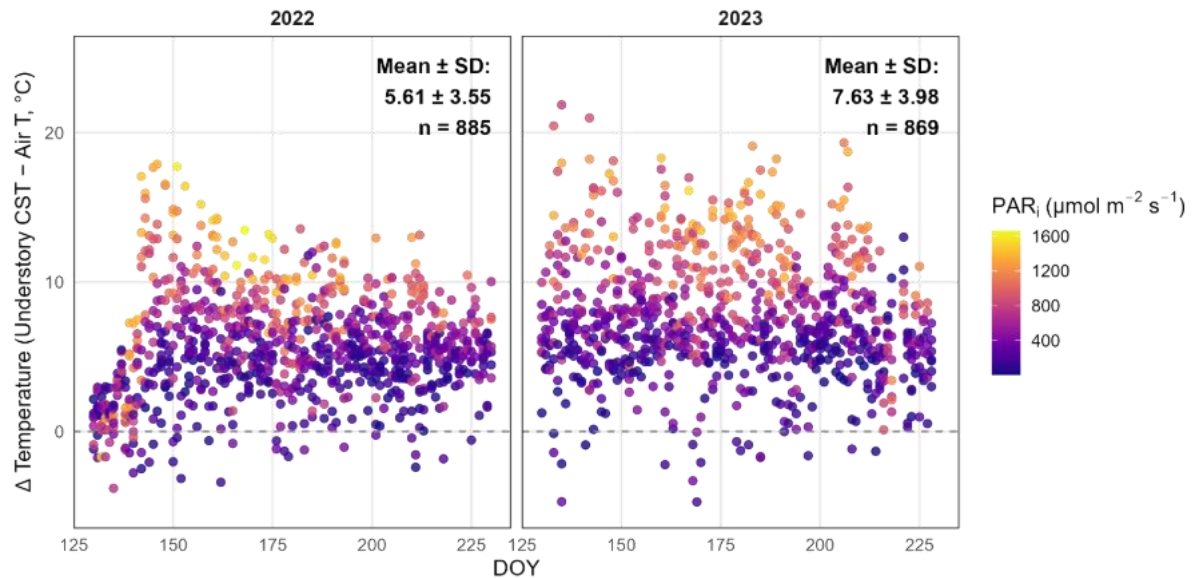


Figure S4: Seasonal dynamics of the temperature difference between understory surface temperature (CST) and above-canopy air temperature (Air T) in 2022 (left) and 2023 (right). Each point represents one measurement plotted against day of year (DOY). Point colour indicates photosynthetically active radiation (PAR, $\mu\text{mol m}^{-2} \text{s}^{-1}$). Positive values indicate warmer understory surface conditions relative to above-canopy air. The outbreak year (2023) exhibited a larger mean temperature difference (7.63 ± 3.98 °C; $n = 869$) compared to 2022 (5.61 ± 3.55 °C; $n = 885$), consistent with reduced canopy buffering and enhanced radiative heating of the understory.

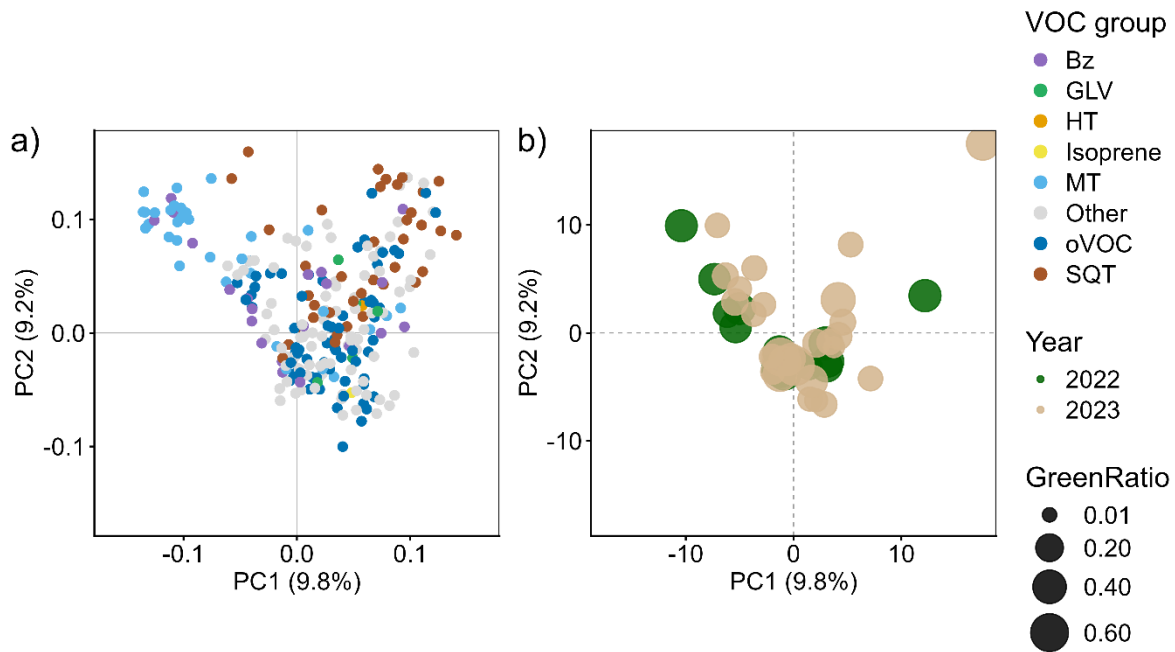


Figure S5: Principal component analysis (PCA) of BVOC blend composition in graminoid plots, based on the proportional contribution of individual compounds to total emissions. (a) Compound loadings (each point represents one BVOC), coloured by BVOC group: isoprene (Iso), monoterpenes (MT), sesquiterpenes (SQT), green leaf volatiles (GLV), homoterpenes (HT), other oxygenated VOCs (oVOC), and Other BVOCs. (b) Sample scores (each point represents one BVOC sample), coloured by sampling year, with point size indicating plot GreenRatio

Time-lapse RGB and thermal imagery preprocessing

Image preprocessing was performed by following the data screening workflow in Feng et al., (2026). In summary, low illumination images acquired during nighttime and dusk/dawn were filtered out based on the solar angles ($<5^\circ$) calculated from timestamp and coordinate. At each timestamp, the thermal camera captured five consecutive images. The mean canopy surface temperature was calculated for each image, and the median of these five mean values was used to represent the thermal measurement at that timestamp. The thermal images were corrected for vignetting (i.e., signal fall-off towards the edges of the images). Image registration was performed to ensure spatial consistency between thermal and RGB time-lapse imagery. A pair of RGB-thermal images acquired as close as possible to March 20th, 2023, at 10:23 were selected to be representative for the whole dataset, so that a single geometric transformation could be used to register all images. A total of 47 pairs of matching control points (CPs) were manually identified in both RGB and thermal image (Fig. S6). Normalized cross-correlation was adopted to further refine the location of the CPs within the thermal image. A pixel-wise polynomial (third order) geometric transformation was derived and applied to co-register the thermal images (Fig. S7). The processed images were resampled to match the spatial resolution of RGB images. Finally, the RGB images and transformed thermal images were cropped to the

common extent. To remove edge artifacts, a 50-pixel buffer was applied. The processing minimized geometric distortions and ensured that thermal measurements correspond to the correct physical locations in the RGB image.

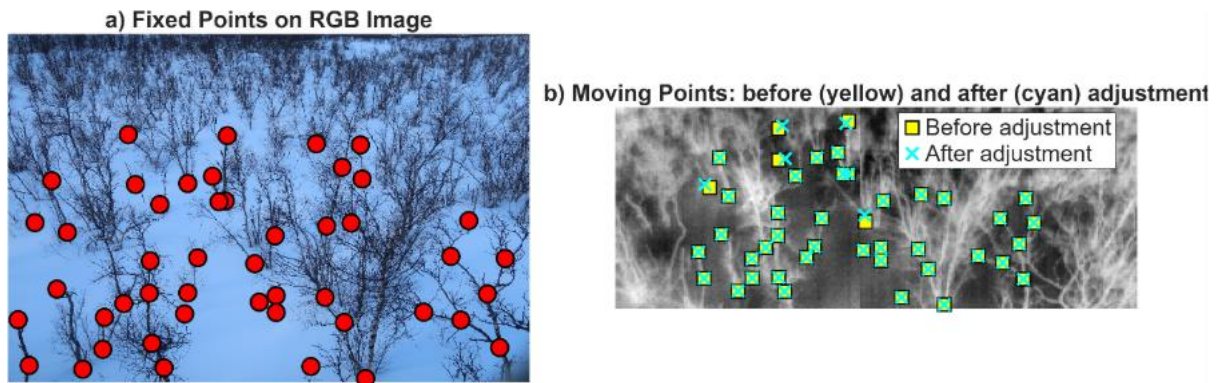


Figure S6: Selected reference fixed points on the RGB image (a) and moving points on the corresponding thermal image. In total, 47 pairs of control points were selected. The moving points were further adjusted by normalized cross-correlation between the images.



Figure S7: Comparison of the reference RGB image (natural colour composition) and the co-registered thermal data displayed as blended image. Both were cropped to the common extent.

To train and validate the RF classifier for separating birch canopy, understory vegetation, and non-green surfaces in the tower RGB imagery, we manually labelled a set of reference pixels. In total, 683 sampling points of birch, understory, and non-green pixels (e.g., branch, bare soil, snow, litter) were selected from 100 randomly chosen daytime RGB images using a custom GUI interface, ensuring balanced representation across classes. The sampling points were then split into training (70%) and testing (30%) subsets for model development and evaluation. Pixel-level classification was then performed using the RF model, which achieved an overall accuracy of 0.95 on the training data and 0.84 on the independent test data. The pixel-based supervised classification enabled us to perform pixel-wise extraction of corresponding canopy surface temperature acquired from the nearest thermal image.

See Fig. S8 for examples of time-lapse RGB images (Fig. S8a), the classification results of birch and understory canopies (Fig. S8b), and the co-registered thermal images (Fig. S8c). See Laursen et al. (2026a) for the repository of co-registered thermal and RGB time-lapse imagery, and Laursen et al. (2026b, v. 1.3) for the source code used for processing and analysis of the time-lapse images.

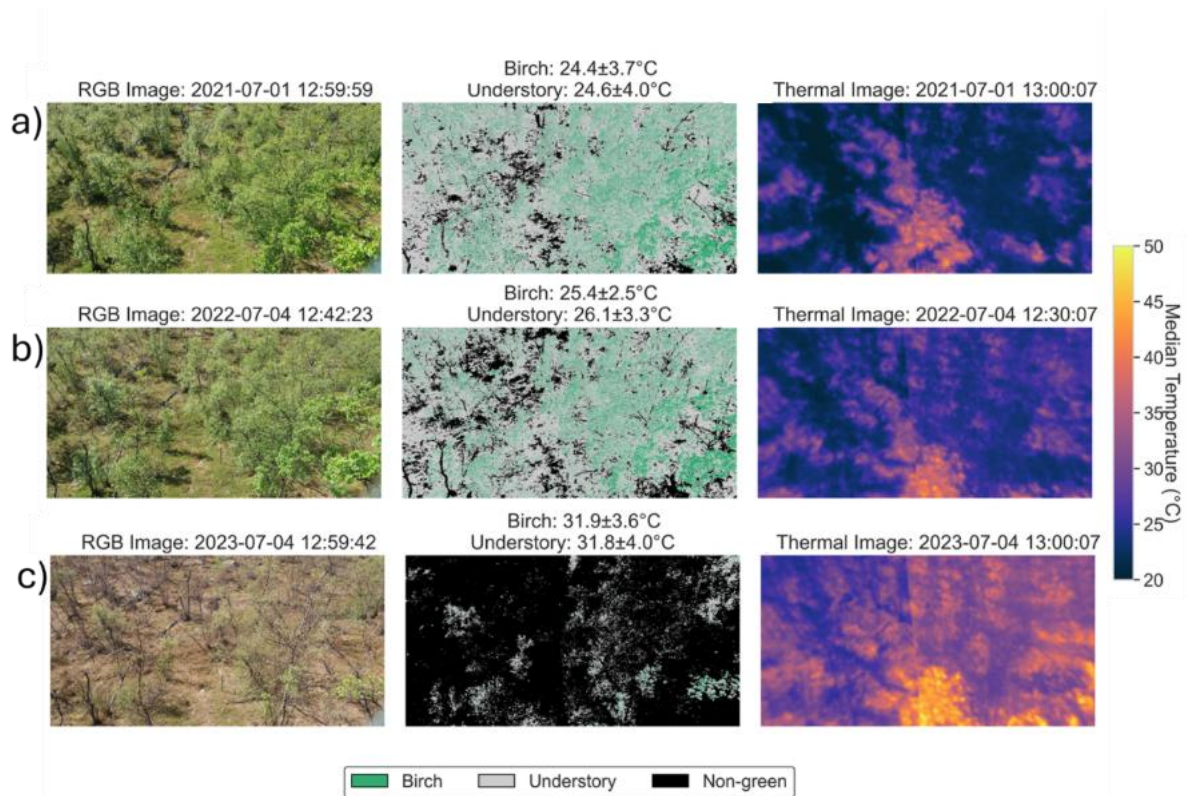


Figure S8: Examples of time-lapse RGB images (left column), the RF classification (middle column) of birch and understory canopies, and the co-registered thermal images (right column). The date of RGB images, the average canopy surface temperature (± 1 SD), and the matched nearest thermal image time were labelled on the corresponding subfigures. The five consecutive thermal images were shown as the median canopy surface temperature.

Supplementary references

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