



Mountain pine time series mapping with Sentinel-2 and assessing their ecological role in Alpine vegetation dynamics

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ABSTRACT

Mountain pine (*Pinus mugo*) is a critical species in the krummholz zone of alpine ecosystems and vital to understanding treeline dynamics under ongoing climate change. Despite their various ecosystem functions, their spatial distribution remains poorly quantified across complex mountain terrain. In this study, Sentinel-2 multi-temporal optical imagery, along with topographic and textural features, is used to train a random forest model and map the species in southern Germany at 10-m resolution. The classification achieves an F1 score of 87.5–90.4% under spatially independent validation, and was applied to generate annual mountain pine distribution maps from 2017 to 2025. Applying the approach to higher-resolution UAS data acquired near Zugspitze in Summer 2025 highlights the sensor-scale limitation. This is evidenced by underdetection in the Sentinel-2 maps at higher elevations, particularly in landscapes with smaller, fragmented patches, due to mixed pixels at the Sentinel-2 scale. The annual mountain pine time-series maps highlight patch dynamics, distribution in relation to terrain, and a detectable upslope shift in the upper boundary of the distribution within the German part of the European Alps. To demonstrate the ecological relevance of these maps, an exploratory fixed-effects analysis suggests that greenness is influenced mainly by growing-season and early-winter temperature, pointing to an energy-limited system favoured by warming conditions. Our results highlight the potential of high-resolution species-level mapping using machine learning in data-limited regions. The approach provides scalable workflows for other species in alpine ecosystems, supporting robust monitoring amid ongoing environmental change.

1. Introduction

The IPCC has identified the European Alps (hereafter "the Alps") as a hotspot for climate change, with temperatures increasing by 1.6–2°C over the last century, twice the global average (IPCC, 2023; Obleitner et al., 2024). This changing climate in the Alps is causing significant disturbances from loss of biodiversity to the upslope movement of the treeline. Erschbamer et al. (2011) reported up to a 18% increase in species richness at the highest summits of the Italian Alps, linked to upward migration due to climate warming. Although climate change is not the only driver of changes in biodiversity, Niedrist et al. (2009) report a significant decline in species richness, caused by land abandonment, which leads to increased shrub encroachment at higher elevations, and by intensive grazing

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practices at lower elevations. Anthropogenic activities, directly through land-use changes or indirectly through climate change, are therefore drastically affecting biodiversity in the European Alps.

The migration of species can be quantified by the movement of the treeline, described as the opening of the canopy, with a gradual shift from tall, upright trees to small, shrublike species (Körner, 2021). This transition belt, from the upper montane forests to the alpine belt in the Alps, is also known as the krummholz zone (Holtmeier, 1981). Research on treeline advancement in response to climate change has increased since the late 19th century (Harsch et al., 2009), with 60% of publications from the last two decades, reflecting growing attention to recent environmental changes (Holtmeier and Broll, 2019). These changes provide more suitable conditions for shrub expansion, leading to encroachment by woody plants at the treeline ecotone (Francon et al., 2023), which in the European Alps is dominated by species such as *Pinus Mugo* and *Larix decidua* (Körner, 1998, 2021).

Pinus mugo Turra (mountain pine) dominates the krummholz vegetation in the Alps (Boratyńska et al., 2015) and is distinguished by its low-growing, shrub-like form with many spreading stems and dense, two-needled shoots (Ballian et al., 2016). Mountain pines are widespread across Europe within the subalpine zone of the European Alps, the Carpathian Range, and the Apennines in Italy (Calabrese et al., 2018; Rösch et al., 2022; Šibík et al., 2010; Švajda et al., 2011). Among European pine species, they are the most cold-tolerant, though this tolerance can lead to stunted growth. Despite this, they provide numerous ecosystem functions, such as stabilizing loose soil and rocks through their extensive root systems. This protects the ground from erosion, intense surface runoff, and avalanches (Stiegler and Binder, 2016). Under climate change, mountain pines are favoured by rising temperatures and can subsequently expand into higher-elevation areas in the alpine zone (Dirnböck et al., 2003; Lukášová et al., 2021). In contrast, anthropogenic pressures remain a major threat to them, with land-use practices causing significant alterations to their distribution (Ballian et al., 2016). Examples include logging for pasture maintenance and harvesting mountain pine for oil extraction; the latter is valued in the wellness and cosmetic industries for its therapeutic effects on respiratory ailments (Manziona et al., 2024).

Biodiversity change in mountain environments is not driven by climate alone. Land abandonment is one such factor: mountain pine has expanded considerably since the 1950s by colonizing former grazing areas (Dai et al., 2017), as reduced land-use pressure opened favourable conditions upslope (Calabrese et al., 2018). Mountain pines have been studied in the Majella National Park, Italy, to understand whether their expansion is more influenced by land abandonment or climate change (Palombo et al., 2013). Dirnböck et al.

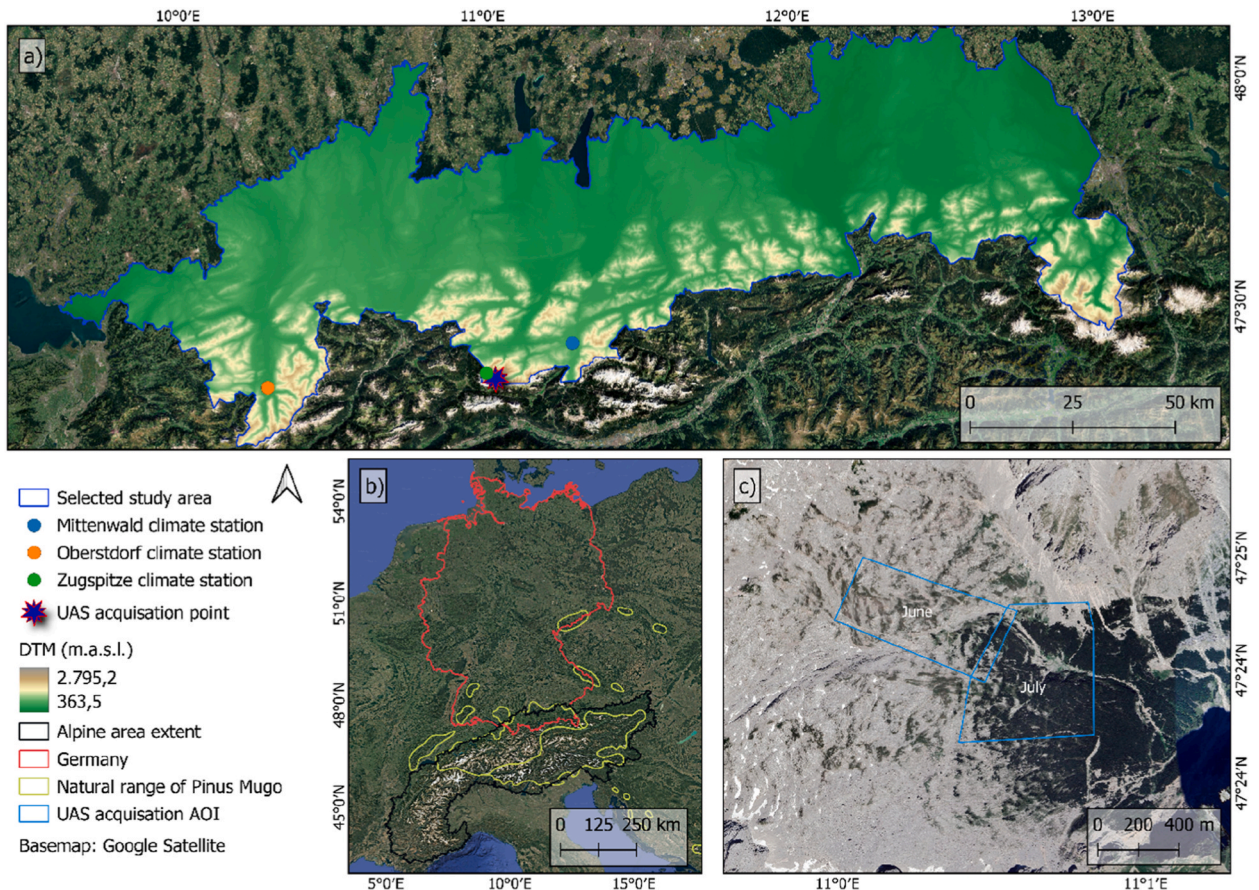


Fig. 1. a) Study area in the German Alps with stations corresponding to climate data used in the analysis, b) selected study area through the intersection of Germany and the Alpine extent, also showing the natural distribution of mountain pine in Europe. c) UAS study area in the Reintal valley showing two acquisitions.

(2003) investigated the dynamics of their expansion in relation to future climatic and land use scenarios in the Austrian Alps.

Vegetation studies in high-elevation alpine environments have relied on fixed plots to record changes over time (Keller et al., 2000; Lamprecht et al., 2018; Zettlemoyer et al., 2024), with observations limited to discrete points due to the complex terrain. Advancements in remote sensing techniques have provided a step forward in the mapping and monitoring of alpine vegetation. High-resolution aerial imagery has been used to assess the expansion of mountain pines in the Majella National Park, Italy (Palombo et al., 2014); the central Tatra Mountains, Slovakia (Solr, 2013); and the Tatras in Poland to estimate leaf area (Zwijacz-Kozica et al., 2005). More recently, spaceborne data have also been used to assess the favorability of mountain pines in the Romanian Carpathians (Roşca et al., 2019), to map mountain shrublands in the French Alps (Bayle et al., 2019), and in Switzerland (Rüetschi et al., 2021). Despite these advances, no consistent, multi-year, high-resolution map of mountain pine exists for the German Alps, limiting ecological monitoring and conservation planning.

Thus, this study aimed to generate high-resolution time-series maps of mountain pine in the German Alps and assess spatial resolution limitations through UAS-based comparison. Building on these maps, we conducted exploratory analyses of terrain characteristics, NDVI phenology, and climate-vegetation relationships. These illustrate the ecological insights such time-series products can enable, acknowledging that the nine-year observation period constrains the strength of ecological conclusions.

2. Material and methods

2.1. Study area

To define our study area (Fig. 1a), we intersected the natural distribution of mountain pine published by the European Commission (de Rigo et al., 2016) with the extent of Germany. This revealed the highest concentration of mountain pines in the German Alps, using the alpine extent defined by the Alpine Convention (Fig. 1b).

Most of this area lies in southern Bavaria, forming the northern fringe of the Alps, with Zugspitze reaching 2962 m above sea level (a.s.l.). The Area of Interest (AOI) covers ~11,150 km², half of which is forested. Non-forest vegetation is dominated by calcareous grasslands, shifting from tall forb-grass communities in the montane belt to sedges and dwarf shrubs at higher elevations. The montane region along the border with Austria, part of the Northern Calcareous Alps, is characterized by Triassic to Cretaceous limestone and dolomite bedrock. The northern part of the AOI has a mean annual temperature of 9°C, but it drops to -4.3°C at the higher summits in the south. Similarly, the mean annual precipitation ranges from 1100 to 2750 mm yr⁻¹ (DWD Climate Data Center, 2025).

2.2. Data

2.2.1. Reference data generation

Previous studies mapping alpine vegetation and shrubs have trained machine-learning classifiers on multi-temporal vegetation indices and contextual and topographic features from remote-sensing imagery, achieving high classification accuracy (Rüetschi et al., 2021; Wakulińska and Marcinkowska-Ochtyra, 2020). Like Rösch et al. (2022), we trained a machine learning model to predict mountain pine. As no training data on mountain pine was available in Germany, we manually delineated reference polygons for six classes: mountain pine (target), forest, grassland, bare rock, water, and urban by interpretation of the Bavarian Digital Orthophotos (DOP20) from 2024, provided by the Bavarian Agency for Digitisation, High-Speed Internet and Surveying (LDBV). As part of the Bavarian aerial survey, they provide orthophotos at 20 cm resolution biennially. Inspection of the reference polygons against the older imagery confirmed they retained their original land-cover class throughout the study period. Taller conifers were included among the forest/absence samples and separated from mountain pine using crown morphology and shadow cues in the high-resolution imagery. To extract sample points from these reference polygons, a Sentinel-2 (S2) NDVI composite was used for NDVI-based thresholding, and the points were thinned to minimize spatial clustering. The resulting dataset included 14,000 positive points and 21,000 negative points, which were split 70/30 into training and validation sets using a polygon-grouped split, such that all points from a given reference polygon were assigned to either training or validation, preventing spatial leakage.

2.2.2. Sentinel-2 data

Monthly composites were created from S2 data using Google Earth Engine, covering June to October, spanning the growing season and including October to capture the NDVI decline in deciduous species while avoiding the increased snow contamination of later months. Clouds, cloud shadows, and snow were masked using the QA60 band and Scene Classification Layer. To address missing pixels, a gap-filling step was employed, replacing masked values with the annual median. We used the Blue, Green, Red, Near-infrared (NIR), and resampled Red-Edge (RE) spectral bands at 10 m, which were pre-processed to create monthly cloud-free composites (Kollert et al., 2021).

2.2.3. Unmanned aerial system (UAS) data

To assess the sensor-scale limitation of the S2 classification, a similar workflow was applied to higher-spatial-resolution UAS data. For this, UAS missions were conducted on a local scale in the Reintal valley near the Zugspitze peak in Germany. A DJI Mavic 3M was used for two flights, in June 2025 and July 2025, to collect RGB and multispectral (NIR, RE) data. The flights were conducted with a terrain following altitude of 120 m Above Ground Level, with a speed of 9.7 m/s, a 75% side and 80% front overlap, acquiring the data with a Ground Sampling Distance of 5.5 cm/pixel. Orthomosaics and Digital Surface Model (DSM) were created using Agisoft Metashape software (Agisoft PhotoScan Professional, 2025). Arosics co-registration software implemented in Python (Scheffler et al.,

2017) was used to improve alignment between the datasets. To remove illumination gradients, local contrast normalisation (Kurilin et al., 2015) was applied. The orthomosaics were resampled to 1 m resolution and co-registered to match the S2. The combined coverage from both UAS acquisitions (UAS AOI in Fig. 1C) was ~63.6 ha (1730–2208 m a.s.l.), representing a single local landscape context rather than the broader alpine gradient.

2.2.4. Terrain data

Two datasets from the LDBV were utilized: the DSM at 20 cm, and the Digital Terrain Model (DTM) at 1 m resolution. Both datasets were downloaded for all administrative regions within the AOI, then merged and resampled to 10 m and 1 m grids matching the S2 and UAS data, respectively.

2.2.5. Independent occurrence records (GBIF)

While reference data is sparse in most ecological studies, data on mountain pines was particularly limited, as they are not included in any existing forest maps for Germany. Given the inherent bias arising from the manual mapping technique and the image source, external data were used to independently assess our approach. For this, we used data retrieved from the Global Biodiversity Information Facility (GBIF) (GBIF Secretariat, 2026). For our study, we downloaded more than 65,000 occurrence points for *Pinus mugo Turra* in Germany. These were filtered to exclude garden and botanical observations while retaining subspecies and human observations. In a coordinate quality check, points with uncertainty greater than 1 km were removed, drastically reducing the number of points in our AOI to 878. These points were enhanced with contextual information using the elevation layer and Land Cover data from the European Union's Copernicus Land Monitoring Service CLC+ (Copernicus Land Monitoring Service, 2023).

2.2.6. Climate data

Climate data were collected to explore how mountain pines are influenced by climatic change and to characterize their climatic associations. The primary source was the German national meteorological service (Deutscher Wetterdienst (DWD)). To retrieve precise data, climate stations in the proximity of our classified pines and matching elevation ranges were considered. These stations were in Oberstdorf (815 m), Mittenwald (919 m), and on the Zugspitze (2956 m), as shown in Fig. 1a. Daily records of temperature, precipitation, and snow depth were obtained from November 2016 to October 2025 and aggregated into weekly data. As these provided only three discrete observation points, we also downloaded the monthly 1 km-gridded precipitation and mean air temperature products from the DWD for the analysis period (2017 to 2025) to obtain more spatially continuous data, which were then resampled to match the S2 resolution.

2.3. Data processing

2.3.1. Feature extraction

For the predictor features, we computed two vegetation-based spectral indices: the Normalized Difference Vegetation Index (NDVI) (Tucker, 1979), using the Red and NIR bands, and the Normalized Anthocyanin Reflectance Index (NARI) (Bayle et al., 2019), using the

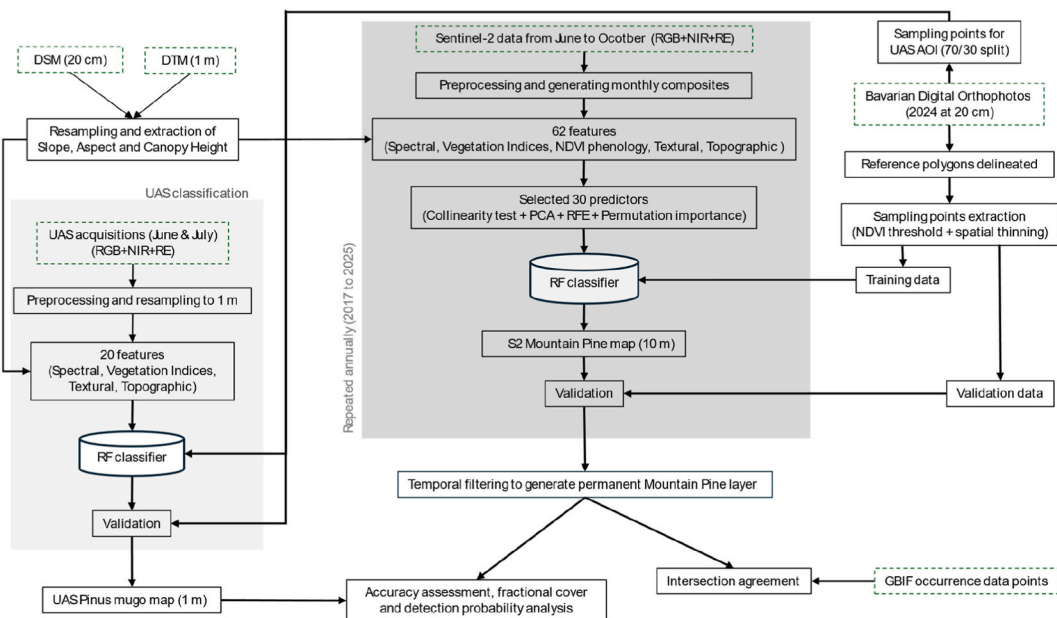


Fig. 2. Workflow for predicting and validating S2 and UAS-based mountain pine maps.

Green and Red-edge bands. NARI was developed because red-edge reflectance properties highlight anthocyanin accumulation in alpine shrublands (Gitelson et al., 2007).

Topographic features have proved important in differentiating alpine species, as their distribution is strongly influenced by elevation and certain exposures (Kovačević et al., 2020; Spracklen and Spracklen, 2019; Wakulińska and Marcinkowska-Ochtyra, 2020). Thus, we used the DTM to compute slope and aspect layers, while Canopy Height (CH) was derived by subtracting the DTM from the DSM (Zhang et al., 2020). Rösch et al. (2022) further reported that incorporating textural characteristics can enhance discrimination between mountain pine and other coniferous trees, as mountain pine stands typically occur in dense clusters and exhibit a more uniform structural pattern than those of other species in subalpine environments. To capture these properties, we derived gray-level co-occurrence matrix (GLCM) features (Haralick et al., 1973). GLCM texture metrics were computed from the monthly S2 NIR composites, which contain valuable information on vegetation density and health (Grabska-Szwagrzyk et al., 2024; Hall-Beyer, 2017). Following the results from Rösch et al. (2022), who identified the most suitable GLCM window size for mapping mountain pines with S2 imagery, all texture features were computed using a 9×9 moving window and four directional offsets (0°, 45°, 90°, 135°). We extracted five standard GLCM statistics: 1) Homogeneity, 2) Contrast, 3) Entropy, 4) Mean, and 5) Variance, producing a set of five texture layers for every month. The final 62 predictors are listed in Table A.1 attached in Appendix A.

2.3.2. Feature importance and temporal transfer of the model

From the 62 features, collinearity was first reduced by computing pairwise Pearson correlations and removing one feature from each pair with $|r| > 0.95$. Principal Component Analysis (PCA) of the remaining predictors was used to guide the number of features to retain, and the features were then ranked using Recursive Feature Elimination (RFE) with a Random Forest estimator, retaining the 30 highest-ranked original predictors. To avoid information leakage, the correlation filter and RFE were refitted within each cross-validation fold rather than on the full dataset. Relative contributions of the selected features were assessed using permutation importance on the fitted model (Figure A.1b); this is descriptive and does not influence selection. With the final predictors and the training set, an RF model was trained in Python (Pedregosa et al., 2018). The classifier consisted of 500 trees to predict a binary mountain pine presence map for 2024. Then, this approach, as shown in Fig. 2, was applied to all years from 2017 to 2025. Topographic and structural layers were held constant, while multispectral, textural, and phenological features were recomputed per year from the corresponding imagery. The reference data initially collected for 2024 were reused across all years, with their temporal validity assessed against historical orthophotos to confirm that mapped presence and absence locations remained stable over the study period.

2.3.3. Validation and analysis of annual mountain pine maps

Model performance and annual map accuracies were evaluated with the 10,600 points in the independent validation set. Confusion matrices, Overall Accuracy (OA), Kappa coefficient, and F1 scores were computed for each map. To further assess the influence of spatial autocorrelation, a spatial block cross-validation sensitivity analysis was performed for the 2024 model using block sizes ranging from 1 to 25 km.

Following map validation, ordinary least squares regression was applied to the nine-year time series to evaluate trends in the elevational range and total area of mountain pine. A Gini index was calculated to quantify the inequality of patch-size contributions to the total mountain pine area. Originally developed to measure economic inequality, the index has recently been applied in ecological studies to assess distributional disparities (Martin and Conway, 2025). The index score ranges from 0 (total equality) to 1 (maximum inequality). To distinguish genuine ecological change from classification noise, we applied post-classification temporal smoothing, common in land-cover time-series analysis, rather than morphological filtering, which would have removed smaller, fragmented patches. We used a temporal majority filter with a 3-year sliding window, followed by excluding unstable pixels based on a flip-count layer and removing pixels that changed class more than 3 times (Hermosilla et al., 2015; Zhu and Woodcock, 2014).

Based on temporal majority filtering, a confidence-tiered map was generated by counting per-pixel presence across annual maps, defining a core tier (mapped in all nine years), a near-core tier (eight years), followed by a less-stable tier. Each tier's distributions of elevation, slope, aspect, canopy height, and NDVI were compared across tiers. The core tier was adopted as the permanent mountain pine layer for subsequent NDVI-climate analysis, maximising confidence that each pixel corresponds to mountain pine and reducing mixed-pixel bias. This permanent mountain pine layer was also assessed for spatial correspondence with the independent GBIF occurrences. Marcer et al. (2022) report that only 38% of the 180 million records presented by GBIF up to 2022 had coordinates, and only 18% provided coordinate uncertainty information. Because of this, we evaluated correspondence across buffer radii of 50, 100, 250, and 500 m. As GBIF aggregates presence-only observations that also lack coordinate uncertainty information, we used these points as an independent cross-reference rather than as ground-truth validation.

2.3.4. UAS-based sub-pixel detection analysis

From the UAS data, vegetation indices, and five texture features were computed, like the S2 workflow (Fig. 2). Terrain and structural features were derived from the DTM, while reference data were generated using DOP20 within the UAS AOI (Fig. 1c), with a 70/30 split. The UAS RF models are independent local classifiers, trained and applied entirely within the UAS AOI, with no S2 model or features transferred. Additionally, due to radiometric shifts between acquisitions, separate models were trained for each acquisition; the outputs were then mosaiced and validated on the 30% holdout split. This UAS classification was aligned with the S2-based map. This was used to compute a UAS fractional mountain pine cover, which was overlaid with the S2 permanent mountain pine layer for a pixel-wise confusion analysis and a detection probability curve linking the fractional cover to the probability that an S2 pixel is mapped. This explains the fraction of an S2 pixel that must be covered by mountain pines for it to be classified as such for the specific

local region.

2.3.5. Phenology analysis

To understand the phenology, the growing season (June to October) NDVI from 2017 to 2025 was computed. To extract reliable NDVI values, stricter filtering was applied, keeping scenes with less than 20% cloudy pixels and masking pixels characterized as s2cloudless. The S2 scene classification layer was also incorporated to retain only vegetation and bare soil pixels. Atmospheric contamination and hazy pixels were removed using reflectance-based thresholding (Makarau et al., 2014; Zhang et al., 2002). For every valid pixel with at least two clean observations per month, the median was calculated. This masking resulted in no valid pixels for certain months but provided a stronger basis for analyzing the true vegetation signal. The multiyear NDVI-based phenology was examined for interannual and intraannual patterns, the peak growing season, and annual shifts. Phenological patterns were analyzed in relation to elevation and compared between the north and south slopes to investigate an aspect-modulated elevation gradient. CH was included to assess its influence on phenology across elevations and aspects.

2.3.6. Climate analysis

Both the station and gridded data were aggregated to compute seasonal climatic variables, including winter temperature, precipitation, and snow depth, as well as mild winter weeks, defined as consecutive weeks with a mean temperature greater than -5°C . Summer precipitation, temperature, and heat sum were computed to highlight growing season energy and water supply. These were compared with the magnitude of summer NDVI (July–October). While winter targets were correlated with the difference of NDVI (ΔNDVI) from one summer to the other, highlighting how mountain pines respond to climatic conditions from the preceding winter season.

For the station data, pixels within a 10 km buffer around each station were used to extract the median mountain pine NDVI, and seasonal climate was correlated with NDVI using Pearson's correlation. With only three stations, relationships are reported as exploratory. For the gridded data, resampled monthly temperature and precipitation layers were paired with S2-based NDVI pixels, forming a balanced panel of $\sim 746,000$ pixels observed across the nine years. To account for spatial autocorrelation and time-invariant terrain effects (elevation, aspect, slope, canopy), we estimated the climate–NDVI relationship using a two-way fixed-effects panel model (Baltagi, 2021; Wooldridge, 2010). Pixel fixed effects compare each pixel against its own multi-year mean, removing all static

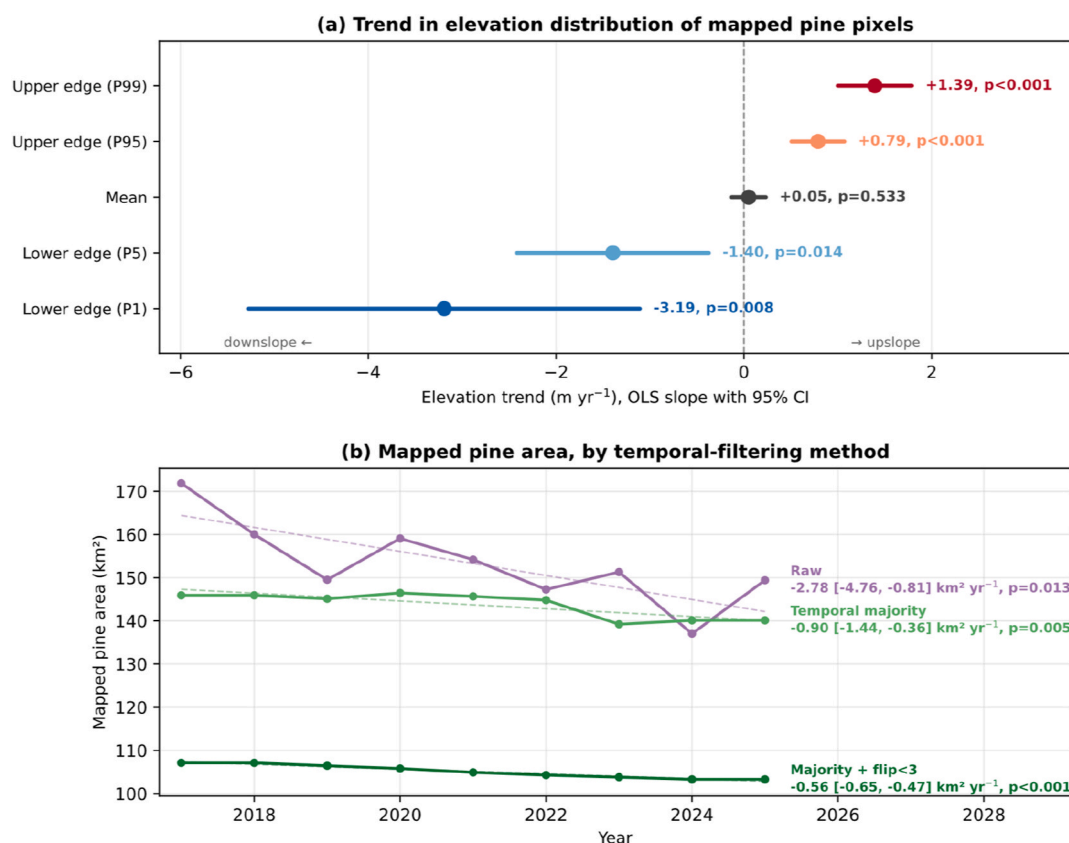


Fig. 3. Trends in the elevation distribution and mapped area of mountain pines, under temporal-majority (w3) + flip < 3 filtering. (a) OLS slope (point) with 95% CI (whisker) for each elevation statistic, slope, and p-value annotated. (b) Mapped area by year for three filtering methods. Trends from OLS regression on year ($n = 9$).

site characteristics and isolating within-pixel interannual variation, while year fixed effects control for region-wide anomalies. Predictors were standardised (coefficients = NDVI response per +1 SD), with standard errors clustered on 1 km spatial blocks to account for spatial dependence (Colin Cameron and Miller, 2015). While pixel fixed effects remove the static level of each terrain variable, we additionally estimated the within-pixel climate–NDVI coefficient separately within elevation, aspect, and slope bins to test whether the strength of the climate response is modulated by terrain.

3. Results

3.1. Feature selection and classification performance

Correlation filtering ($|r| > 0.95$) and RFE reduced the 62 candidate features to a final set of 30 original predictors. The cumulative variance explained from PCA reached 95.2% at 20 components and 98.6% at 30 components (Figure A.1a), and 30 was therefore chosen as the target set size. Canopy height and DTM elevation ranked highest in permutation importance, followed by GLCM texture features, while spectral bands contributed least (Figure A.1b). These 30 features were generated annually and used to train one model per year, producing annual mountain pine extent maps from 2017 to 2025. Across all annual models with the polygon-grouped split, the F1 score ranged from 93.1% to 94.8%, and the Kappa value ranged from 0.88 to 0.91. Spatial block cross-validation for 2024 showed a gradual decline in F1 score as block size increased, from 90.4% at 1 km to 87.5% at 25 km (Appendix A, Figure A.2).

3.2. Annual mountain pine maps and stability patterns

The annual maps reveal the mean elevation of mountain pine occurrence is around 1600 m a.s.l., ranging between a mean minimum of 583 m and a mean maximum of 2611 m through the nine years of the time-series. We detected a mean of 34,000 patches annually, with a mean patch size of 4500 m² and a median of 200 m². Patch distribution remains strongly skewed; the Gini coefficient is ~ 0.93 across all maps. Mean annual mapped pine area (temporally filtered series) was 105 km² with the mapped area declining at $-0.56 \text{ km}^2 \text{ yr}^{-1}$ (95% CI $[-0.65, -0.47]$, $p < 0.001$; Fig. 3b), with steeper declines in the raw and majority-only series (-2.78 and

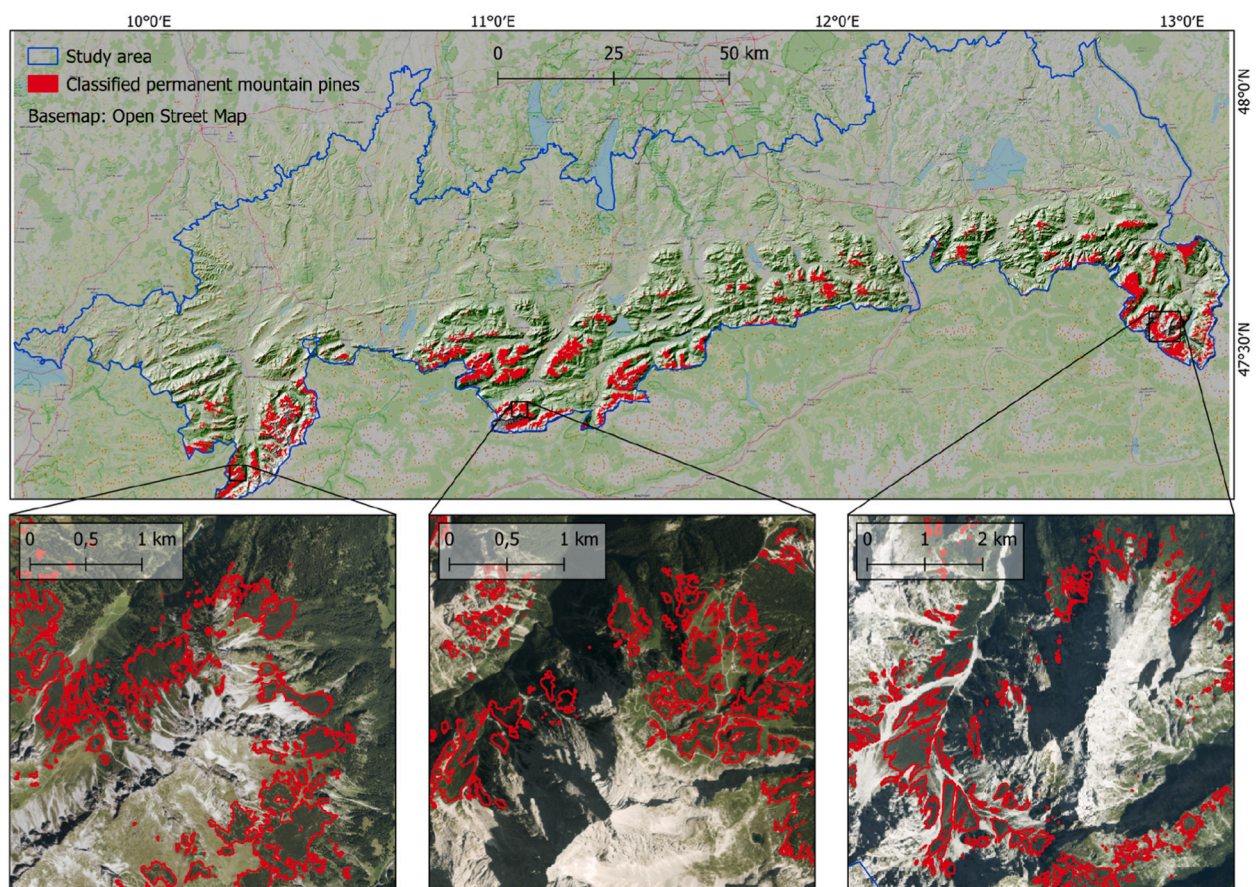


Fig. 4. Permanent mountain pine layer, with close-up views outlining the mapped extent overlaying Bayern Orthophoto © LDBV, DOP20, CC BY 4.0, modified for visualization.

$-0.90 \text{ km}^2 \text{ yr}^{-1}$, respectively). The area-weighted mean elevation showed no detectable trend ($+0.05 \text{ m yr}^{-1}$, 95% CI $[-0.13, 0.23]$, $p = 0.533$). Distribution margins, by contrast, moved asymmetrically: the upper margin shifted upslope (P95: $+0.79 \text{ m yr}^{-1}$, 95% CI $[0.51, 1.07]$; P99: $+1.39 \text{ m yr}^{-1}$, 95% CI $[1.00, 1.79]$; both $p < 0.001$), while the lower margin declined (P5: -1.40 m yr^{-1} , 95% CI $[-2.42, -0.37]$, $p = 0.014$; P1: -3.19 m yr^{-1} , 95% CI $[-5.28, -1.11]$, $p = 0.008$) (Fig. 3a).

The permanent mountain pine layer, derived from the core tier (Fig. 4), accounted for 72.9 km^2 , with the near-core adding 21 km^2 . Across stability tiers, slope, elevation, canopy height, and NDVI showed no distinction; only aspect differed, with the core tier predominantly south-facing ($\sim 46\%$ vs $\sim 37\%$ north-facing) and progressively less stable tiers increasingly north-facing (least stable: $\sim 34\%$ vs $\sim 51\%$ north-facing). Patch structure diverged strongly between tiers: core patches were few but large, comprising 6% of the total patch count while accounting for over half the total area, with an average patch size of 5775 m^2 and the largest contiguous patch of 1.86 km^2 . The less stable tier contained numerous small patches averaging 266 m^2 , with the largest patch of 0.03 km^2 .

3.3. Cross-reference with independent GBIF data

Independent GBIF occurrences coincided with mapped mountain pine in 27.6% of cases at a 50 m buffer and 58.8% at 100 m, increasing to 84.0% at 250 m and 87.6% at 500 m. This strong dependence on buffer size is consistent with the positional uncertainty of the occurrence records relative to the 10 m pixel rather than with classification quality. Agreement in low-growing woody cover was comparatively stable across radii, while the occurrences in needle-leaved forest increased from 10.2% to 54.0% between the 50 m and 250 m buffers (Fig. 5).

3.4. UAS-based sub-pixel detection limits

The UAS classification was assessed using the 30% validation split, yielding a within-scene F1 score of 97.3%. Fig. 6 shows the UAS orthomosaic, mountain pine classification (1 m), along with the overlapping S2-based map (10 m). Comparing mapped extents from both sensors yielded an F1 score of 81%.

Comparing the UAS fractional cover with S2 classification (Fig. 7a), shows a strong positive calibration response. The probability detection curve shows that a pixel is classified as mountain pine in the S2 map when the UAS fractional value exceeds 0.6 (Fig. 7b), characterising the S2 detection limit for this local context. The histogram confirms most pixels have a fraction of 0.1, indicating small, scattered patches in the region.

3.5. Terrain and structural distribution of mountain pines

The distribution of mountain pines within the AOI highlights the highest concentration at mid-elevations of 1400–1800 m a.s.l. (Fig. 8b) and on moderately steep slopes of $20\text{--}40^\circ$ (Fig. 8c). South-to southeast-facing slopes are noticeably denser than others, and CH is low to moderate, with a median of 3.5 m (Fig. 8a) and a notable proportion under 1 m. CH also reveals a gradual decrease along the elevation gradient; stands reach a mean height of 5–6 m at mid elevations (1200 m) but drops to 1 m beyond 2000 m a.s.l. Similarly, for aspect, south/east-facing slopes have the highest canopy heights, averaging 5–7 m, which gradually decrease as moving towards west

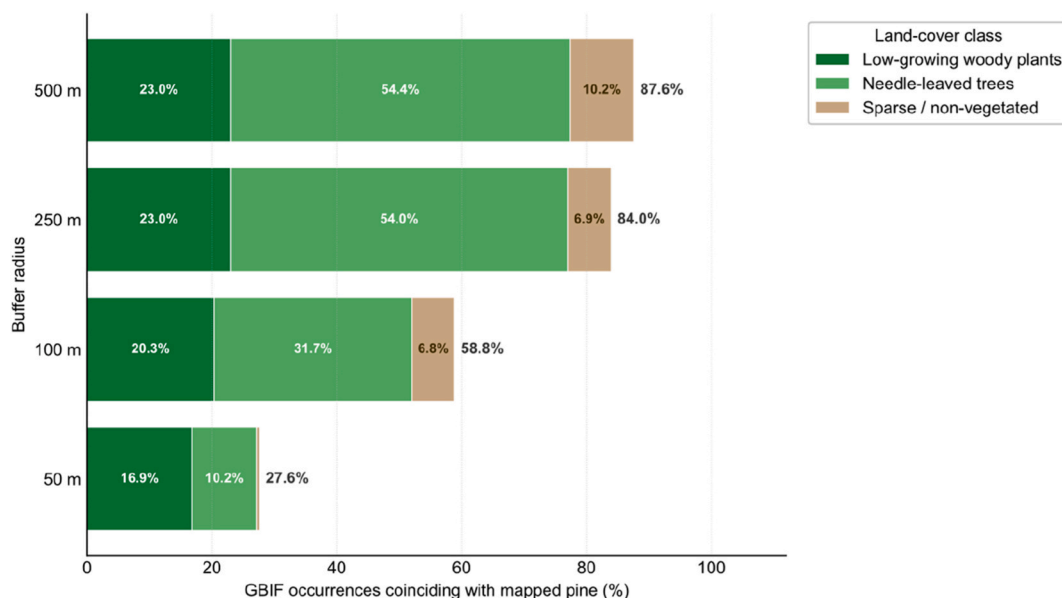


Fig. 5. Agreement between the mountain pine layer and GBIF occurrences, across buffer radii stratified by land-cover context.

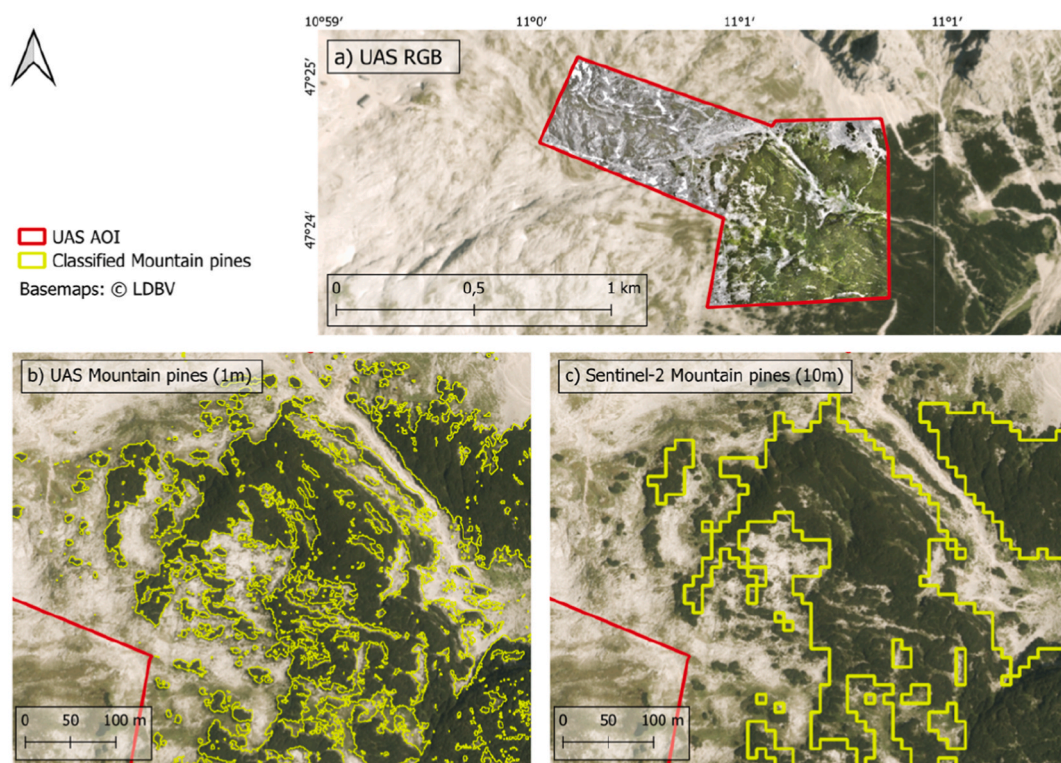


Fig. 6. a) UAS Orthomosaic and mapped mountain pine patch boundaries with b) UAS at 1m, c) Sentinel-2 at 10m overlaying Bayern Orthophoto © LDBV, DOP20, CC BY 4.0, modified for visualization.

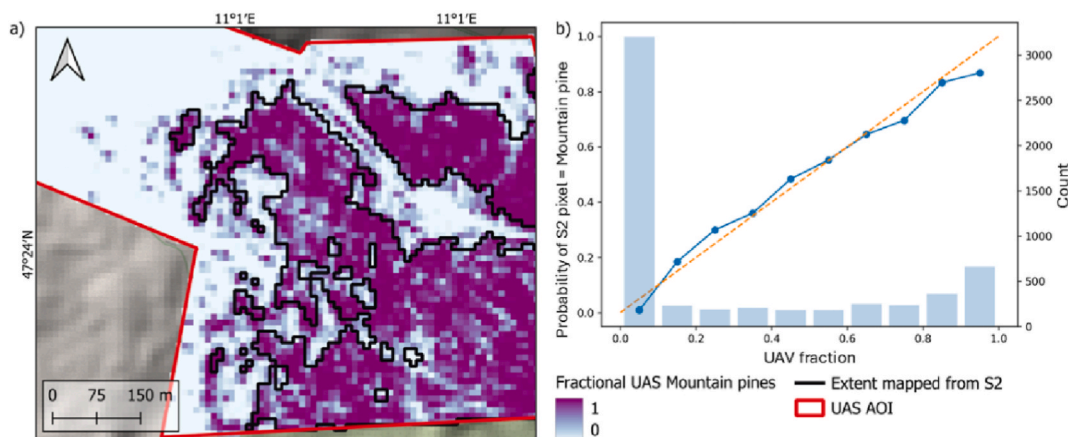


Fig. 7. a) UAS fractional cover overlaid with S2 mapped extent, b) relationship between UAS fractional cover and Sentinel-2 detection probability with blue line showing the observed detection probability, the orange dashed line representing the 1:1 line, and the bars indicate pixel counts per fractional-cover bin (secondary y-axis).

and northwest (Fig. 8e). An increase of CH can be observed on steeper slopes, tallest at 60°, while the shortest canopies are on gentle slopes (Fig. 8f).

3.6. NDVI phenology of stable mountain pines

The species shows a modest seasonal amplitude with an NDVI increase detected in July (Fig. 9a). Summer NDVI drops systematically with elevation; the maximum is recorded between 1200 and 1600 m a.s.l. (Fig. 9b) and with every 300 m elevation gain, a drop of 0.02–0.03 in NDVI values. The pattern is more pronounced on north-facing slopes than on sun-exposed ones, indicating a buffering

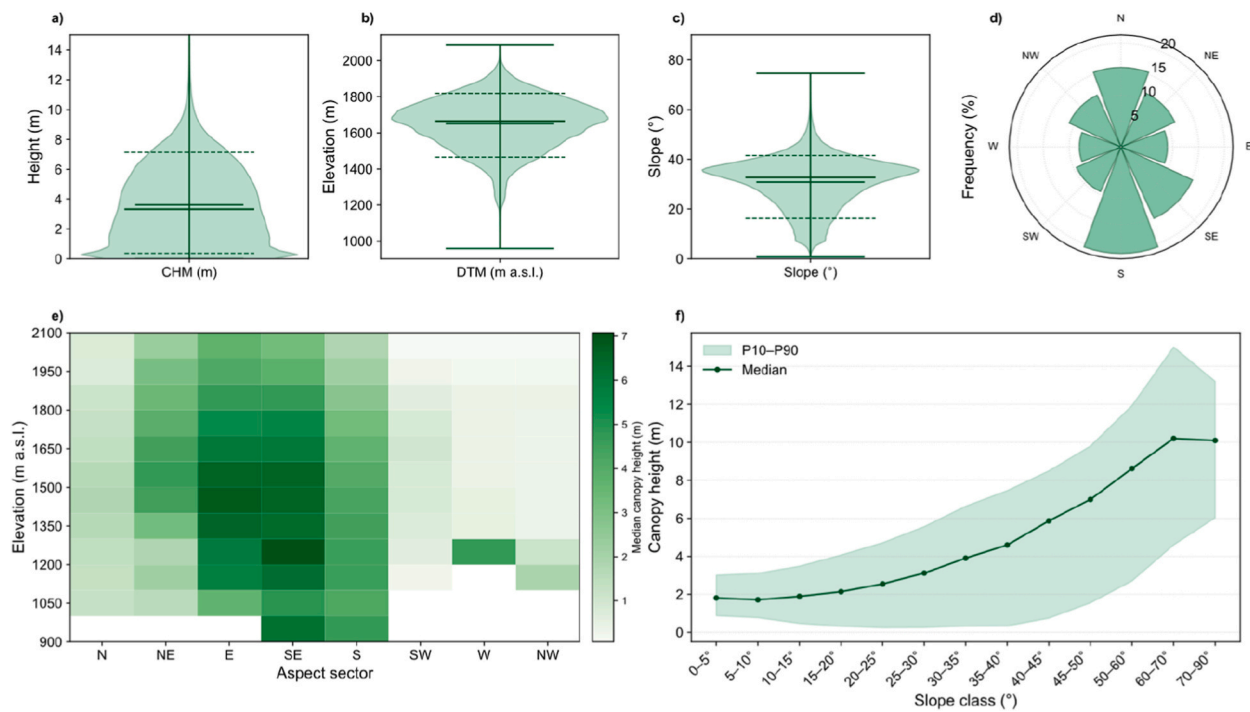


Fig. 8. Summarizing topographic and structural distribution of mountain pines in German Alps.

effect.

3.7. Climatic influence on mountain pine greenness

3.7.1. Local analysis using station data

Within the 10 km station buffers, the clearest signal was an elevation-dependent NDVI response to summer temperature. The two

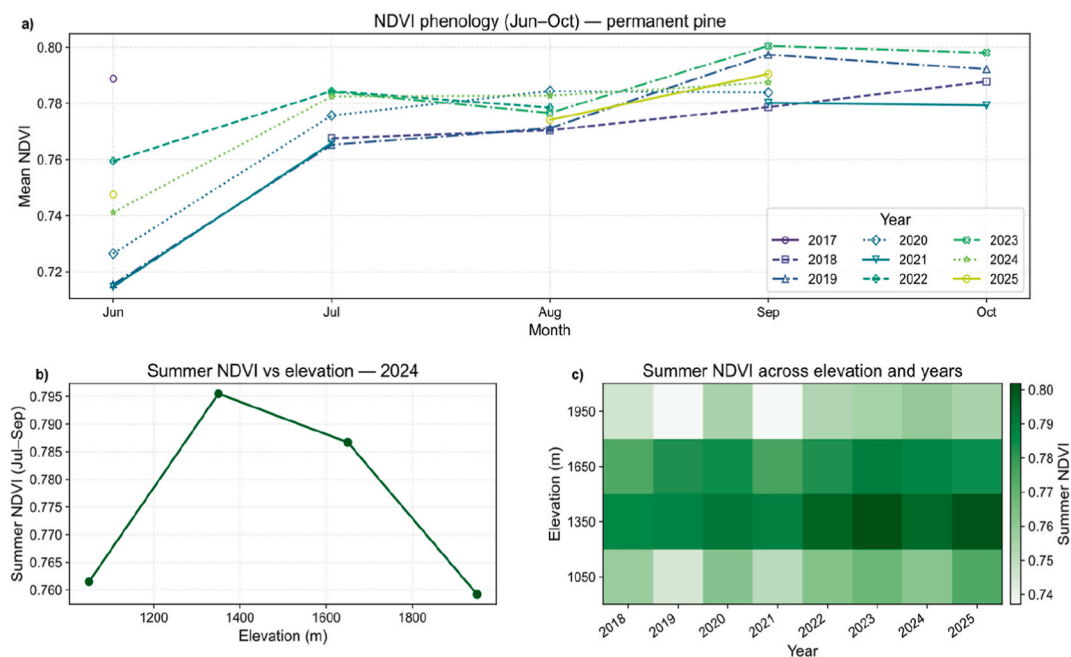


Fig. 9. a) NDVI-based Mountain pine phenology. b) NDVI vs elevation. c) Annual summer NDVI against elevation.

lower-elevation valley stations showed weak negative correlations (Mittenwald $r = -0.07$; Oberstdorf $r = -0.24$), whereas the high-elevation Zugspitze station showed a positive relationship ($r = 0.61$). Winter relationships were weaker; snow depth and winter precipitation had positive effects, indicating greater greenness after wetter, higher-snowfall winters, though the relationship was significant only at the Oberstdorf station. Fig. 10 shows the station locations, buffers, and NDVI relationships with snow depth and summer temperature, while Table A.2 in Appendix A summarises the correlations and their significance.

3.7.2. Regional analysis using gridded raster data

After accounting for spatial dependence and time constant characteristics, climate–NDVI associations were small relative to the NDVI baseline (median ≈ 0.80), reinforcing their exploratory nature. Coefficients express the NDVI change per one standard deviation of each driver, with terrain-stratified responses summed in Fig. 11. Among summer drivers, summer temperature was positively associated with NDVI ($\beta = +0.0015$, $p < 0.001$), reinforcing the elevation-dependent pattern (Fig. 11) also observed in station data (Fig. 10b) and highlighting temperature limitation at higher elevations.

Among winter drivers, the most robust signal was a positive effect of early-winter temperature: warmer December associated with greater following-summer greenness ($\beta = +0.0013$, $p < 0.001$), the largest and most stable winter coefficient. Winter-season temperature was also positive ($\beta = +0.0007$, $p < 0.001$) while mild winter weeks showed a weak negative association ($\beta = -0.0009$, $p < 0.001$). The terrain stratification (Fig. 11) showed that the positive summer and early-winter temperature responses were broadly consistent across aspect, elevation, and slope, whereas winter precipitation remained non-significant across nearly all terrain classes.

4. Discussion

The annual mountain pine maps reveal consistent spatial patterns and a detectable elevational shift, which are discussed below alongside sensor-scale constraints and exploratory ecological relationships.

4.1. Spatial and elevational dynamics

Our results indicate a modest upslope shift confined to the upper margin of the mapped distribution, with the 99th and 95th elevation percentiles increasing by 1.39 and 0.79 m yr^{-1} , respectively (both $p < 0.001$). We do not interpret the per-year maximum elevation as a trend, as it is governed by individual extreme pixels. Our upper-margin rate is broadly consistent with, though somewhat higher than, the citizen-science estimate of Rösler et al. (2024), who recorded a 51 m increase in the uppermost *Pinus mugo* occurrences

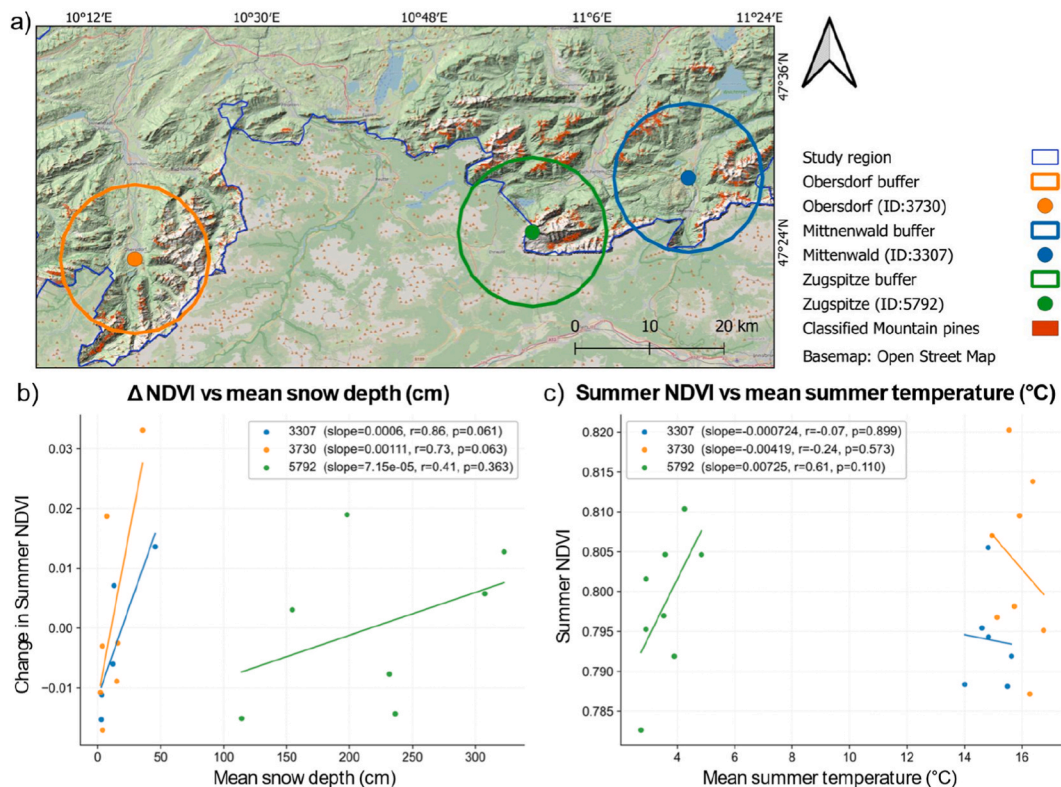


Fig. 10. a) Location of climate stations with their respective buffers, along with scatter plots highlighting the exploratory relation of mountain pine NDVI to b) mean snow depth (cm) and c) mean summer temperature (°C).

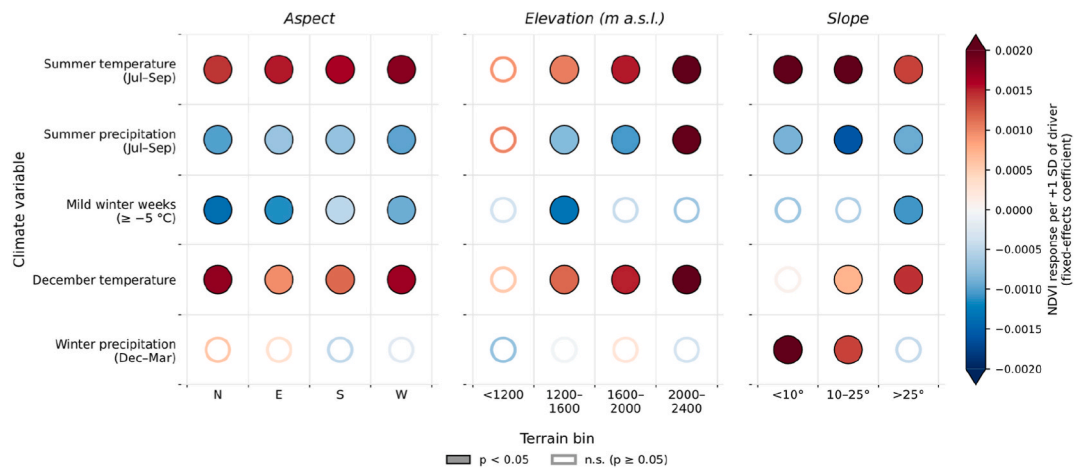


Fig. 11. Terrain-stratified climate–NDVI response from the two-way fixed-effects panel. Each cell shows the standardised fixed-effects coefficient, NDVI response per +1 standard deviation of the driver, for the climate variable (rows) within a terrain bin (columns). Color indicates the sign and magnitude of the coefficient, while filled circles are significant at $p < 0.05$, with standard errors clustered at 1 km spatial blocks; open circles are non-significant (ns).

in the Bavarian Alps over a century. The difference is plausibly methodological as their reliance on public observations may under-represent remote, terrain-restricted high-elevation occurrences. Both approaches, however, point to slow realised upslope movement, far below the 500 m shift that the thermal gradient alone would permit (Rösler et al., 2024), a lag commonly attributed to soil and substrate limitation at high altitude.

Other studies focusing on the spread of the species, for example, in the Lezer Mountains in the Southern Carpathians in Romania, also report $1.4 \text{ km}^2 \text{ yr}^{-1}$ expansion from 1986 to 2002 (Mihai et al., 2007). Similarly, in the High Tatra Mountains, Slovakia shows a 2.15 km^2 increase in the area covered by mountain pine from 1955 to 2002 (Solár and Janiga, 2013). Both studies relate the spread to land abandonment, reporting two-dimensional areal expansion rather than elevational movement. Our study area instead shows a net contraction of mapped area ($-0.56 \text{ km}^2 \text{ yr}^{-1}$) with no change in the area-weighted mean elevation. The mapped population is strongly dominated by a small number of large patches, yielding a consistently high size inequality (Gini ≈ 0.93 , stable throughout 2017–2025), as also reported in the Sarntal Valley, South Tyrol (Rösch et al., 2022). This stability, alongside the contraction, indicates that area is being lost at the margins of established stands rather than through fragmentation or new patch formation, distinguishing our population from the colonizing dynamics in the Carpathian and Tatra populations.

4.2. Phenology and climate response

NDVI-based mountain pine phenology shows evergreen behavior with no decline until October (Fig. 9). Photosynthetic activity begins as NDVI increases from June to July, coinciding with new shoot sprouting. Wachowiak et al. (2018) reported that *Pinus mugo* exhibits earlier bud bursts than *Pinus sylvestris* and *Pinus uliginosa*, and that intra-species variance is highest for *Pinus mugo* between eastern populations in the Carpathians, which flush earliest, compared to western alpine *Pinus mugo*, which flush much later, as our results also show. This also highlights the general diversity among populations and the species' adaptive capabilities.

Linking these NDVI patterns to climate revealed that, once spatial autocorrelation and time-invariant terrain were accounted for through a fixed-effects framework, the climate–NDVI relationships were weak, consistent with the short nine-year record and the exploratory nature of this analysis. The most robust winter signal was observed between early-winter temperature and subsequent summer greenness, consistent with the dominant pattern reported for *Pinus mugo* in the High Tatra Mountains from MODIS-based NDVI (2000–2020), where warmer early winters favoured greenness in the subalpine zone (Lukasová et al., 2021).

We also observed a negative association between mild winter weeks and subsequent greenness. As has also been reported in subarctic communities, warm spells during winter cause extensive damage to dwarf shrub vegetation in northern Scandinavia, resulting in 87% less growth in the subsequent summer (Bokhorst et al., 2009). Lab-based freezing experiments revealed that mountain pine needles can compartmentalize ice and have exceptional frost hardiness, surviving temperatures as low as -85°C (Stegner et al., 2023). Despite their capacity to withstand such extreme temperatures, numerous studies have highlighted the risk from spring frost, which remains a limiting factor (Bachofen et al., 2016). Mid-winter warm spells can trigger partial dehardening, increasing the risk of subsequent frost and making fluctuating temperatures a greater threat to mountain pines, consistent with, though not confirmed by, the negative mild-winter-week association in our results.

In contrast, the summer-temperature response was ecologically coherent, with summer temperature positively affecting mountain pine greenness across all aspects, and the effect strengthened from mid to high elevations (Fig. 11). Consistent with temperature-limited productivity near the upper distribution limit of mountain pine, where low temperatures constrain tissue formation rather than photosynthesis (Körner, 1998), capturing both direct thermal limitation and growing season length. The same gradient emerged

independently at the high-elevation Zugspitze station. Summer precipitation showed a weak negative association, most plausibly reflecting wetter summers coinciding with greater cloudiness and reduced solar radiation rather than moisture limitation in this snowmelt-fed setting (Körner, 1998). Together, these signals indicate that growing-season greenness is governed more by available energy than by water, consistent with the observed mountain pine under milder, less snowy conditions at lower elevations (Dirnböck et al., 2003; Švajda et al., 2011). Continued summer warming may therefore render these sites progressively more favourable, a hypothesis consistent with the upslope expansion discussed above.

4.3. Limitations

Several constraints bound the interpretation of these results. First, the nine-year observation period is too short to detect ecological range shifts; the upslope and area trends should be read as mapping-detected signals that require field verification rather than as confirmed range dynamics, and all climate–NDVI relationships are exploratory and hypothesis-generating rather than confirmatory. Second, the reference data were delineated in 2024 and applied across all annual maps. Although the high-elevation distribution of mountain pine is temporally stable, the per-year accuracy figures therefore characterize the temporal consistency of a fixed reference rather than independently validated annual accuracies. Third, because a polygon-level split does not guarantee spatial independence, we additionally evaluated spatial block cross-validation; presence-class F1 declined from 94% to 88% under block cross-validation at scales up to 25 km. The climate analysis is subject to the same autocorrelation structure, which the fixed-effects specification and block-clustered standard errors are designed to mitigate but cannot fully eliminate. Classification noise on north-facing slopes, driven by low solar illumination, terrain shadows, and unfavourable sensor-terrain geometry, represents a further source of uncertainty. Post-classification temporal filtering was applied to reduce this noise while preserving small patches, since the median mountain pine patch spanned only two Sentinel-2 pixels. Finally, while scene classification and atmospheric filtering remove cloud, snow, and haze contamination, NDVI retains residual uncertainty due to illumination and terrain geometry on steep, north-facing slopes, which may add noise to climate–NDVI estimates. At the sub-pixel scale, the UAS comparison near Zugspitze indicates that Sentinel-2 reliably classifies a pixel as mountain pine only when fractional cover exceeds 0.6, meaning fragmented patches below this threshold are systematically underdetected; this resolution ceiling would be further amplified by coarser sensors such as Landsat or MODIS. The UAS assessment is restricted to a small area near Zugspitze and represents a local, sensor-scale finding rather than a region-wide measure of accuracy.

4.4. Outlook

Looking ahead, the established mountain pine classification approach can be extended to a longer time series to provide high-resolution maps for monitoring changes in elevation and area, and applied to neighboring countries such as Austria and Italy to create unified, continuous mountain pine maps across the Alpine region. Such maps would support monitoring and comparison of management practices across borders. The workflow can also be replicated to map other alpine vegetation species and to generate shrubland maps using similar training data. As the first detailed source of mountain pine extent maps in Germany, our products could underpin ecological studies of the krummholz zone and alpine ecosystems, their productivity patterns, and roles in the carbon and water cycles. Moreover, these maps could serve as a basis for analyzing the role of mountain pines in preventing landslides and avalanches, thereby improving understanding of their ecosystem functions.

5. Conclusion

The machine learning-based mountain pine mapping approach with S2 data highlights the importance of texture and terrain features, with an overall accuracy of ~90%. Applying the workflow to higher-resolution UAS data reveals S2's limitations in mapping small, fragmented patches. Annual maps show a detectable shift in the upper elevation boundary, whereas patch analysis reveals high inequality, with fewer, larger patches dominating the total mountain pine area. Mean height is around 3 m, with the highest concentration on the south to southeast slopes between 20° and 40°, with the highest NDVI values between 1200 and 1600 m a.s.l. peaking in July to September. Linking this to climate through an exploratory fixed-effects analysis indicates that mountain pine greenness is governed mainly by growing-season and early-winter temperature, pointing to an energy-limited system in which warmer conditions are broadly favourable. A weaker signal suggests milder winters impose stress through dehardening, while snow and winter precipitation showed insignificant effects over the nine-year record. At higher elevations, increased summer temperatures enhance photosynthetic activity, suggesting that warming may continue to favour upslope expansion.

Statement of human and animal rights

Ethical considerations in the conduct and reporting of research: Protection of human subjects and animals in research.

When reporting experiments on human subjects, authors should indicate whether the procedures followed were in accordance with the ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1975, as revised in 2008. If doubt exists whether the research was conducted in accordance with the Helsinki Declaration, the authors must explain the rationale for their approach and demonstrate that the institutional review body explicitly approved the doubtful aspects of the study. When reporting experiments on animals, authors should indicate whether the institutional and national guidelines for the care and use of laboratory animals were followed.

CRediT authorship contribution statement

Basil Tufail: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Moritz Rösch:** Writing – review & editing, Visualization, Data curation. **Elio Rauth:** Writing – review & editing, Visualization. **Julian Fäth:** Writing – review & editing, Visualization. **Tobias Ullmann:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Data and code availability

- The annual mountain pine maps for Southern Germany from 2017 to 2025, along with the permanent layer, have been published at Zenodo (<https://doi.org/10.5281/zenodo.19691239>).
- The analysis code for the mapping procedure is available on GitHub (<https://github.com/basu26/Mountain-Pine-mapping/tree/main>).
- Orthophotos (DOP20), DSM (DOM20), and DTM (DGM1) provided by the Bavarian Surveying Administration (LDBV) are accessible through the Bavarian [Geoportal](#) under the OpenData framework (CC BY 4.0).
- Climate data can be accessed via [the DWD CDC portal](#).
- Species record data can be accessed via [the GBIF website](#).
- Sentinel-2 data employed is available from [Google Earth Engine](#).

Declaration of generative AI technologies

During the preparation of this work, the author used ChatGPT and Claude to improve coding efficiency and readability of some sections. After using this tool, the authors reviewed and edited the codes and content where required and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Predictor Features, Dimensionality Reduction, and Model Performance

Table A.1

Full set of 62 features with selected final subset of 30 predictor variables used for model training in bold.

Feature ID	Feature name	Category
F01	Red_June	Spectral
F02	Green_June	Spectral
F03	Blue_June	Spectral
F04	NIR_June	Spectral
F05	Contrast_June	Texture
F06	Homogeneity_June	Texture
F07	Entropy_June	Texture
F08	Mean_June	Texture
F09	Variance_June	Texture
F10	NDVI_June	Vegetation
F11	NARI_June	Vegetation
F12	Red_July	Spectral
F13	Green_July	Spectral
F14	Blue_July	Spectral
F15	NIR_July	Spectral
F16	Contrast_July	Texture
F17	Homogeneity_July	Texture
F18	Entropy_July	Texture

(continued on next page)

Table A.1 (continued)

Feature ID	Feature name	Category
F19	Mean_july	Texture
F20	Variance_July	Texture
F21	NDVI_July	Vegetation
F22	NARI_July	Vegetation
F23	Red_August	Spectral
F24	Green_August	Spectral
F25	Blue_August	Spectral
F26	NIR_August	Spectral
F27	Contrast_August	Texture
F28	Homogeneity_August	Texture
F29	Entropy_August	Texture
F30	Mean_August	Texture
F31	Variance_August	Texture
F32	NDVI_August	Vegetation
F33	NARI_August	Vegetation
F34	Red_September	Spectral
F35	Green_September	Spectral
F36	Blue_September	Spectral
F37	NIR_September	Spectral
F38	Contrast_September	Texture
F39	Homogeneity_September	Texture
F40	Entropy_September	Texture
F41	Mean_September	Texture
F42	Variance_September	Texture
F43	NDVI_September	Vegetation
F44	NARI_September	Vegetation
F45	Red_October	Spectral
F46	Green_October	Spectral
F47	Blue_October	Spectral
F48	NIR_October	Spectral
F49	Contrast_October	Texture
F50	Homogeneity_October	Texture
F51	Entropy_October	Texture
F52	Mean_October	Texture
F53	Variance_October	Texture
F54	NDVI_October	Vegetation
F55	NARI_October	Vegetation
F56	NDVI_seasonal_range	NDVI phenology
F57	NDVI_mean	NDVI phenology
F58	NDVI_autumn_decline	NDVI phenology
F59	Elevation	Topographic
F60	Slope	Topographic
F61	Aspect	Topographic
F62	Canopy height	Topographic

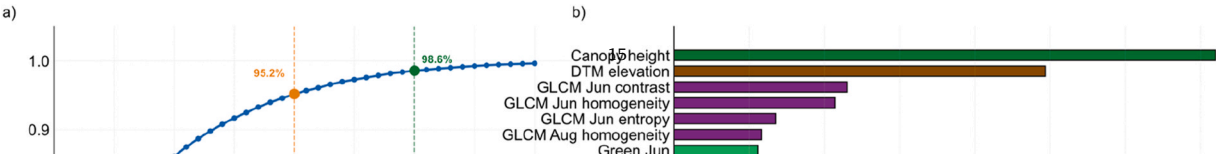
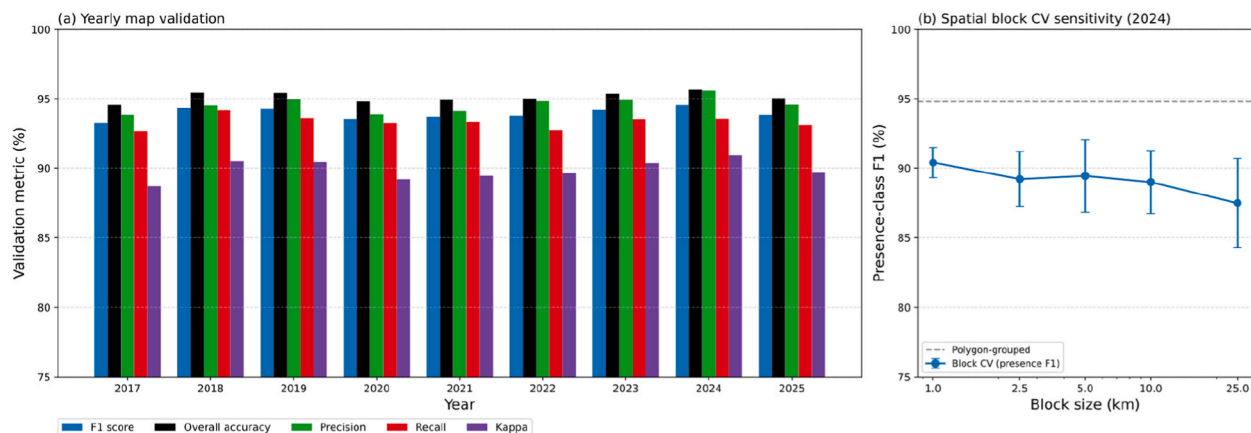


Fig. A.1. a) PCA scree curve showing variance for 20 and 30 features, b) Feature importance for selected 30 variables.**Fig. A.2.** Random Forest validation performance. (a) Per-year validation metrics for the annual mountain pine maps (2017–2025), computed against the 2024 reference set. (b) Sensitivity of presence-class F1 to spatial block cross-validation block size for the 2024 model (1–25 km; error bars denote ± 1 SD across folds), shown against the polygon-grouped F1 for reference.**Table A.2**

Climatic variables recorded at the 3 stations and their correlation with NDVI (significant in bold)

Station	Variable	Correlation r	Correlation (p-value)
Mittenwald (3307)	Months with snow depth >5 cm	0.7	0.12
	Winter max snow depth (cm)	0.88	0.05
	Winter temperature (°C)	−0.77	0.13
	Winter precipitation (mm)	0.37	0.47
	Summer temperature (°C)	−0.07	0.9
Oberstdorf (3730)	Months with snow depth > 5 cm	0.29	0.52
	Winter max snow depth (cm)	0.77	0.04
	Winter temperature (°C)	−0.03	0.95
	Winter precipitation (mm)	0.9	0.01
	Summer temperature (°C)	−0.24	0.57
Zugspitze (5792)	Months with snow depth > 150 cm	0.31	0.5
	Winter max snow depth (cm)	0.34	0.45
	Winter temperature (°C)	−0.24	0.61
	Winter precipitation (mm)	0.56	0.19
	Summer temperature (°C)	0.61	0.11

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