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Key Points:

- Latent heat fluxes of 15 Mediterranean forests were reconstructed for more than 20 years based on satellite imagery
- In late Summer/early Fall months, most forests showed significant λET increases, which often occurred despite decreasing precipitation
- A conceptual scheme is proposed to explain the water-availability and biomass status of forests and support plant response to climate

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Detecting Forest Water-Availability and Biomass Patterns Through a Retrospective Study in a Mediterranean Region

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Abstract Latent heat (λET) fluxes are a major component of the hydrological cycle globally. According to recent models and experimental observations, during droughts, wetter regions respond by increasing λET , while drier regions exhibit decreasing trends due to vegetation water stress. To dissect the λET signature of natural forests in a Mediterranean region, typically regarded as a dry environment, in this work, we reconstructed the λET fluxes, gross primary production, and water use efficiency (WUE) of 15 natural unmanaged forests in Central Italy from 2000 to 2022, and explored their dependencies on local temperature and precipitation. Historical λET data were estimated through a time-domain parameterization of the traditional “triangle method,” which leverages satellite imagery to compute actual latent heat flux as a residual term of the land surface energy balance, while WUE was delivered through the Vegetation Photosynthesis Model. Based on our results, forests arrange along a gradient of water-availability and biomass conditions whereby, following λET enhancement, biomass first increased and water reserves were developed to afford the dry season. However, when water savings became insufficient, WUE decreased and was then followed by biomass reduction. Consideration of soil moisture data will provide further insights on forest resilience and water-availability under future climatic scenarios.

1. Introduction

As climate change is accelerating the exchange of water between the atmosphere and land systems (Y. Wang et al., 2023), it is paramount to understand how drought will affect biomes globally (Colangelo et al., 2021; Fyllas et al., 2017; Hidalgo-Triana et al., 2023; Wei et al., 2024; J. Zhao et al., 2024). While it was assumed that lack of rainfall induced drier soils and, thus, lower latent heat (λET) fluxes rates, numerous observations have demonstrated a consistent and significant increase in λET during droughts, the so-called “drought-paradox” (Teuling et al., 2013). λET was enhanced during droughts in wet regions, where sunny and warm weather tend to decouple λET fluxes from soil moisture decreases (Li et al., 2023). Conversely, in drier regions, λET is thought to decrease due to vegetation water stress. However, such drought-induced λET increase has been documented across a well diversified spectrum of climates and environments, spanning from temperate forests to dry low-biomass regions (Beamesderfer et al., 2020; M. Zhao et al., 2022), in both low-magnitude short-term and severe prolonged droughts (Peterson et al., 2021; M. Zhang et al., 2019), as well as at low to high elevations (Mastrotheodoros et al., 2020; Teuling et al., 2013).

Intensified λET fluxes during droughts have far-reaching implications for the hydrological cycle. In fact, increased λET amplifies soil drought and heatwaves (Teuling, 2018), thus yielding the depletion of groundwater resources. In this framework, in South-Eastern Australia, persistent λET increases per unit of precipitation (P) during the severe Millennium drought are likely to have prevented runoff recovery in numerous watersheds even after the end of the meteorological drought (Peterson et al., 2021). Dramatically, in such settings, hydrological drought kept lasting even after meteorological drought ended, and this has suggested the instance of tipping points which challenge the watershed hydrological resilience (Tauro, 2021). In alternative scenarios, the λET increase related to revegetation of degraded ecosystems and ecological restoration has been found to induce a strongly significant decrease in surface waters and water depletion at large (Feng et al., 2016; Y. Liu et al., 2023; M. Zhao et al., 2021). At the ecological level, the drought paradox is explained with plants developing enhanced strategies to access deeper soil water (Wu et al., 2013). However, this may also favor species mortality (Biederman et al., 2014; Choat et al., 2018; Gouveia et al., 2017; Senf et al., 2020), changes in the composition of ecosystems, and, ultimately, loss of biodiversity.

λ ET evaluations at fine spatial scales are challenged by the lack of long-term reference observations (Martens et al., 2017; Mueller et al., 2011; Yuan et al., 2024) as well as by the heterogeneity of data sources, ranging from point-wise measurements to global estimations. At the local scale, eddy covariance (EC) tower records are often too spatially sparse and short to accurately capture drought conditions (Baldocchi et al., 2001; Chu et al., 2017). Traditional methods such as lysimeters provide high-precision measurements but offer very limited spatial representation, are costly, and subject to issues such as the oasis and boundary effects (Wegehenkel et al., 2008; WMO, 2021/2018; Z. Zhang et al., 2020). At larger scales, methods such as the water balance approach lack the temporal resolution necessary to capture daily or finer variations in λ ET (K. Wang & Dickinson, 2012). Moreover, water balance methods are prone to uncertainties from errors in input variables measurement and estimation, as well as missing data. Similarly, they rely on the spatial coverage of input variables, which can be unavailable, sparse, or unreliable in certain regions (Ali et al., 2023; Y. Liu & Gupta, 2007; McMillan et al., 2018). At a global scale, earth system models, also lack the adequate spatial resolution and representation of plant traits that account for vegetation strategies to water stress (De Kauwe et al., 2015; Fowler et al., 2016; M. Zhao et al., 2022).

Another considerable limitation to the comprehension of the ecosystem λ ET fluxes derives from consideration of single dry events rather than multi-year periods. In fact, cycles of alternating precipitation and soil water anomalies may interact with the λ ET and temperature anomalies through dynamics which can only be partially quantified at the short timescale (Massari et al., 2022). Remote sensing observations can mitigate such criticalities by offering spatially high-resolution imagery for several decades to monitor λ ET and plant environmental stress condition (Blin & Suárez, 2023; Kalma et al., 2008; D. Liu et al., 2024; Ollivier et al., 2021). Computation of the surface energy balance from satellite imagery and in situ data has resulted in accurate latent heat flux (λ ET) estimations at the field and individual canopy scale (Paciolla et al., 2025; Tauro et al., 2022), thus supporting the feasibility of this approach to further dissect the vegetation response to drought.

Toward a deeper comprehension of the interplay between climatic drivers and the water cycle in typically dry environments, in this work, we studied the λ ET response of 15 natural unmanaged forest areas in Mediterranean ecosystems for a time period spanning from 2000 to 2022. Our research objectives entailed: (a) reconstructing the λ ET signature of each forest area for the past 20 years, (b) investigating such signature in relation to local temperature and precipitation records, (c) detect eventual λ ET patterns and propose potential ecological mechanisms to explain the current λ ET response of vegetation. In our investigation, we focused on forest areas located at diverse mean elevations and distance from the coast. The λ ET signature was evaluated by computing actual instantaneous λ ET as a residual term of the land surface energy balance equation (Allen et al., 2005, 2007; Bastiaanssen et al., 1998; Norman et al., 1995). To minimize the dependence on ancillary ground-based measurements, we applied a time-domain parameterization of the traditional “triangle method” (Gampe et al., 2016; Jiang & Islam, 1999, 2001; Minacapilli et al., 2016; Stisen et al., 2008). Compared to the standard scheme, this time-domain approach does not require uniformity in atmospheric conditions, and exploits the pixel temporal variability of land surface temperature and vegetation indices to determine the boundary conditions of the triangular feature space. We further leveraged λ ET estimations to reconstruct the interactions between forest carbon and the water cycle. Namely, we estimated the instantaneous water use efficiency (WUE) as the ratio of gross primary production (GPP, the amount of chemical energy produced as carbon biomass in a given period of time) delivered through the Vegetation Photosynthesis Model (VPM) and λ ET. Knowledge of temporal trends of WUE provided insights on the long-term effects of temperature and precipitation as well as guidance for potential management of Mediterranean forests.

2. Materials and Methods

In this Section, we define and provide a characterization of the study sites. We describe the methodology for reconstructing historical λ ET estimations, detail the analysis for processing λ ET and climate data, and report the methods to compute GPP and WUE.

2.1. Protected Areas

We considered natural protected areas (PAs) as identified by the Lazio Region and comprised in the Province of Viterbo (Regione Lazio-Direzione Ambiente, Cambiamenti Climatici, Transizione Energetica e Sostenibilità, Parchi, 2023). These PAs have been established to safeguard their ecosystems' bio- and geodiversity, and they

include regional parks, state reserves, regional reserves, natural monuments, and the Natura 2000 network as identified by (Regione Lazio-Direzione Ambiente, Cambiamenti Climatici, Transizione Energetica e Sostenibilità, Parchi, 2023). We selected PAs that are exclusively covered by natural forests, based on the land use map from the Copernicus land monitoring service (European Environment Agency, 2019d). Within these areas, we excluded portions defined as both “loss” and “gain” according to Global Forest Watch (Global Forest Watch, 2024). Tree loss is defined as the permanent or temporary removal or mortality of tree cover (trees equal to and higher than 5 m) for any reason, both human-caused and due to natural disturbance (Hansen et al., 2013). Tree gain is defined as the establishment of forests within the year 2000 non-forest land (Potapov et al., 2022). Therefore, our study sites were 15 forested PAs, where tree cover persisted over the study period, see Figure 1. The sites vector files were intersected with the digital elevation model (DEM) of the Province of Viterbo as developed by IGMI (2003). The DEM is available at 20 m resolution but was resampled and aligned to match 30 m resolution for consistency with satellite imagery. For each PA, we computed the slope as the angle of inclination of the terrain, the aspect as the slope direction, and latitude for each cell of the DEM.

The mean elevation and distance from coastline are reported in Table 1 for each PA. To this end, we first extracted the coastline for Northern Lazio and converted it to point vector layer. Then, we calculated the centroid for each PA vector file, and estimated the closest eulerian horizontal distance to the coast. Mean elevation for the PAs was extracted from each PA's DEM file.

2.1.1. Weather and Climate

The Province of Viterbo is characterized by a hot-summer Mediterranean climate, with an average yearly temperature of 14.4°C and an annual mean rainfall of 810 mm. Hourly air temperature and precipitation data from 2000 to 2022 were obtained from 22 weather stations (Ws) managed by Centro Funzionale Regione Lazio, see Figure 1. These data were used to derive air temperature at the time of satellite imagery acquisition. Namely, we identified the set of weather stations laying in or close to the PA (within an average distance of 21 km from the PA centroid). We reconstructed air temperature and precipitation time series by considering the values of the closest weather station to each PA. In case of missing temperature and/or precipitation data, we referred to the second to seventh closest weather station of the considered set. Temperature data were corrected for elevation by assuming a lapse rate of $-1^{\circ}\text{C}/100\text{ m}$. For simplicity and due to the large variability of this parameter as a function of elevation and climate (Brunetti et al., 2014), we adopted a consistent lapse rate for all the weather stations across all seasons throughout the study period.

Monthly and seasonal rainfall and temperature trends were conducted on a subset of eight weather stations (W1, W7–9, W13, W20–22, based on data availability) using the non-parametric Mann-Kendal test (Mann, 1945; R Core Team, 2024). Following Beiter et al. (2020), seasons were defined as follows: Spring (including the months of March, April, and May); Summer (June, July, and August); Fall (September, October, and November), and Winter (December, January, and February). A temperature trend analysis was conducted for the weather station of Viterbo (W7), where daily temperature data are available since 1927. Yearly anomalies (ΔT) were computed by subtracting the historical mean from yearly temperature data. Data were not available for years: 1938, 1942–1950, and 1983–1987. Likewise temperature, a trend analysis on yearly precipitation was conducted for the weather station of Viterbo on a daily time series available from 1916 to 2022. Precipitation anomaly (ΔP) was also computed by subtracting the historical mean from the yearly values. Data were not available for years: 1920, 1938, 1942–1950, and 1984–1986. For both temperature and precipitation, data were fitted with a linear regression, and the coefficient of determination (R^2) and p -value for the F -test (p) were computed. Significance and strong significance were defined for $p < 0.05$ and $p < 0.01$, respectively.

Further characterization of dryness/wetness within the study period was assessed computing the standardized precipitation index (SPI) and the standardized precipitation evapotranspiration index (SPEI) for weather data available at the weather station of Viterbo (W7) and for the reconstructed air temperature and precipitation time series at each PA. The SPI index quantifies precipitation deviation from average. Negative values indicate dry conditions, while positive values refer to wet conditions. The SPEI index is based on the climatic water balance, with values transformed into standardized normal values (Vicente-Serrano et al., 2010). Negative SPEI values represent drier than normal conditions, whereas positive values correspond to wetter than normal conditions. We computed both SPI and SPEI at the 3-month, and 12-month scales using the inbuilt R-statistical software SPEI

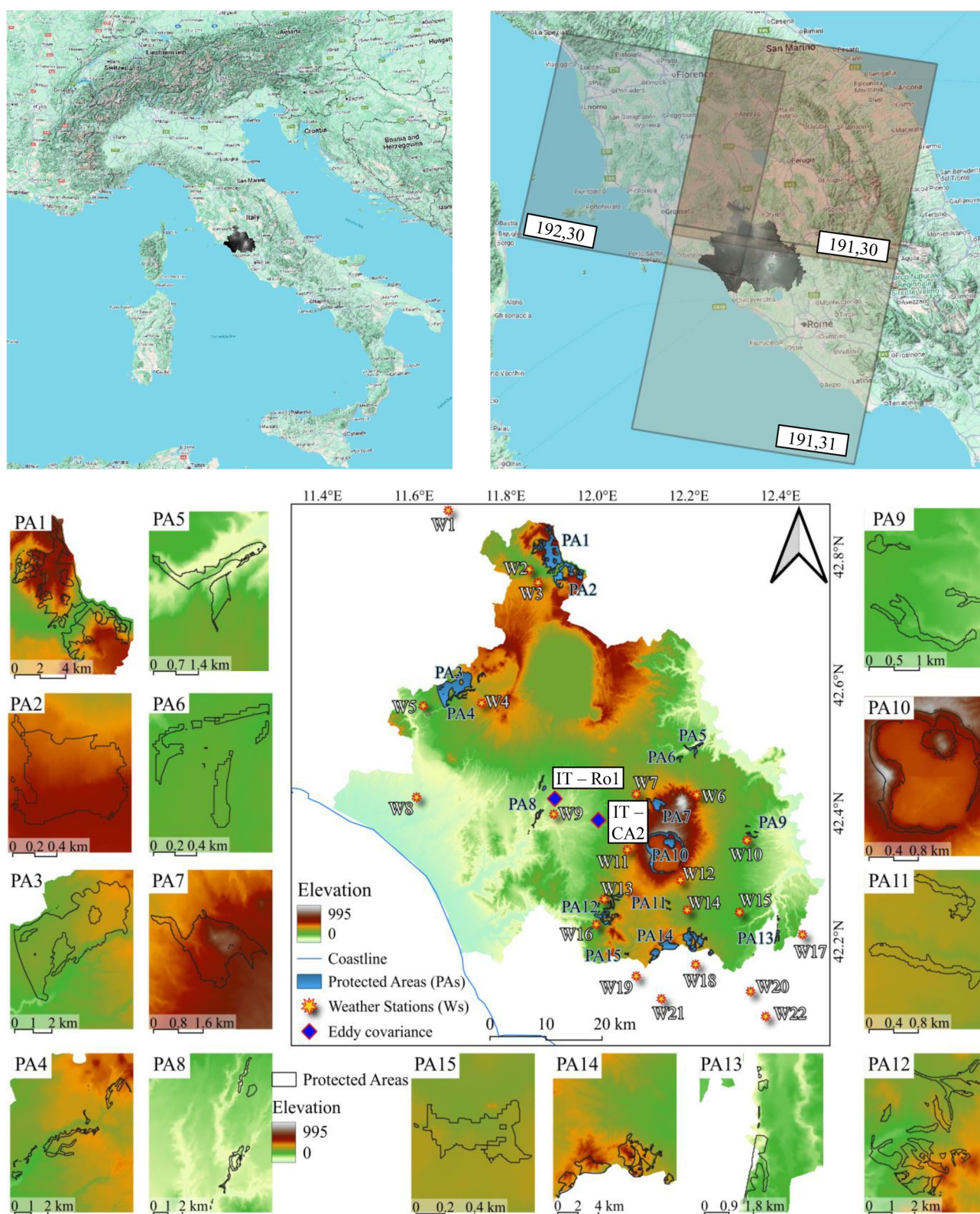


Figure 1. Top left, location of the Province of Viterbo in Italy. Top right, footprint of Landsat imagery adopted in this study. Bottom, protected areas overlaid onto the digital elevation model of the Province of Viterbo. Yellow stars indicate weather stations (Ws) and blue markers show the locations of the eddy covariance towers (IT-Ro1 and IT-CA2).

Table 1

Protected Areas' (PAs) Mean Elevation Above Mean Sea Level, Area, Horizontal Distance From the Coastline, and Depth to the Impermeable Layer (S: Shallow < 80 cm and D: Deep > 80 cm)

PA	Mean elevation (m)	Area (km ²)	Distance from coastline (km)	Depth to impermeable layer
PA1	487	21.30	57.18	9% S, 91% D
PA2	526	0.61	56.72	D
PA3	355	15.66	28.72	D
PA4	348	1.75	29.61	D
PA5	198	1.49	52.53	S
PA6	260	0.17	49.28	58% S, 42% D
PA7	654	3.30	42.13	D
PA8	138	1.48	24.03	D
PA9	197	0.61	49.95	D
PA10	739	11.32	38.70	D
PA11	366	0.41	31.20	D
PA12	334	4.82	24.74	D
PA13	179	0.89	40.97	D
PA14	438	12.33	27.24	D
PA15	352	0.14	20.32	D

package (Beguería & Vicente-Serrano, 2023). Drought status and severity classes are based on gridMET Data set categorization (Abatzoglou, 2013).

2.1.2. Soil Data and Vegetation

A 1 km × 1 km description of the PAs' soils is provided through the European Soil Data Center (ESDAC, 2024; Panagos et al., 2012, 2022). The depth to the impermeable layer is reported in Table 1, where shallow (S) and deep (D) indicate less and greater than 80 cm, respectively. While information on the texture of the subsoil is not available through ESDAC (2024), a characterization of the topsoil is reported in Table 2. Therein, a coarse texture

refers to a clay content >18% and sand content >65%; a medium texture refers either to a clay content comprised between 18% and 35% and a sand content ≥15% or to a clay content >18% and a sand content comprised between 15% and 65%; a medium fine texture indicates a clay content <35% and a sand content <15%. According to ESDAC (2024), soil types are differentiated based on the terminology of the F.A.O. legend for the Soil Map of the World at scale 1:5,000,000, further adapted to European landscapes.

According to European Environment Agency (2019a, 2019b, 2019c, 2019d), Regione Lazio-Direzione Ambiente, Cambiamenti Climatici, Transizione Energetica e Sostenibilità, Parchi (2023), most PAs are broad-leaved forests, with the exception of PA1, whose 88.83% is a broad-leaved forest and 11.17% is a mixed forest, and PA2, 98.45% broad-leaved and 1.55% mixed forests. The available water capacity of top and subsoils are reported in Table 3 as available through ESDAC (2024).

In Table D1, we provide an inventory of plant species observed in the PAs. Species such as *Quercus cerris* L., *Quercus ilex* L., *Fraxinus ornus* L., *Quercus pubescens* Willd., *Fagus* L., and *Acer monspessulanum* L. are among the most frequently observed. Additionally, species commonly cultivated in the surrounding areas such as hazelnut (*Corylus avellana* L.) are also observed in some of the PAs. This area is well-suited for hazelnut farming due to its Mediterranean climate, and hazelnut trees show good

Table 2

Protected Areas (PAs') Topsoil Texture

PA	Coarse	Medium	Medium fine
PA1	1%	4%	95%
PA2	–	–	100%
PA3	45%	55%	–
PA4	–	100%	–
PA5	–	–	100%
PA6	17%	–	83%
PA7	100%	–	–
PA8	17%	83%	–
PA9	100%	–	–
PA10	100%	–	–
PA11	100%	–	–
PA12	6%	82%	12%
PA13	0.43%	99.57%	–
PA14	100%	–	–
PA15	–	100%	–

Table 3
PAs' Topsoil and Subsoil Available Water Capacity According to (ESDAC, 2024)

PA	Very low	Low	Medium	High	Very high
PA1					
Topsoil	–	–	–	5%	95%
Subsoil	–	–	9%	5%	86%
PA2					
Topsoil	–	–	–	–	100%
Subsoil	–	–	–	–	100%
PA3					
Topsoil	–	–	42%	58%	–
Subsoil	–	–	42%	–	58%
PA4					
Topsoil	–	–	1%	99%	–
Subsoil	–	–	1%	–	99%
PA5					
Topsoil	–	–	–	–	100%
Subsoil	–	–	100%	–	–
PA6					
Topsoil	–	–	42%	–	58%
Subsoil	–	–	100%	–	–
PA7					
Topsoil	–	–	100%	–	–
Subsoil	–	–	100%	–	–
PA8					
Topsoil	–	–	13%	87%	–
Subsoil	–	–	13%	–	87%
PA9					
Topsoil	–	–	100%	–	–
Subsoil	–	–	100%	–	–
PA10					
Topsoil	–	–	97.1%	–	–
Subsoil	–	–	97.1%	2.9%	–
PA11					
Topsoil	–	–	100%	–	–
Subsoil	–	–	100%	–	–
PA12					
Topsoil	–	–	7.7%	84.03%	8.3%
Subsoil	–	–	7.7%	84.03%	8.3%
PA13					
Topsoil	–	–	0.43%	99.57%	–
Subsoil	–	–	0.43%	–	99.57%
PA14					
Topsoil	–	–	100%	–	–
Subsoil	–	–	100%	–	–

adaptation to the local environmental conditions, thriving in well-drained soils and benefiting from the seasonal precipitation patterns.

2.2. Latent Heat Flux and Water Use Efficiency Estimation

In this Section, we illustrate data sources and the methodology for estimating λET , GPP, and WUE. Additionally, we provide information on data and approaches used for validation.

2.2.1. Landsat Imagery

Landsat imagery of the studied PAs collected from 2000 to 2022 was used to model the latent heat flux. A total of 152 images of scene (191,031), where the first number indicates the path and the second the row, 115 images of scene (191,030), and 140 images of scene (192,030) were processed, see Figure 1. Occasionally, scenes (191,030) and (191,031) were captured on the same date and, thus, we only processed scene (191,031). Only two PAs (PA3 and PA4) were entirely contained in the three scenes. A total of seven PAs (PA1, PA2, PA5, PA6, PA7, PA8, and PA9) were captured in scenes (191,030) and (191,031). Additional six PAs (PA10, PA11, PA12, PA13, PA14, PA15) were visible only in scene (191,031). Processed images included acquisitions from Landsat 7 (2000–2012), and Landsat 8–9 (2013–2022). The maximum cloud cover was set to 10%. The implemented surface energy balance model relied on the use of six radiance bands at the spatial resolution of 30 m $\times$ 30 m, and of the surface temperature L2 product. Land surface temperature was originally developed at 100 m $\times$ 100 m resolution and then downsampled to 30 m $\times$ 30 m. From 2003 to 2012, the scan-line corrector of Landsat 7 failed and, therefore, relative outputs were not compensated for the forward movement of the satellite and images show a black striped pattern as result of the satellite zig-zag.

2.2.2. Surface Energy Balance

Instantaneous actual λET was estimated by applying the modified Priestley-Taylor model by Jiang and Islam (2001) as modified by Stisen et al. (2008). This “triangle” method is based on the relationship between remotely sensed surface temperature and a vegetation index, and it has been demonstrated to be adequate to estimate surface λET over extended and heterogeneous areas (de Tomás et al., 2014; Minacapilli et al., 2016; Tang et al., 2010; Tauro et al., 2022). According to this scheme, λET (Wm^{-2}), with λ being the latent heat of vapourization, can be found as

$$\lambda ET = \phi \left[(R_n - G) \frac{\Delta}{\Delta + \gamma} \right] \quad (1)$$

where ϕ represents the actual surface resistance to evapotranspiration, R_n (Wm^{-2}) is the surface net radiation, G (Wm^{-2}) is the soil heat flux, Δ ($kPaK^{-1}$) is the slope of the saturated vapor pressure versus air temperature, and γ ($kPaK^{-1}$) is the psychrometric constant. Herein, Δ is calculated as a function of air temperature, T_a (K), according to Allen et al. (1998) (Equation 13). The parameter γ is computed as a function of the atmospheric pressure (Equation 7 in Allen et al. (1998)), which in turn is dependent on the elevation of the experimental plot as inferred from the DEM.

R_n is computed by summing the incoming shortwave, R_{sw} , and longwave, R_{lw} , net radiations as $R_n = (1 - \alpha)R_{sw} + R_{lw}$, with α the shortwave albedo.

Table 3
Continued

PA	Very low	Low	Medium	High	Very high
PA15					
Topsoil	–	–	–	100%	–
Subsoil	–	–	–	100%	–

Note. Classes are defined as follows: very low ($\sim 0 \text{ mm m}^{-1}$), low ($< 100 \text{ mm m}^{-1}$), medium ($100\text{--}140 \text{ mm m}^{-1}$), high ($140\text{--}190 \text{ mm m}^{-1}$), very high ($> 190 \text{ mm m}^{-1}$).

According to Allen et al. (1998), $R_{sw} = \tau \frac{S_0}{d^2} \cos \theta$, with τ the atmospheric transmissivity, S_0 the solar constant ($1,367 \text{ W m}^{-2}$), θ (rad) the solar zenith angle, and d (AU) the Earth-Sun distance. The θ angle is calculated from geographical latitude, solar declination, solar hour angle, slope and azimuth data calculated at each pixel from the PA DEMs. We computed d from the day of year (Bastiaanssen et al., 1998; Sun et al., 2013), and the atmospheric transmissivity as $\tau = 0.75 + 2 \times 10^{-5} E$, with E (m) the elevation above mean sea level. The incoming longwave radiation was computed as $R_{lw} = \sigma(\epsilon_c \epsilon_a T_a^4 - \epsilon_c T^4)$, where σ is the Stefan-Boltzmann constant ($5.67 \times 10^{-8} \text{ W m}^{-2} \text{ K}^4$), ϵ_c is the surface emissivity (herein set to 0.98 based on data for tree vegetated areas, Qin et al., 2006), ϵ_a is the atmospheric

emissivity computed as in Bastiaanssen (1995), T (K) is land surface temperature (estimated from Landsat Collection 2 scaled surface temperature imagery), and T_a is measured at the closest meteorological station managed by Agenzia Regionale di Protezione Civile (ARPC)-Regione Lazio. Shortwave albedo (α) was computed from Landsat images based on Liang (2000) (Equation 11). Specifically, for Landsat 7 imagery, we computed $\alpha = ((0.356B1) + (0.130B3) + (0.373B4) + (0.085B5) + (0.072B7) - 0.018)/1.016$. For Landsat 8 and 9, we calculated $((0.356B2) + (0.130B4) + (0.373B5) + (0.085B6) + (0.072B7) - 0.018)/1.016$ (Traversa et al., 2021). Landsat Collection 2 surface reflectance data were scaled according to recommendations of the Landsat Mission manual (the scale factor of 0.0000275 and the additional offset of -0.2 were applied per pixel). G was derived from the G/R_n ratio as calculated following Bastiaanssen (2000): $G/R_n = T/\alpha(0.0038\alpha + 0.0074\alpha^2)(1 - 0.98\text{NDVI}^4)$, where T is the surface temperature ($^{\circ}\text{C}$), α is the surface albedo, and NDVI is the Normalized Difference Vegetation Index. G is calculated by multiplying the G/R_n ratio by the value of R_n computed as illustrated above. For imagery collected from 2000 to 2012, NDVI was obtained as $\text{NDVI} = (B4 - B3)/(B4 + B3)$; for imagery collected from 2013 to 2022, we computed $\text{NDVI} = (B5 - B4)/(B5 + B4)$.

The triangle method revolves around the observation that a triangular feature space can be established by analyzing the domain formed by plotting land surface temperatures against a vegetation index (Lambin & Ehrlich, 1996; Yang et al., 2008). In Minacapilli et al. (2016), a similar triangular domain was found for satellite data collected over a time period of 13 years and analyzed through the time domain triangular method (TDTM). In this paper, we applied the TDTM to imagery collected over 23 years. Analyzing such a long interval of time enabled a robust identification of the warm and cool edges of the δT – NDVI space for each PA. More specifically, for each pixel of every PA, we developed the δT – NDVI feature space by considering all δT and NDVI values attained at that pixel for all dates of Landsat imagery. According to Stisen et al. (2008), Minacapilli et al. (2016), ϕ was calculated as

$$\phi_{ij} = \frac{\delta T_{ij,\max} - \delta T_{ij}}{\delta T_{ij,\max} - \delta T_{ij,\min}}(\phi_{\max} - \phi_{ij,\min}) + \phi_{ij,\min} \quad (2)$$

$$\phi_{ij,\min} = \phi_{\max} F_{c,ij} \quad (3)$$

$$F_{c,ij} = \left[\frac{\text{NDVI}_{ij} - \text{NDVI}_{ij,\min}}{\text{NDVI}_{ij,\max} - \text{NDVI}_{ij,\min}} \right]^2 \quad (4)$$

whereby the subscripts i, j denote a generic pixel, $F_{c,ij}$ indicates the fractional cover at the generic pixel, and the differences (δ) among minimum (min) and maximum (max) variables were obtained by analyzing the temporal variability of each pixel during the entire studied time period (2000–2022). $\delta T_{ij,\max}$ indicates the difference between the maximum temperature at the pixel and T_a ; δT_{ij} was computed by subtracting T_a from the temperature of the generic pixel; and $\delta T_{ij,\min}$ is the difference between the minimum temperature at the pixel and T_a . The parameter $\phi_{\max}$ was assigned a constant value of 1.35 (Pereira, 2004). The fractional vegetation cover $F_{c,ij}$ was estimated as a function of NDVI, which is used to quantify vegetation greenness and density. $\text{NDVI}_{ij,\max}$ and $\text{NDVI}_{ij,\min}$ refer to maximum and minimum values determined over the entire time period at the generic pixels. The exponent of $F_{c,ij}$ was set to 2 according to T. N. Carlson and Ripley (1997), T. Carlson (2007). Therefore,

thermal and NDVI boundaries were determined per each pixel considering its minimum and maximum δT and NDVI values attained across all the analyzed dates.

Although the analyzed imagery had a maximum cloud cover of 10%, PAs exhibited clouds on several dates. To exclude images taken on cloudy days, we further computed the true-color images for all PAs by stacking radiance bands B2, B3, and B4, and visually inspected the pictures for all dates. We also excluded from further processing dates on which the δT – NDVI space clearly indicated the presence of clouds (Jiang & Islam, 2001). The effects of cross-sensor differences in spectral response, radiometric calibration, and atmospheric correction between Landsat 7 and 8–9 are investigated in Appendix A.

2.2.3. Water Use Efficiency

Instantaneous WUE was computed for each PA from 2000 to 2022 to evaluate the capacity of the forests to balance carbon sequestration and water consumption. First, GPP was modeled using the VPM parameterized by setting the minimum, maximum, and optimal temperature for photosynthetic activities to -1°C , 40°C , and 20°C , respectively, which are recommended values for temperate Mediterranean deciduous broadleaf forests (DBF) as those found in the studied PAs (Frouin & Pinker, 1995; Xiao et al., 2004). We then computed WUE as $\text{WUE} = \text{GPP}/\text{ET}$, with GPP evaluated in $\text{gm}^{-2} \text{s}^{-1}$ and evapotranspiration, ET, in mm (Z. Zhang et al., 2023). The sensitivity of GPP to VPM parameters as well as their influence on drought response are investigated in Appendix A.

2.2.4. Eddy Covariance Validation Data

Latent heat flux values estimated with the TDTM were validated against EC data obtained from two stations managed by the Fluxnet global network. To this end, the surface energy balance was computed for two additional small scale watersheds comprising the EC stations. The EC IT-Ro1 was located at (42.4081, 11.9300) latitude and longitude, within few kilometers from Rocca Respampani. Nearby vegetation included a turkey oak (*Quercus Cerris* L.) coppice forest. Vegetation was classified as DBF, that is, lands dominated by woody vegetation with a percent cover greater than 60% and height exceeding 2 m. It consisted of broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods (Rey et al., 2002; Tedeschi et al., 2006). Data are available at half hour temporal resolution, from 2000 to 2008 and, therefore, validation of simulated energy fluxes in this watershed was limited to such time interval.

To provide further validation, an additional neighbor EC tower (IT-CA2) was also identified. The IT-CA2 tower was at (42.3772, 12.0260) latitude and longitude, and featured rotation crop grassland/winter wheat. The site was classified as cropland (CRO), that is, lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems). Data are available from 2011 to 2014 at a temporal resolution consistent with IT-Ro1. Obviously, and similar to IT-Ro1, validation to simulated energy fluxes is conducted only from 2011 to 2014.

EC data comprise T_a , which was used to fill in the gaps within the reconstructed T time series of nearby PAs (see Section 2.1.1), and R_n , λET , sensible heat flux, H (Wm^{-2}), and GPP, which were used for validating modeled data. To this end, wind speed, wind direction, friction velocity, and canopy height from EC towers were also used. Canopy height was typically available at yearly resolution.

The one-dimensional Schuepp footprint model (Schuepp et al., 1990) was applied by setting the maximum distance at which the flux footprint was relevant to the distance at which 80% of the integration flux is achieved. Alternative two-dimensional footprint models could not be implemented due to the unavailability of cross-wind parameters for both EC stations. To allow comparison of the modeled to measured latent heat flux values, only pixels aligning along the computed footprint were retained in satellite-based λET maps. Each pixel value was weighed according to the normalized footprint model. The sum of such weighed values was then compared to EC measurements recorded at times consistent (within half an hour) with satellite imagery acquisition.

2.3. Data Analysis

Forest signature was reconstructed by calculating the spatial average of λET across each PA. To provide an idea of the heterogeneity of the λET response within a selected PA, we computed statistics (mean and standard deviation)

for each analyzed satellite image, see Appendix B. In Section 3, we report minimum, maximum, and average values for the time series of the coefficient of variations computed for each PA.

To adequately dissect forests' response in the studied time period, we aggregated data at several levels. First, the ensemble behavior of all the forests was estimated by computing the standardized regional anomaly of λET ($\overline{\Delta\lambda\text{ET}}^R$) as follows. For each PA, we computed monthly λET for each year from 2000 to 2022 by averaging values computed from satellite images taken in a given month and year. Then, we calculated regional monthly λET values by averaging across all PAs. For each month, we estimated the historical mean over the entire study period (from 2000 to 2022). Finally, monthly $\overline{\Delta\lambda\text{ET}}^R$ data were obtained by subtracting the historical monthly means from the regional monthly means, and then computing the ratio of such difference to the absolute value of the historical monthly means. A similar procedure was applied to T data to obtain standardized regional anomalies ($\overline{\Delta T}^R$).

The seasonal behavior at each PA was studied by computing λET anomaly ($\Delta\lambda\text{ET}$) as follows: (a) monthly values were aggregated according to the hydrological seasons introduced in Section 2.1.1, (b) seasonal averages were computed on a yearly basis, (c) long-term (i.e., from 2000 to 2022) averages for each season were calculated by averaging long-term monthly means, and (d) long-term averages were subtracted from yearly seasonal averages.

To further identify year-by-year trends of λET standardized anomalies ($\overline{\Delta\lambda\text{ET}}$) were also computed for each PA at the 3-month, and 12-month scales by calculating historical means over 3 and 12 months and then subtracting them from 3- and 12-month time series of λET , respectively. These were then divided by the absolute value of historical means. Similarly, the procedure was applied to T and P data toward standardized anomalies for each PA ($\overline{\Delta T}$ and $\overline{\Delta P}$). The dependence of each forest's response on climate was studied through Granger causality test (Granger, 1969). Namely, for each PA, we tested if time series of 3- and 12-month SPEI Granger-caused $\overline{\Delta\lambda\text{ET}}$ at 3- and 12-month scales, respectively. To this end, we detrended data time series using the singular spectrum analysis, assuming unknown periods and lags. Significance and strong significance for the Granger test were defined for $p < 0.05$ and $p < 0.01$, respectively.

Trend analyses over time were performed by computing λET , GPP, and WUE at the monthly level as detailed above. Such monthly data were fitted with a linear regression model. The significance of the model was evaluated by computing the coefficient of determination R^2 and the p -value for the F -test, with significance achieved for $p < 0.05$.

3. Results

In this Section, we present results for climate data, report validation for the λET estimation methodology, and then illustrate forest response at the regional and PA level.

3.1. Climate in the PAs

Since 1927, yearly average temperature in Viterbo has exhibited a strongly statistically significant increase ($R^2 = 0.14$, $p \ll 0.01$). However, yearly average temperature has not been significantly increasing in the time window 2000–2022. Yearly temperature anomalies have generally been positive since 1988, with the exception of years 2005, 2008, and 2010. Within the studied time window (2000–2022), years 2000–2003 and 2022 were particularly warm ($\Delta T \in [1.35, 1.85]$), Figure 2. Conversely, precipitation anomaly did not exhibit any clear trend from 2000 to 2022, with a total of 13 years with negative versus 10 years with positive values.

Analysis of the SPI and SPEI indicated that both indices were in phase and generally lagged of 1 year with respect to ΔP . Overall, the indices showed an alternating pattern of moderate-to-severe dry years with a return period of approximately 4 years and moderately to very wet years with a return period of about 6 years from 2000 to 2022. In the entire studied time window, 11 moderate-to-extremely dry seasons alternated with about eight very-to-extremely wet seasons.

At the seasonal scale, statistically significant ($p < 0.05$) temperature increases have been observed from 2000 to 2022 during the Summer at five (W1, W9, W13, W20, W21) out of eight weather stations. At the monthly scale, five weather stations recorded significant ($p < 0.05$) temperature increases in July and September (W1, W9, W13, W20, W21). Two showed increases in August (W9, W20) and November (W1, W20). Single stations

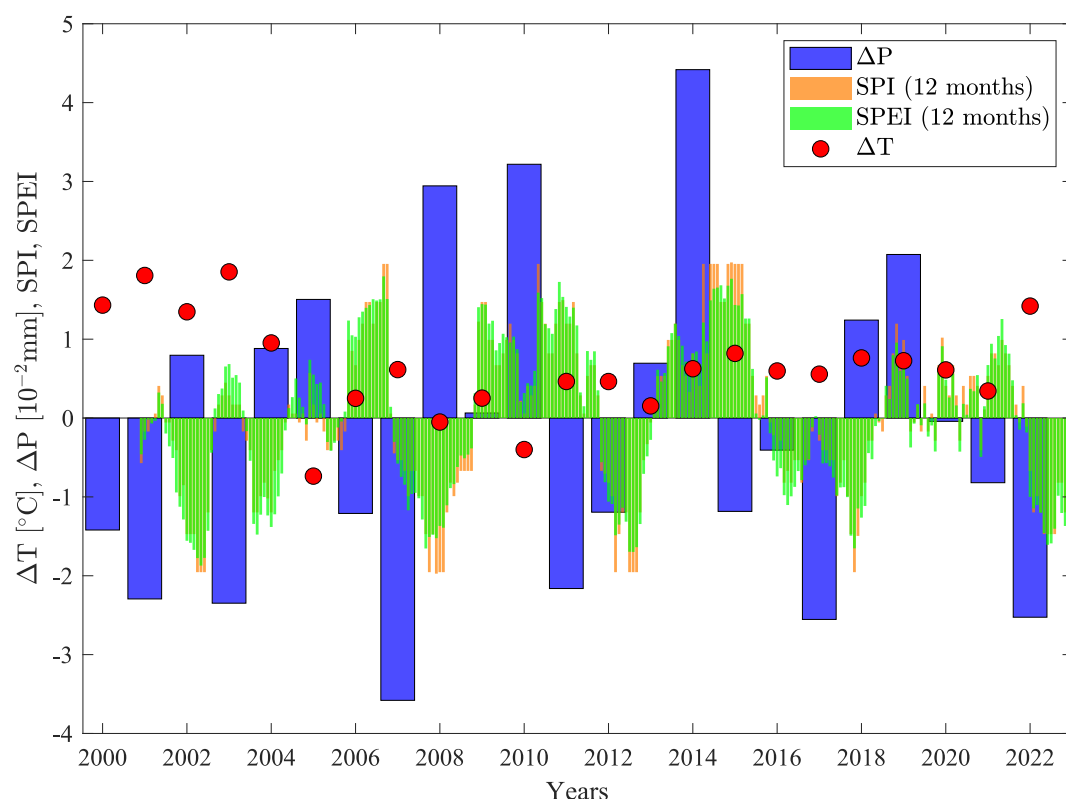


Figure 2. ΔT , ΔP , standardized precipitation index, and standardized precipitation evapotranspiration index from 2000 to 2022 at the weather station of Viterbo (W7).

presented increases in February (W20), June (W20), October (W1), and December (W20). The weather station of Viterbo (W7) exhibited strong statistically significant temperature increases in the months of April and June in the 2000–2022 window.

3.2. Validation of the TDTM

To ascertain the validity of the TDTM, the standard determination of the triangular feature space was executed for each date and PA. In Figure 3a, we display the standard triangular domain for an arbitrarily selected PA (PA3) as obtained on a randomly selected date. Further, we also report the TDTM scatterplot for a single pixel within PA3, where the dependency on the doy is detailed through the colormap. In Figure 3b, the identified edges are coherent with the forest seasonal dynamics: data points collected during days 150–250 (June to early September) are closer to the warm edge, while data observed in days 1–150 (January to late May) and 250–365 (September to December) tend to cluster around the wet edge. The high density of data points in Figure 3b toward high NDVI values highlights the presence of dense canopies in the area.

Comparisons of modeled against EC-measured R_n , λET , H , and GPP values are displayed in Figure 4 for both EC sites. Satellite-based H data were computed as residuals of the surface energy balance.

Markers in Figure 4 refer to EC towers located both in the forest (IT-Ro1, circles) and the crop sites (IT-CA2, squares), whereby orange and cyan denote data collected in dry and normal/wet years, respectively. Dry/normal/wet years are defined based on the SPEI values reported in Figure 2. Even if data points relative to the crop area were exiguous, land cover type did not result in significant differences in the validation. With regards to R_n and H data, satellite and EC values observed in the forest site (IT-Ro1) in normal/wet years were slightly more in agreement than in dry years. Overall, the agreement between Fluxnet-derived and satellite-based data was good, and in line with similar studies (Elfarkh et al., 2023; Guzinski et al., 2014).

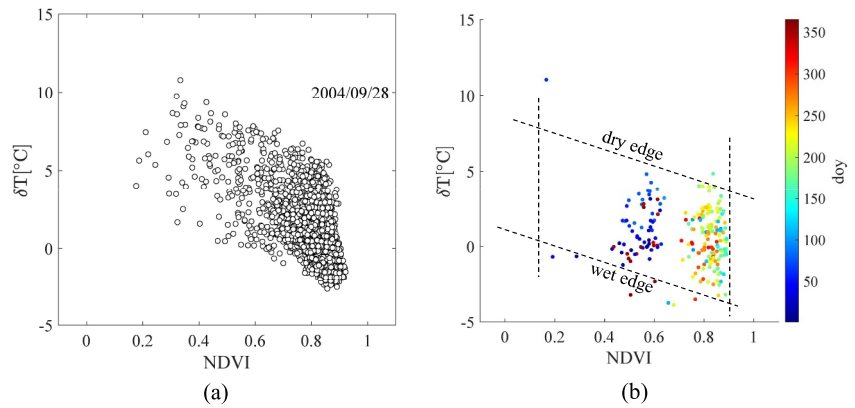


Figure 3. Triangular feature spaces: (a) standard triangular domain for PA3 based on data collected on 28 September 2004 and (b) time domain triangular method scatterplot for a representative pixel in PA3 as a function of day of year (doy).

3.3. Forest Response

Forest response within a given PA was generally consistent and homogeneous, as reported in Table 4. Average CVs ($\overline{CV}$) ranged from 13.58% up to 46.39%. The higher spatial variability exhibited by PA10 is attributed to the specific morphology of this area, which encloses the mountain ridge surrounding the volcanic Vico Lake. Since both sides of the mountain lay in PA10, solar radiation conditions and shadow effects lead to more nuanced λET data.

Forests' response was highly connected to climate. In fact, the connection between SPI, SPEI, and $\overline{\Delta \lambda ET}$ was quite strong, as ascertained through Granger causality. Overall, a successful Granger test at the 12-month level

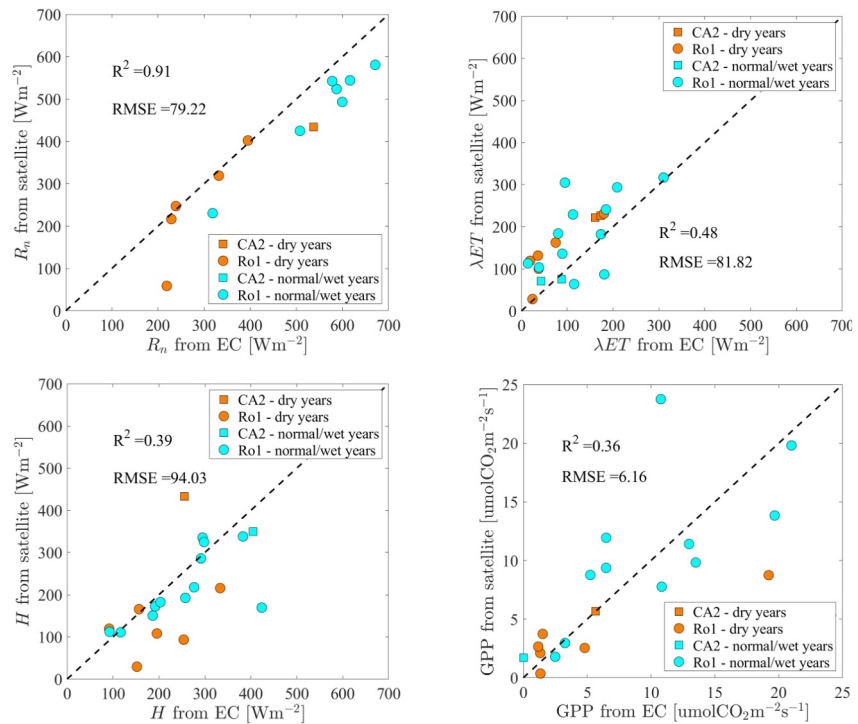


Figure 4. Comparison of time domain triangular method-modeled R_n , λET , H , and gross primary production against eddy covariance measurements.

Table 4
Average Coefficient of Variation $\overline{CV}$ As Well As Minimum and Maximum CV Values for the Time Series of Monthly λET Data

PA	$\overline{CV}$ (%)	min CV (%)	max CV (%)
PA1	29.29	12.45	75.35
PA2	13.58	5.24	35.00
PA3	14.58	5.60	29.92
PA4	27.81	10.64	45.70
PA5	19.81	7.68	41.06
PA6	17.39	5.55	44.88
PA7	34.45	14.63	73.15
PA8	29.86	10.03	59.99
PA9	19.24	6.51	40.95
PA10	46.39	14.46	121.16
PA11	15.23	7.14	31.27
PA12	28.91	10.68	50.55
PA13	29.84	17.24	54.29
PA14	28.46	11.58	61.91
PA15	26.14	13.38	61.83

Table 5
Results of the Granger Causality Test (G-Test) for Each Protected Area (PA)

PA	G-test at 3-month	G-test at 12-month
PA1	1**	1**
PA2	0	1**
PA3	1**	0
PA4	1**	1**
PA5	1*	1*
PA6	1**	1**
PA7	1**	0
PA8	1**	0
PA9	0	1*
PA10	1**	0
PA11	1**	0
PA12	0	1**
PA13	0	1**
PA14	0	0
PA15	1**	1**

Note. A value equal to 1 indicates rejection of the null hypothesis and, therefore, SPEI caused $\Delta \lambda ET$. The symbols * and ** stand for statistical significance and strong statistical significance, respectively.

indicates that the forest λET annual response can be predicted by SPEI. Rejection of the null hypothesis at the 3-month level suggests intra-annual causality of the SPEI signal at the seasonal scale. In Table 5, we report results of the Granger test (G-test) if SPEI caused $\Delta \lambda ET$. Given the consistency of SPI and SPEI results, we only illustrate data for SPEI. A total of 14 out of 15 PAs showed a close dependence of their λET response on climate: 10 forests exhibited a close causal relation between 3-month level SPEI and $\overline{\Delta \lambda ET}$, and nine PAs between 12-month level data. In case of five forests (PA1, PA4–6, and PA15), such causality was statistically significant at both 3- and 12- month scales. Only PA14 exhibited no clear causal relation to SPEI.

The ensemble response of the forests is depicted in Figure 5, where $\overline{\Delta T}^R$ (left) and $\overline{\Delta \lambda ET}^R$ (right) are illustrated per each month of the year and the entire studied period. In the graphs, markers refer to monthly temperature and λET anomaly data, where warm to cold colors indicate years from 2000 to 2022. The vertical black errorbars show standard deviation. With regards to temperature, Winter months displayed the highest variability, while no clear trend could be observed within any month over the studied time period. λET data had consistent variability throughout the year (with the exception of the month of November). In the months of July, October, and December, $\overline{\Delta \lambda ET}^R$ tended to increase from 2000 to 2022 (bluish markers are stacked above reddish markers). This behavior was also appreciable at the local scale of PA4–6, PA8, PA10, PA13, and PA15 for at least one of the above months, see Appendix C. At the scale of the individual PAs, average $\overline{\Delta \lambda ET}$ was consistently close to zero, and 62% of standard deviations ranged between [0.05,0.15].

The time series analysis of the forests' response is illustrated in Figure 6, where $\overline{\Delta \lambda ET}$ (green line) is displayed together with $\overline{\Delta T}$ (red line), $\overline{\Delta P}$ (blue line), and SPEI (black line). All parameters were computed at the 12- month scale, and time series are plotted against a patterned background that highlights seasons with different colors (cyan for Winter, green for Spring, yellow for Summer, and red for Fall). Yellow star markers depict months when positive $\overline{\Delta \lambda ET}$ was simultaneous with positive $\overline{\Delta T}$ and negative $\overline{\Delta P}$. These data imply that the increase in $\overline{\Delta \lambda ET}$ was probably driven by the increase in T and occurred despite the shortage of water recharge from precipitation during that month. We refer to such occurrences as “drought paradox” (DP) events.

A majority of the PAs displayed alternating SPEI, which was mostly in phase with $\overline{\Delta P}$ data. PA5–7 showed similarly negative (indicating dryness) SPEI values since 2012: this similarity is due to the proximity of such forests to two weather stations (W6 and W7) that were jointly used to reconstruct the T and P time series. All forests have experienced months at mild (SPEI less than -1.29) to extreme drought (SPEI less than -2.00) from 2000 to 2022. In some cases, dryness had prolonged to several years (PA5–7). The occurrence of DP events was quite diversified across the PAs, with a minimum of one in PA3 up to 57 in PA13. As expected, their instance was frequent toward the end of periods at negative SPEI.

To further explore λET response within PAs, Figure 7 illustrates the significance level of linear models fitted on monthly λET data, GPP, and WUE data (from left to right). Light green and brown cells indicate decrease and increase, respectively, while dark green and brown cells refer to statistically

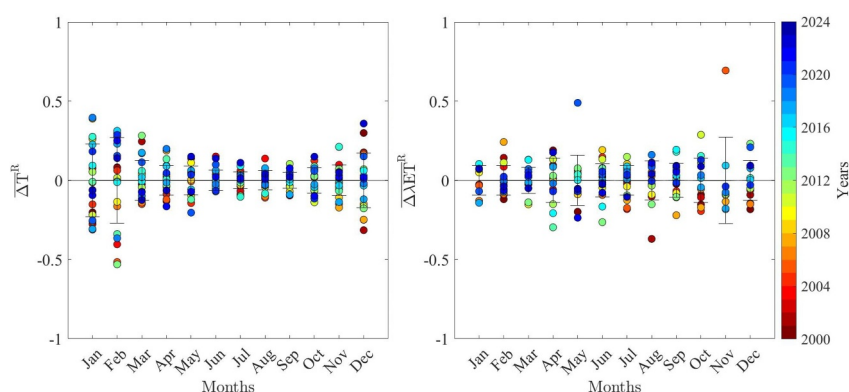


Figure 5. Left, $\overline{\Delta T^R}$ and right, $\overline{\Delta \lambda ET^R}$ per month of the year. The colorbar indicates years from 2000 to 2022.

significant decrease and increase, respectively. A total of 12 out of 15 PAs exhibited statistically significant increases in λET along the year, while only five PAs exhibited decreases. Within PAs exhibiting increases, seven PAs had increasing λET fluxes in the months of September and December, four had an increase in August, and three in October. PA15 recorded exclusively increasing λET for eight months; four PAs (PA1, PA8, PA12, and PA13) exhibited both statistically significant increases and decreases, while PA14 showed only a statistically significant decrease in December. Four PAs (PA4, PA8, PA10, and PA15) showed significant increases both in Fall and Winter months.

With regards to GPP and WUE, statistically significant responses were less than those for λET . A total of 11 and 12 PAs exhibited at least one month with a statistically significant (either positive or negative) response both for GPP and WUE, respectively. Four PAs (PA2, PA5, PA7, and PA11) displayed significant GPP increases during the growing season (March to May), while six PAs (PA2, PA5, PA7, PA8, PA11, and PA14) had significantly positive increases in WUE in the same season. In the month of December, GPP increased significantly for five PAs (PA5, PA8, PA9, PA10, and PA15). This phenomenon is in agreement with λET values observed in the same month. Probably due to the generally positive λET tendency of Summer months, all PAs exhibited at least one month at negative WUE from August to November; in five PAs (PA4, PA5, PA8, PA10, and PA15), such decreases were statistically significant.

The seasonal response of each PA is illustrated in Figure 8. Above seasons exhibiting significant λET trends, colored boxes indicate either an increase (light brown and upward arrow) or a decrease (light green and downward arrow). A majority of PAs (13 out of 15) showed a clear pattern whereby Summer fluxes were on average higher than in the Fall and Spring. However, PA2 and PA8 displayed different behaviors: fluxes were in line during all seasons, Fall and Spring λET were higher in PA8 and PA2, respectively. In PA8, such observations were related to the fact that λET had been significantly increasing from 2000 in all seasons but Spring, when a statistically significant decrease was found. The decrease in λET in Spring also resulted in a statistically significant decrease in GPP in the month of April, while increasing λET fluxes in late Summer and early Fall caused a significant decrease in WUE in the month of October.

4. Discussion

4.1. Forest Response to Climate

Our findings show that, in the studied period, yearly temperature in Viterbo had been almost constantly warmer than the historical average. However, yearly T did not exhibit a significantly increasing trend neither in Viterbo nor at the additional weather stations present in the studied PAs. T significantly increased over the Summers at most of the considered weather stations. Nonetheless, such a temperature increase was not mirrored by changes in precipitation, which was mostly constant since 1916 in the entire region (Vicente-Serrano et al., 2025).

The increments in λET fluxes during the Summer were consistent with the finding of significant T increases in the months of July and September at most weather stations in the region. Summer T and λET did not significantly

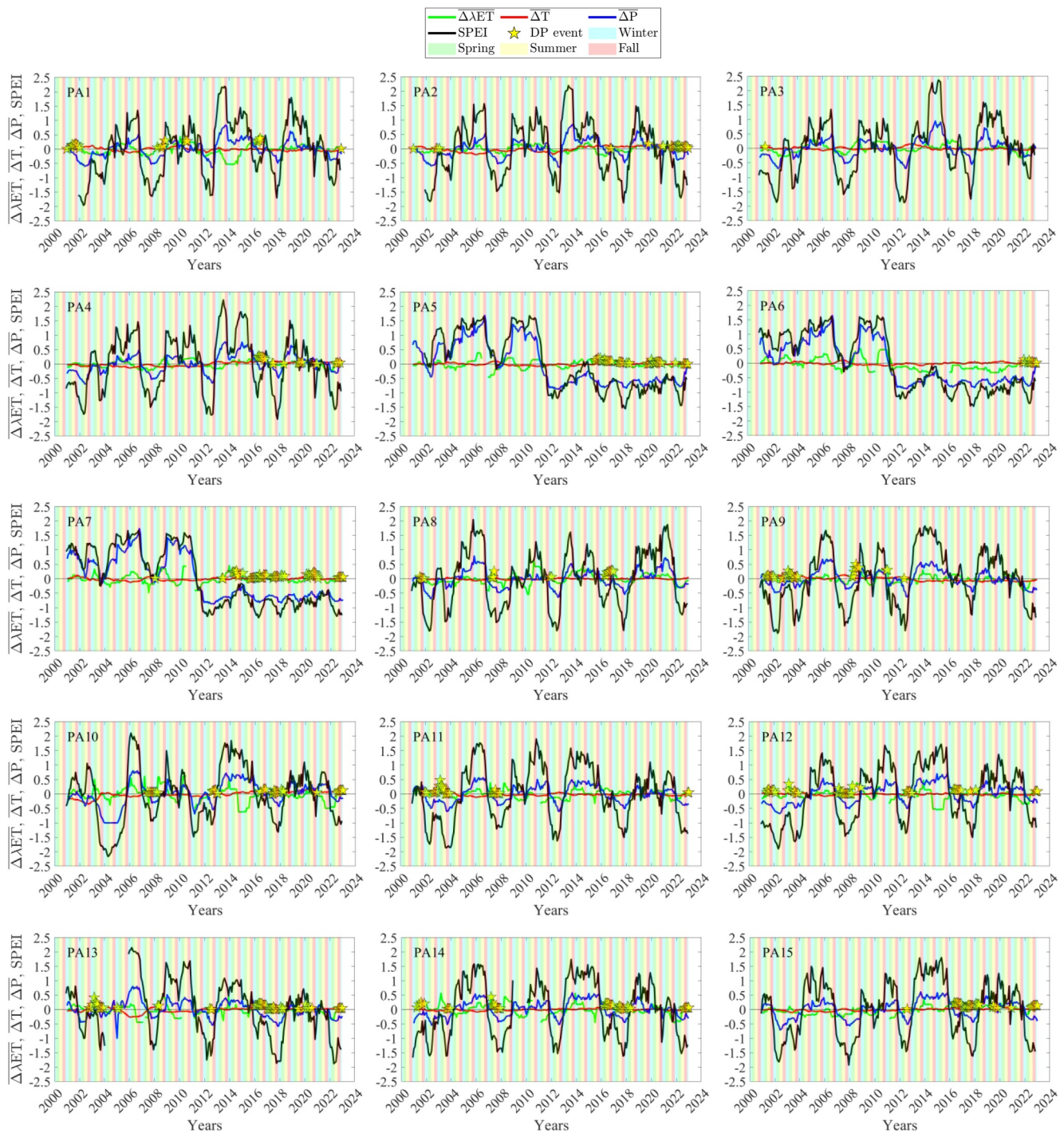


Figure 6. Timeseries of $\overline{\Delta\lambda ET}$ (green line), $\overline{\Delta T}$ (red line), $\overline{\Delta P}$ (blue line), and standardized precipitation evapotranspiration index (black line) for all protected areas and the entire study period. The background highlights seasons with different colors: cyan for Winter, green for Spring, yellow for Summer, and red for Fall.

affect C assimilation by plants, as demonstrated by the rare presence of both significantly negative and positive GPP trends. Therefore, most forests efficiently survived moderate drought during warm Summers. However, since the dry season extended through the early months of the Fall, plants most likely put in place drought tolerant mechanisms and, thus, maintained cooling (persisting enhanced λET) while productivity was unchanged. The fact

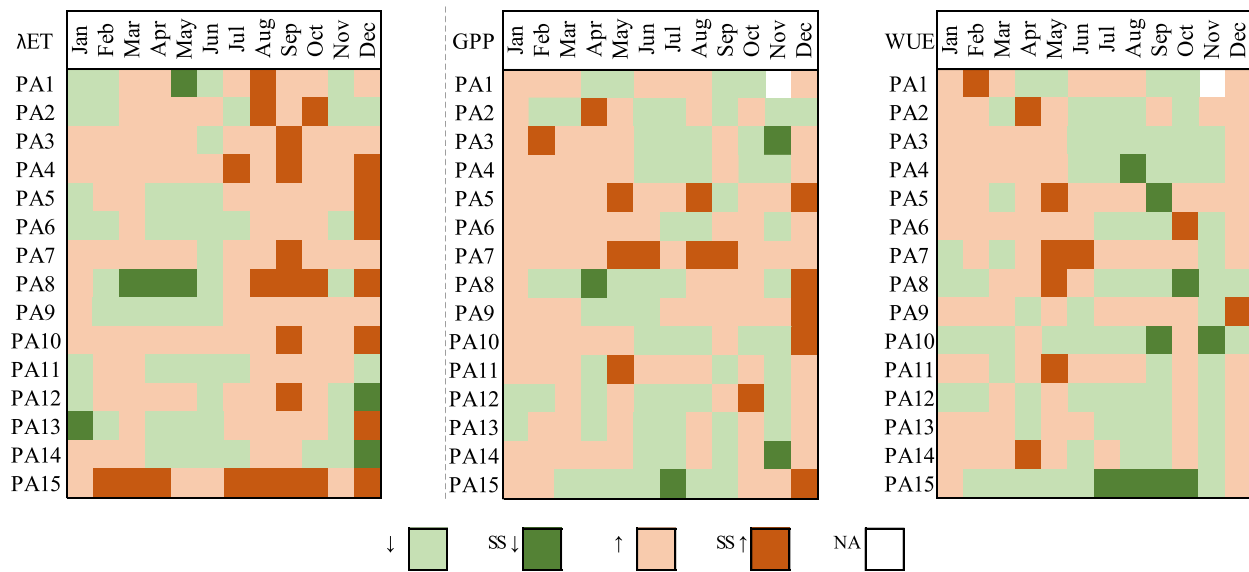


Figure 7. From left to right, significance level of linear models fitted on: monthly λ ET data, gross primary production, and water use efficiency data. Light green and brown cells indicate decrease and increase, respectively, while dark green and brown cells refer to statistically significant decrease and increase, respectively. Empty white cells refer to models fitted on less than three observations.

that GPP did not exhibit significant decreases may support the hypothesis that soil water has not been a limiting factor so far to plant growth and transpiration in the majority of PAs.

$\Delta\lambda$ ET was rarely related to increasing T (two significant increases in Winter for PA15 and Fall for PA6) and ΔP (three significant increases in the Summer for PA4, PA13, and PA14). In several seasons, $\Delta\lambda$ ET tended to be above average despite the negative ΔP (see Figure 6). These findings suggest that forests in the region were experiencing seasonal “drought paradox”, whereby above-average temperatures and constant or decreasing precipitation are paralleled by increased λ ET. Even if detailed soil water data were not available in the area, simple consideration of the water balance ($P = ET + Q + \Delta S$) indicates that such increase in ET fluxes was occurring at the expense of surface waters (Q , i.e., rivers, lakes, and reservoirs), as well as groundwater (ΔS). The fact that positive $\Delta\lambda$ ET persisted despite negative ΔP suggests that plants’ drought tolerant strategies entailed accessing deeper groundwaters, which tended to be less impacted by seasonality effects. This finding along with the independence of $\Delta\lambda$ ET on ΔT both support the hypothesis that the forests’ λ ET response is controlled by complex dynamics, which may take place at longer temporal scales than just on a seasonal or yearly basis (Massari et al., 2022).

While vegetation in different PAs shares similarities, the general composition of the studied forests is highly heterogeneous, spanning from tall trees to herbaceous species (see Table D1). We neglected the dependence of the λ ET response on tree age since the PAs are well established old forests, where no management was carried out in the last decades. Elevation conditions and distance to coastline are quite diversified among PAs. Soil textures also show variability, while both the topsoil and subsoil available water capacity ranged from medium to very high. These soil conditions have favored the growth of a richness of plants, which encompass both typically anisohydric (see, for instance, *Quercus cerris* L., Wolkerstorfer et al., 2011) and more isohydric (such as, for instance, *Fagus sylvatica* L., Nguyen et al., 2017) species. In spite of such variety, the λ ET signature observed at all PAs supports that, across all sites, vegetation was triggering water management strategies to tolerate the alternating pattern of rather long moderate-to-severe dry Summers and moderate-to-very wet conditions.

Similar increases in λ ET as a response to drought have been reported both at a global level (M. Zhao et al., 2022) as well as in Mediterranean climates (Jaafar & Sujud, 2024). For instance, during the prolonged drought of 2004, λ ET reached twice the amount of precipitation in a eucalyptus plantation (Rodrigues et al., 2011). Studies also revealed that during droughts in a Mediterranean climate, the normal range of λ ET is maintained by depleting subsurface soil water storage and groundwater by extensive root systems (Giardina et al., 2023; Rungee

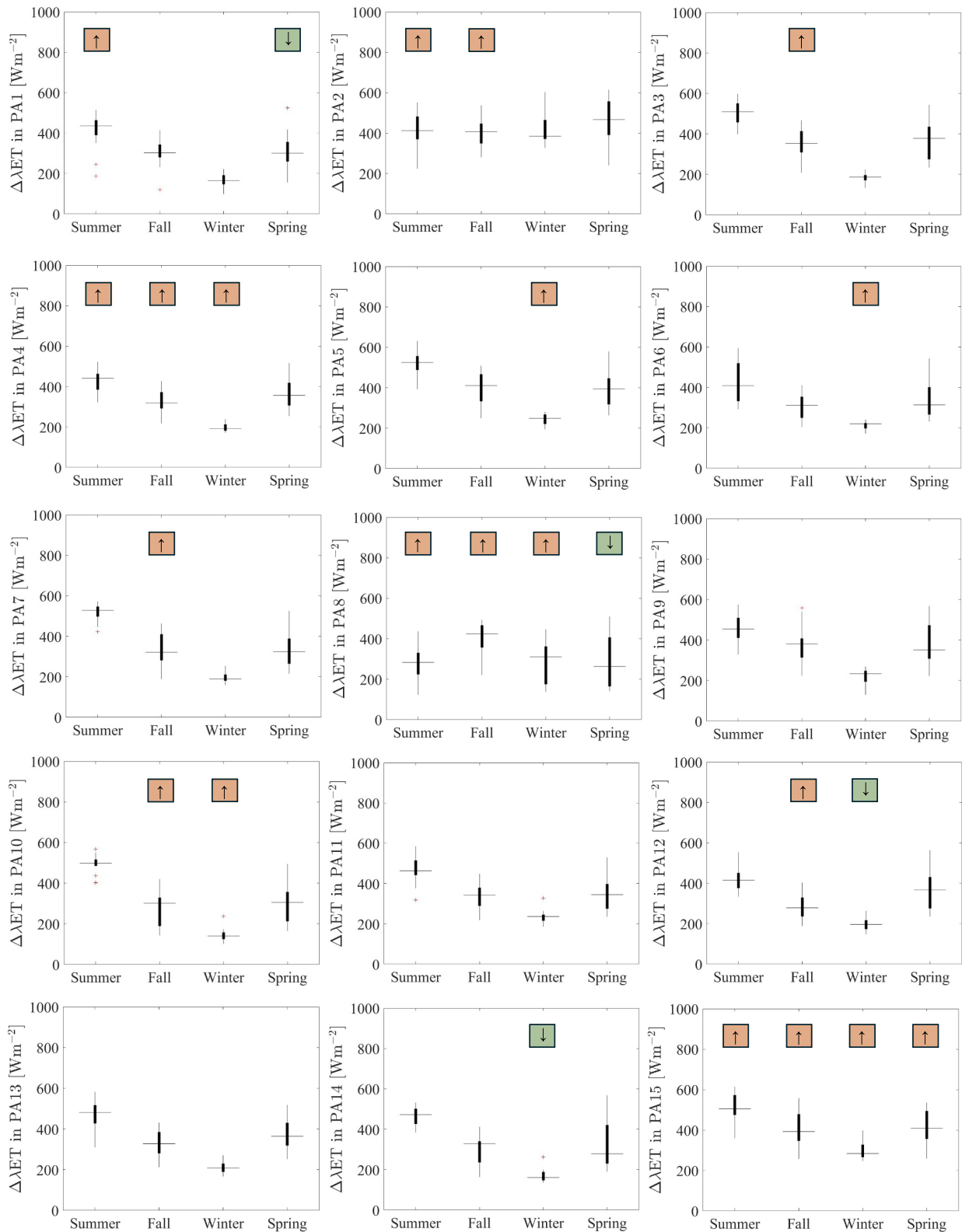


Figure 8. Boxplot of λET seasonal response per protected area. On each box, the central mark indicates the median, and the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively. The whiskers extend to the most extreme data points not considered outliers, and the outliers are plotted individually using the “+” marker symbol. Colored boxes indicate either an increase (light brown and upward arrow) or a decrease (light green and downward arrow) in λET .

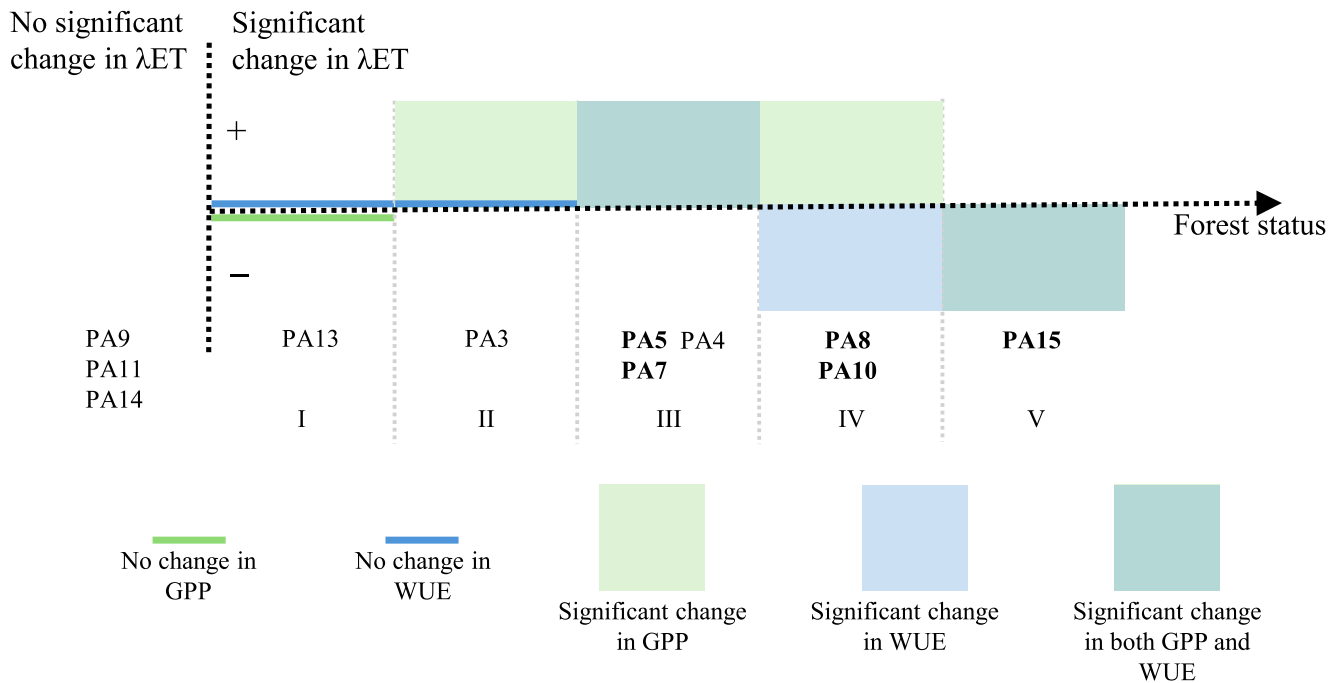


Figure 9. Classification of forest water-availability and biomass status under increasing λET conditions. From left to right, protected areas are arranged according to the sign of the correlation between λET , gross primary production and water use efficiency along a growing degree of severity in water-availability and biomass productivity.

et al., 2019). Similarly, antecedent rainfall from non-drought years and prior canopy expansion led to higher λET rates, which contributed to forest die-off during the 2012–2015 drought in California forests (Goulden & Bales, 2019). Vargas et al. (2013) also support such trend, where the mean daily λET in drought was similar to no drought conditions, which further impacts the water-availability in Mediterranean oak woodlands.

4.2. A Classification of Forest Water-Availability and Biomass Status

The observed results suggest that the warm season, which is characterized by increased λET fluxes, was gradually shifting to late Summer and early Fall months, and even Winter months (especially December) resulted in significantly increased fluxes. Generally positively (even if not all statistically significant) increasing λET fluxes in late Summer up to Fall months were mirrored by negative WUE trends in the same period. Conversely, no clear pattern could be observed for GPP in the same months. For a majority of the forests, WUE tended to increase (statistically significantly in some months) in Spring (dark brown cells in March to June in Figure 7), thus suggesting that plants were establishing water savings that most likely helped forests in maintaining high λET rates in Summer and Fall months (see the significant increases in λET and non-significant GPP values in Summer).

In areas experiencing enhanced λET rates during late Summer or early Fall months, the mechanisms of water savings in Winter may have become insufficient for guaranteeing constant WUE values. This is the case of PA8 and PA15, where prolonged λET increases throughout the year have been depleting water-availability and affected the forest biomass (decreasing GPP in Spring). A similar pattern also occurred in PA4 and PA12, where enhanced λET affected water-availability in Summer, though the forest biomass has not been severely impacted yet.

Experimental findings can be summarized in the scheme illustrated in Figure 9 that classifies the range of forest water-availability and biomass statuses observed across all PAs. The scheme is obtained by studying the sign of the correlation between λET , GPP, and WUE signals for all PAs. Out of the entire set of forests, we report in bold in Figure 9 those that exhibited a minimum number of 5 months with statistically significant trends (either positive or negative) jointly in their λET , GPP, and WUE responses (i.e. at least five dark brown

or green cells in Figure 7). Remaining forests (unbolded) either showed a meager number of significant trends or displayed an insufficient number of significant λ ET trends to make adequate classifications (not reported in Figure 9). Forest statuses are arranged along a sequential pattern that indicates, from left to right, more severe water-availability and biomass conditions. The scheme includes a field whereby λ ET fluxes are unchanged (no significant change in λ ET on the left of the scheme) and the forest exhibits no significant correlation between λ ET nor WUE and GPP, and another field that extends on the right and reports the pattern of forest statuses from equilibrium (where no change occurs) to water scarcity (far right of the scheme). Moving from left to right, forests exhibit significantly increasing λ ET fluxes (in any season of the year) that gradually leads to changes in water management and biomass production. The first right-side forest status corresponds to enhanced λ ET that does not correlate with WUE nor GPP, see PA13. In a second step towards more severe conditions, the increase in λ ET initiates the increase in biomass production (PA3). As long as GPP is positively correlated with λ ET, also WUE shows increasing correlation (PA5, PA7, and PA4). This behavior relates to PAs developing mechanisms to save water in Spring months and sustain increased λ ET during the Summer. However, when water savings become insufficient, WUE negatively correlates with λ ET (in PA8 and PA10 significantly increasing GPP in Winter matches statistically significant decreases in WUE in late Fall months). Finally, water scarcity induces a negative correlation between λ ET and biomass, and extends to most seasons during the year (PA15).

Though not directly detectable from our observations, we assume that this pattern of statuses also occurs along a temporal sequence, whereby forests likely exhibit all behaviors in a growing level of severity, even if the duration of each phase may vary in diverse PAs. In our conceptual scheme, λ ET fluxes are the first to warn against the perturbation of the equilibrium in the forest status. Following λ ET, biomass is the first to change, while the response in WUE is delayed. Conversely, when the threshold of water unavailability has been achieved, WUE immediately shifts to negative correlation with increasing λ ET, while biomass is found to first correlate positively with λ ET fluxes, and then invert its sign. This phenomenon may explain the occurrence of DP months, when enhanced λ ET is sustained by increasing biomass even in case of less than average precipitation and scarce water savings. These lags are likely due to physiological mechanisms that plants develop to compensate for water shortage and face adverse climatic conditions. Our scheme shares similarities with established ecohydrological theories and models of plant response to drought. The envisioned increase in biomass ignited by positive λ ET trends (class II in Figure 9) is consistent with the optimality theory for plant stomatal response to water stress (Lavergne et al., 2020; Zhou et al., 2013). According to this framework, stomatal response is near-constant and even slightly increases with declining water availability: this behavior well matches our findings whereby forests develop an ability to thrive in long summer dry seasons. Similar responses have been thoroughly documented in the literature for semi-deciduous and evergreen sclerophyll trees (Myers et al., 1997; Niinemets et al., 2009), which are abundant in the studied PAs. Below-ground complementarity mechanisms that contribute to partition water sources and slow down water availability during drought are captured in class III. This phase may depict typical habits of Mediterranean forest species that, in case of water limitation, interact to reduce tree-tree competition and delay the onset of hydraulic disfunctions (Hajek et al., 2022; Mas et al., 2024). For instance, mixed forest trees develop enhanced canopy packing to mitigate heat stress (Jucker et al., 2015), and anisohydric oak species extend their root system to deeper soils to access additional moisture (Grossiord et al., 2019; Roman et al., 2015). According to our observations, however, prolonged biomass increase ultimately lead to the depletion of water savings (class IV), and, finally, to biomass decrement (class V). The frequency of occurrences of DP months at class IV may warn against more severe water scarcity statuses.

While we recognize the need for future observations to further validate and confirm the illustrated classification, based on our analyses, satellite-based λ ET estimations can be powerful means to detect the status of forests and identify critical hotspots that are more likely to face water scarcity under future drought conditions. In our study, the PAs align along a gradient of water-availability classes, whose identification may be instrumental to support future forest management practices. In fact, combined with climatic observations and projections, this conceptual framework may be used to forecast if and which forests are more likely to face perennial water scarcity or to revert their path towards dryness.

Our study builds on the analysis of a large data set of remote sensing images with a spatial resolution of $30\text{ m} \times 30\text{ m}$ captured over the last 23 years as well as on time series of weather data spanning the last century. From a methodological point of view, taking into account more than two decades of data guaranteed a high number of pixels to adequately define the edges of the time-domain triangular feature space. While very few studies have attempted similar efforts in the literature, several sources of uncertainty certainly affect our results. First, due to cloud cover conditions, the number of satellite observations was not constant throughout the year, and observations tended to be rarer in Winter than Summer. Further, air temperature data were not always available within the studied PAs (which are mostly remote and difficult-to-access), and we had to rely on weather stations within a distance of a few kilometers. Finally, the unavailability of soil moisture data certainly limits the comprehension of how close forests may be to perennial water shortage as well as how transpiration fluxes may be affected by soil water processes.

By attempting to reconstruct the past λET signature of forests in the central region of Italy, our study has opened a number of yet unanswered questions, which deserve future investigation:

- The λET response of forests to climate is not simply controlled by seasonal or yearly T and P but it interacts with vegetation dynamics to generate a gradient of water-availability statuses. Attempting to reconstruct energy and water fluxes in relation to the alternating sequence of dry and wet periods over a multi-year time scale is expected to shed new light on vegetation water management strategies.
- Enriching our data sources with information on surface and soil waters will certainly provide a more comprehensive picture on the state of the forests as well as on their future resilience in the context of climate change. Unraveling future climate-hydrological variability will also be fundamental to inform agricultural practices and guarantee agricultural diversity in the studied area. In fact, understanding these interactions will support sustainable land management and agricultural resilience in the face of climate variability.

5. Conclusions

In this work, we estimated the λET , GPP, and WUE signature of 15 protected forested areas in Central Italy from 2000 to 2022, where λET was computed as the residual term of the land surface energy balance equation through a time-domain parameterization of the traditional “triangle” method. We further compared λET values and anomalies to temperature and precipitation data.

According to our findings, the warm season is gradually shifting to late Summer and early Fall months, when a majority of PAs is experiencing enhanced λET fluxes. In several seasons, such an increase occurred in spite of negative precipitation anomalies, thus supporting the instance of plant adaptation mechanisms to dryness. Experimental evidence supports the instance of a pattern of forest water-availability statuses. At first, enhanced λET fluxes boost biomass growth and are then followed by plant water regulation strategies that promote the establishment of water savings. However, when positive λET and biomass trends persist, water unavailability is attained, and water reserves are rapidly depleted. Finally, negative biomass growth trends are also achieved. Upon consideration of soil moisture data and analysis of future λET response, it will be possible to fully understand how close forests are to perennial water shortage and how resilient these systems will be to future climatic scenarios. In this vein, comparison to alternative modeling approaches, such as, for instance, models that couple the closure of the energy balance with that of the water mass balance (Corbari & Mancini, 2023; Corbari et al., 2011, 2019) will help further unveiling soil moisture and surface energy fluxes in Mediterranean forests.

Appendix A: Physical and Temporal Consistency Assessment

A1. Cross-Sensor Harmonization of Optical Variables

Landsat Collection 2, Level 2 data are highly reliable, and generally do not require cross-sensor adjustment; however, small differences between Landsat 7 and 8–9 may impact data application (Perez & Vitale, 2023; Roy et al., 2016). To assess the effects of using both ETM+ and OLI data, we harmonized satellite imagery data with the Landsat ETM + OLI Harmonization Script (LEOHS), which enables the generation of region-specific

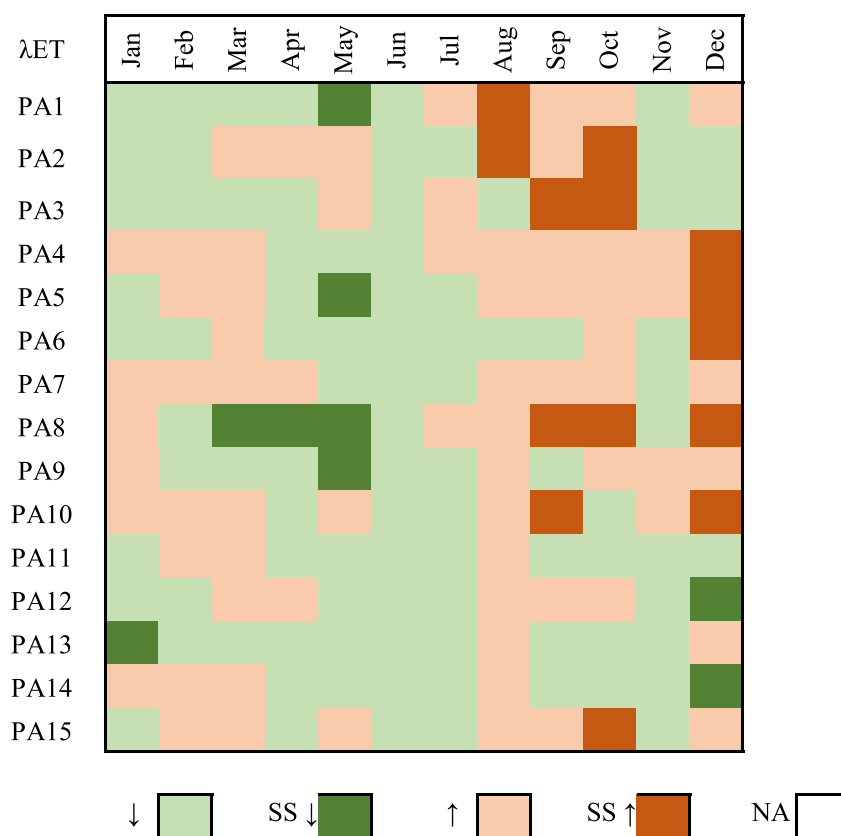


Figure A1. Significance level of linear models fitted on monthly λ ET data computed from harmonized Landsat 7 and 8–9 imagery. Light green and brown cells indicate decrease and increase, respectively, while dark green and brown cells refer to statistically significant decrease and increase, respectively.

harmonization functions and was shown to outperform existing harmonization models (Richardson et al., 2025). The LEOHS Python package was fed with shape files of the PAs, months and years to include in image filtering, and the number of sample points to generate. Harmonization functions were generated for PA1–4 ($R^2 = 0.483 - 0.673$) as well as for the remaining PAs ($R^2 = 0.852$). The functions were applied to recompute NDVI, α , as well as the derived feature-space variable ϕ . Such harmonized variables were then utilized to compute monthly λ ET data; linear models were fitted on such data as in Figure 7 to investigate monthly trends over the study period, see Figure A1.

A number of six out of 15 PAs (i.e., PA1–2, PA6, PA10–11, PA14) exhibited consistent increasing/decreasing trends between original and harmonized data. Remarkably, statistical significance was also consistent for such PAs. The rest of the PAs (PA3–5, PA7–9, PA12–13) displayed small discrepancies in the number of statistical significant trends: in PA7–8 and PA12–13, one statistical significant increasing trend turned to simply increasing in harmonized data. Conversely, in PA3, one simply increasing trend became statistically significant. In PA5 and PA9, one simply decreasing trend became statistically significant. In PA4, two statistically significant increasing trends were simply increasing in the harmonized data. Larger discrepancies were observed in PA15, where statistically significant increases changed from eight to one from the original to harmonized trends. This can partially be explained with the fact that PA15 was the smallest PA (area equal to 0.14 km²), and the harmonization functions (developed jointly for PA5–15) may not be accurate for an area that is much smaller than the area of interest processed in LEOHS.

A2. GPP Sensitivity to VPM Parameters

The selection of the VPM thresholds was in line with typical values for temperate Mediterranean deciduous broadleaf forests. However, to assess the validity of VPM parameters, we investigated flux tower observations at EC IT-Ro1, whose nearby vegetation shares similarities with some of the PAs. To this end, we plotted GPP against air temperature data for the available timeframe (2000–2008) and, following Kumarathunge et al. (2024), fitted values with a parabolic function. According to this analysis, the estimated minimum, maximum, and optimal temperatures for photosynthetic activities were equal to -1.62°C , 38.52°C , and 25.51°C , respectively. While the minimum temperature was consistent with literature data, flux tower data on optimal and maximum values slight differed.

To assess the robustness of GPP estimation to VPM optimal and maximum temperatures (T_{opt} and T_{max}), we identified a range of plausible temperatures and then conducted a sensitivity analysis. T_{opt} was varied in the interval $[20, 26.5]^{\circ}\text{C}$, and T_{max} ranged between $[38.5, 40]^{\circ}\text{C}$, with increments of 0.5°C . The upper value of the T_{opt} range (26.5°C) was estimated by generating 100 samples of 5,000 elements uniformly at random without replacement from the GPP data set of more than 57,800 elements. Such samples were then fitted with a parabolic function and its maximum estimated. The value 26.5°C corresponded to the highest observed T_{opt} out of the 100 functions. The minimum T_{opt} and maximum value for T_{max} were instead set to literature values for Mediterranean forests.

The sensitivity analysis entailed computing GPP based on the harmonized Landsat imagery data as well as changing VPM temperatures for all PAs. While varying T_{opt} , T_{max} was set to 38.52°C ; while varying T_{max} , T_{opt} was set to 25.51°C . Figure A2 reports the significance level of linear models fitted on monthly GPP data as reported in Figure 7 (first line in each box) as well as those re-computed according to the harmonized imagery and varied VPM temperatures. In most PAs (see, for instance, PA4–7, PA9–12, PA14–15), GPP trends were consistent for many of the combinations of VPM parameters. Larger discrepancies were observed in PA1–3, PA8, and PA13. However, in most of such PAs, GPP trends rarely changed sign (from increasing to decreasing or vice versa), while the significance level typically changed (i.e., simply increasing to statistically significant increasing trend).

To evaluate the effects of both harmonized λET fluxes and variable VPM temperatures on the overall response of the PAs, we compared the number of statistically significant trends jointly in λET , GPP, and WUE, and compared them to values in Figure 7. While a general agreement was found across all PAs, PA10, and PA15 exhibited a smaller number of significant trends. For PA15, this was attributed to discrepancies in λET ; for PA10, this was due to the absence of statistically significant WUE trends for T_{opt} ranging between $[22.5, 26.5]^{\circ}\text{C}$ and T_{max} ranging between $[38.5, 40]^{\circ}\text{C}$. Similar to Section 4.2, we further investigated the cross-correlation between harmonized λET and the updated GPP and WUE signals for all PAs, and compared it to the original relationships. Remarkably, four PAs (PA2, PA7, PA9, and PA11) exhibited consistent cross-correlation signs and significance levels with previous relationships for all the combinations of VPM parameters. Seven PAs (PA1, PA3–4, PA8, PA14, PA15, PA10) exhibited discrepancies in the significance level of the λET -GPP or λET -WUE cross-correlations for some combinations of VPM parameters. Three PAs (PA5–6 and PA13) displayed inconsistencies in the sign of the cross-correlations in selected combinations of VPM parameters (one negative vs. positive λET -WUE cross-correlation for $T_{\text{opt}} = 26.5^{\circ}\text{C}$ in PA5; positive vs. negative λET -WUE cross-correlation for $T_{\text{opt}} = [20.5, 26.5]^{\circ}\text{C}$ and $T_{\text{max}} = [38.5, 40]^{\circ}\text{C}$ in PA6; two negative λET -WUE cross-correlations for $T_{\text{opt}} = 26.5^{\circ}\text{C}$ and $T_{\text{max}} = 40^{\circ}\text{C}$ in PA13). Two PAs (PA5 and PA12) showed inconsistencies both in the sign and significance levels of a minority of the cross-correlations. Overall, out of the 15 PAs and 18 combinations of VPM values, only 4.3% of the total λET -GPP or λET -WUE cross-correlations exhibited inconsistent sign, and 15.7% showed inconsistent significant levels compared to relationships developed with non-harmonized fluxes and literature-based VPM temperatures. These results support the robustness of the illustrated framework to preserve the physical and temporal consistency of the observed forest response.

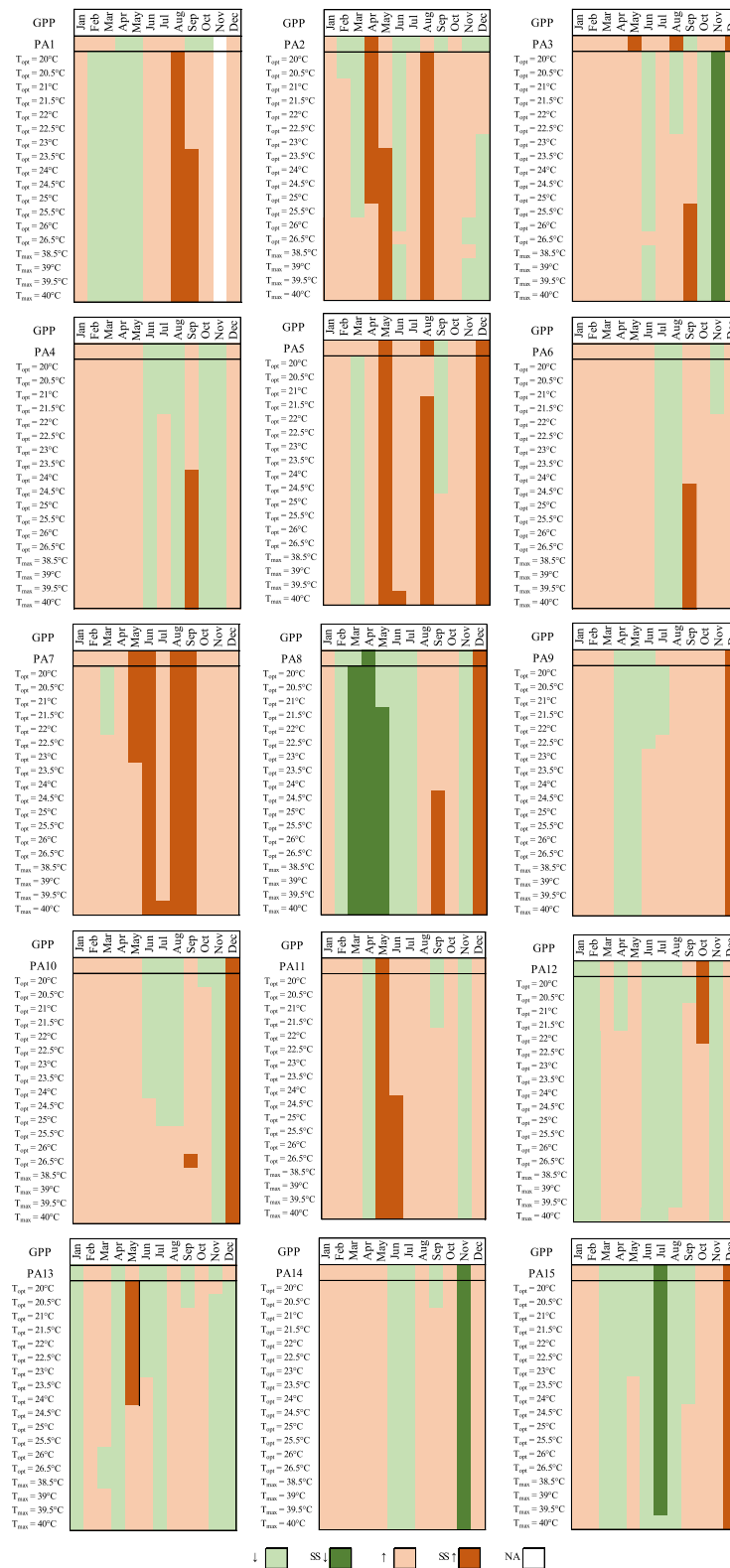


Figure A2. Significance level of linear models fitted on monthly gross primary production data computed from both non-harmonized (first line) and harmonized imagery, and varying Vegetation Photosynthesis Model optimal and maximum temperatures (T_{opt} and T_{max}). T_{opt} was varied in the interval $[20, 26.5]^{\circ}\text{C}$, and T_{max} ranged between $[38.5, 40]^{\circ}\text{C}$, with increments of 0.5°C . Light green and brown cells indicate decrease and increase, respectively, while dark green and brown cells refer to statistically significant decrease and increase, respectively.

Appendix B: PA Internal Variability

Figures B1 to B15 illustrate mean and standard deviations of the λ ET response for each PA and analyzed date in the study period.

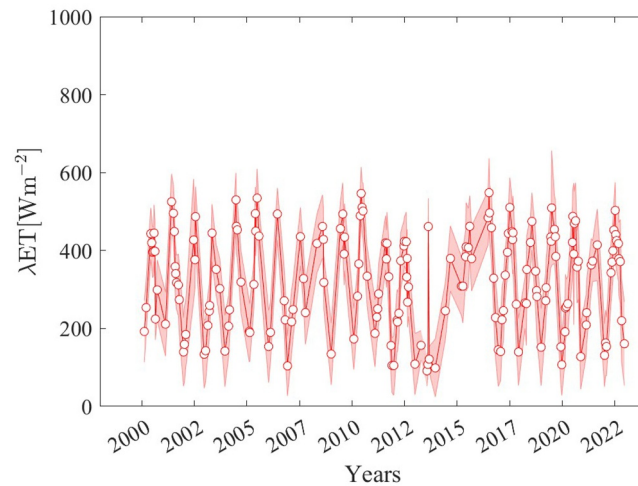


Figure B1. Internal variability of λ ET response for PA1 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

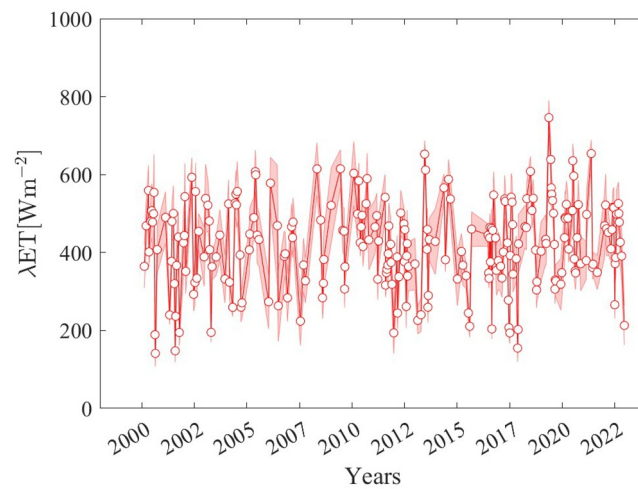


Figure B2. Internal variability of λ ET response for PA2 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

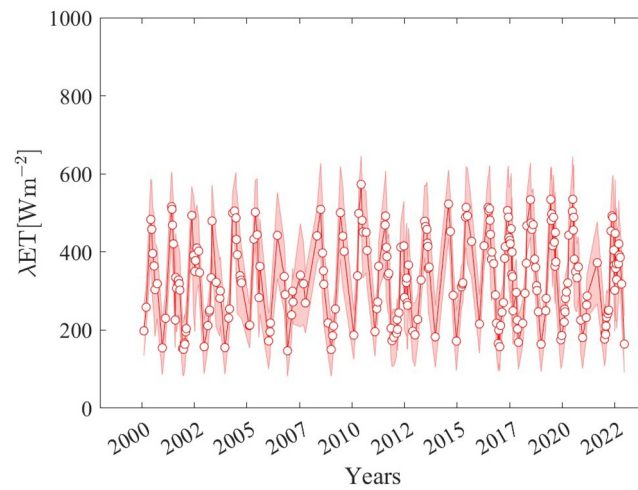


Figure B3. Internal variability of λET response for PA3 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

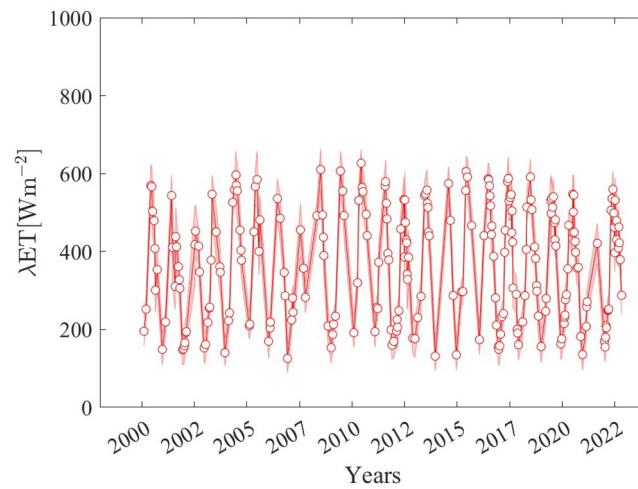


Figure B4. Internal variability of λET response for PA4 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

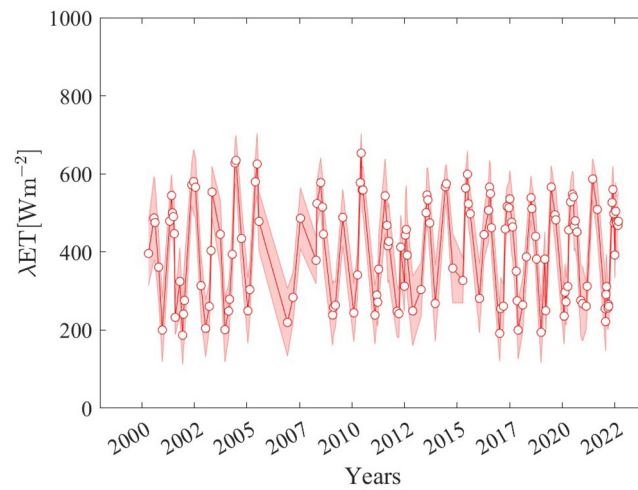


Figure B5. Internal variability of λET response for PA5 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

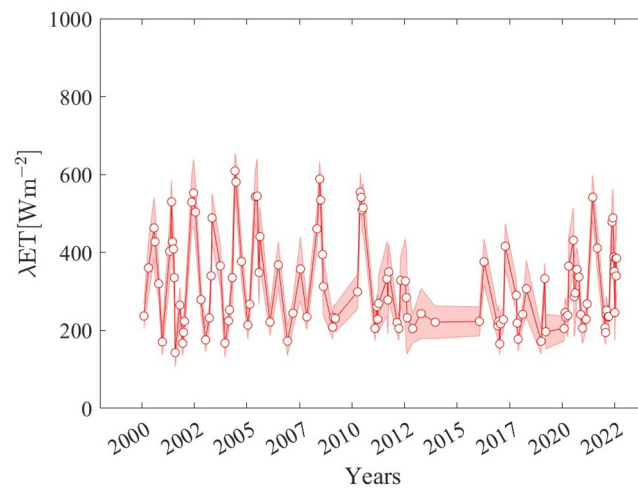


Figure B6. Internal variability of λET response for PA6 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

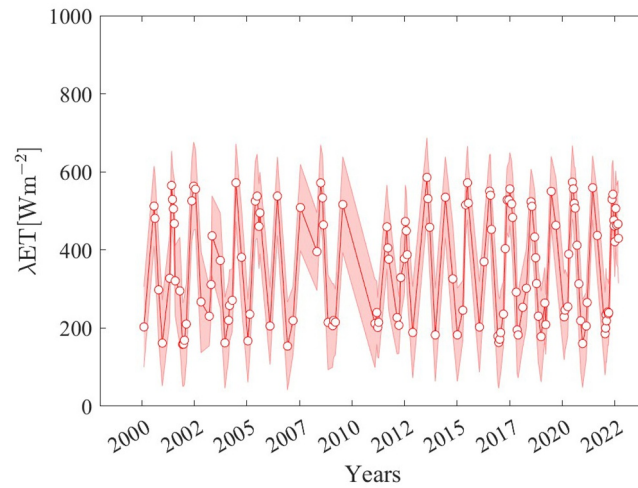


Figure B7. Internal variability of λET response for PA7 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

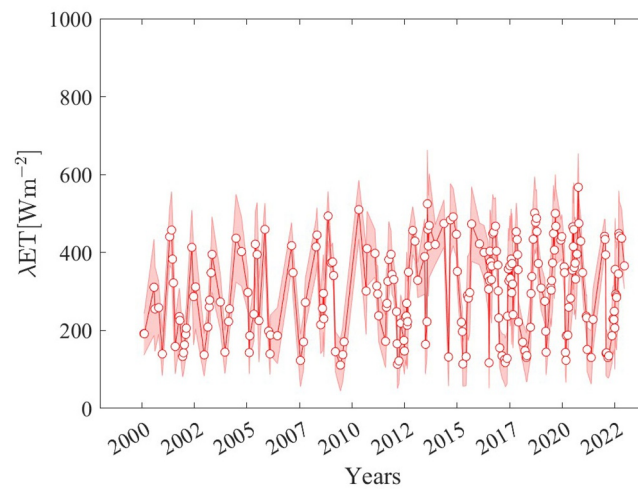


Figure B8. Internal variability of λET response for PA8 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

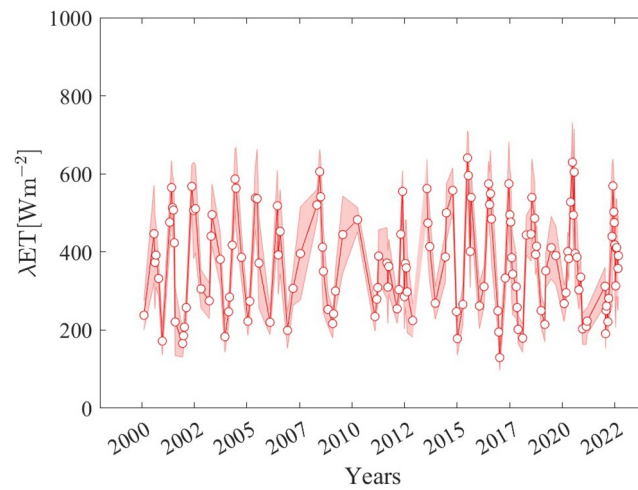


Figure B9. Internal variability of λET response for PA9 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

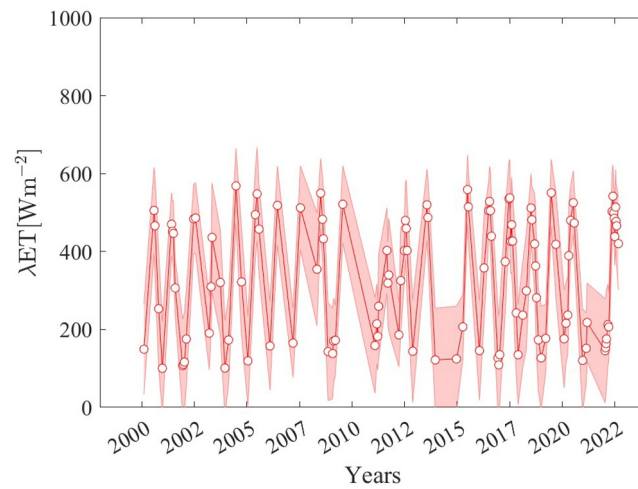


Figure B10. Internal variability of λET response for PA10 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

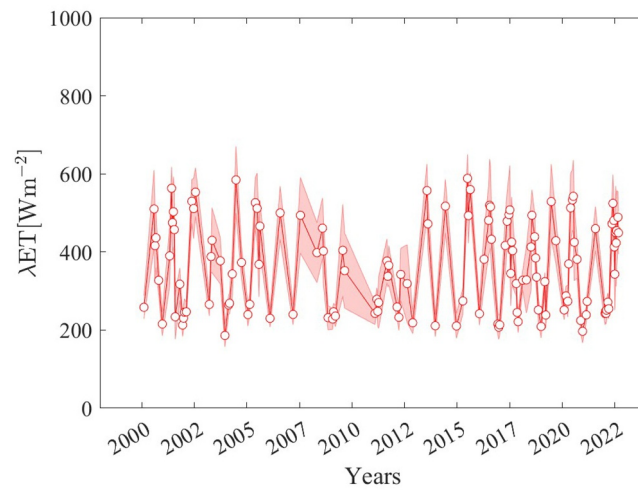


Figure B11. Internal variability of λET response for PA11 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

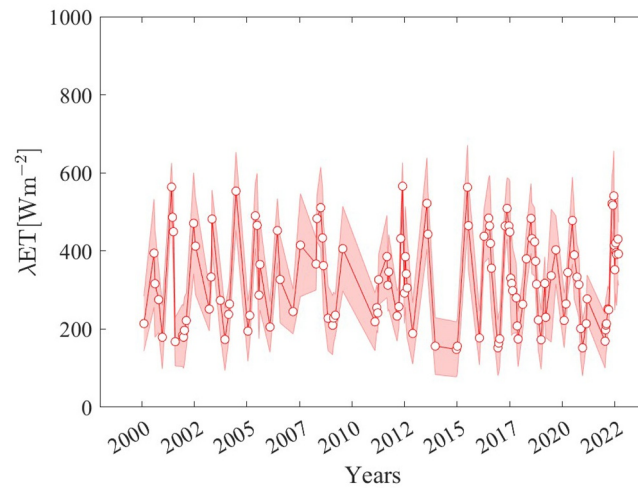


Figure B12. Internal variability of λET response for PA12 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

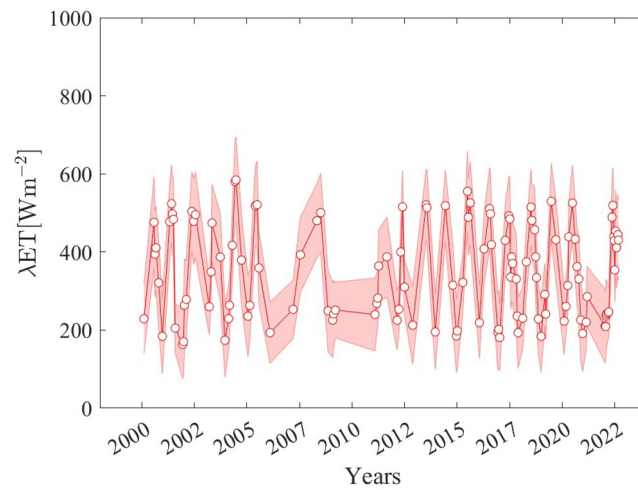


Figure B13. Internal variability of λET response for PA13 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

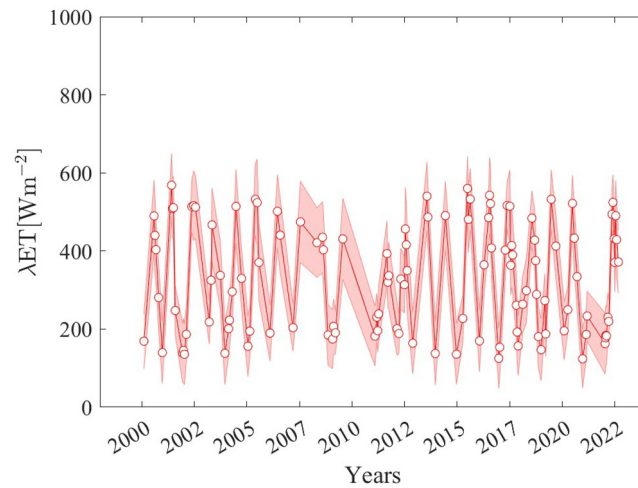


Figure B14. Internal variability of λET response for PA14 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

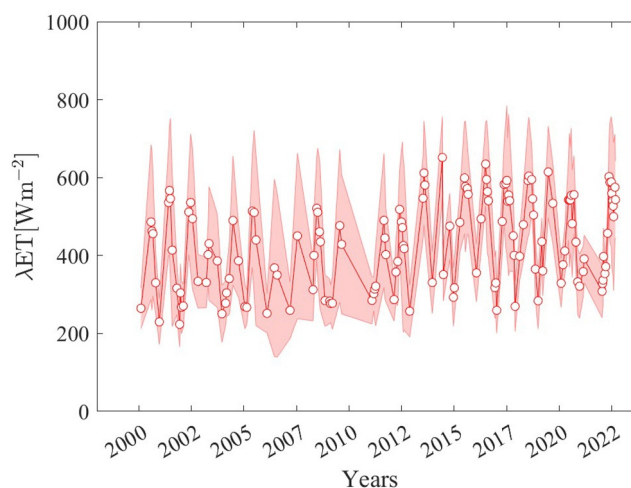


Figure B15. Internal variability of λET response for PA15 at each analyzed date from 2000 to 2022. The red line refers to mean values, and shaded areas indicate standard deviations.

Appendix C: Forests' Average Response During the Year

Figures C1 to C15 illustrate $\overline{\Delta \lambda ET}$ per month of the year at each PA.

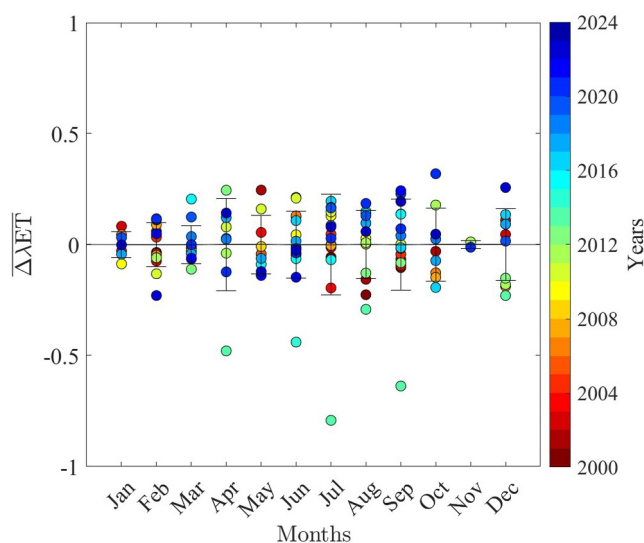


Figure C1. $\overline{\Delta \lambda ET}$ per month of the year at PA1. The colorbar indicates years from 2000 to 2022.

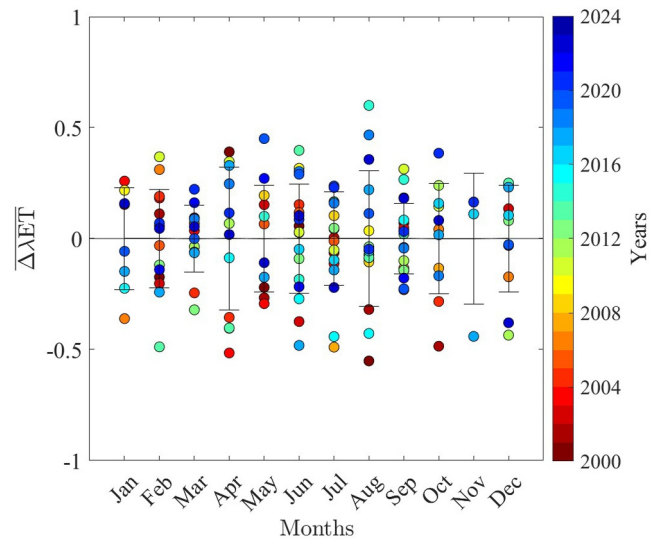


Figure C2. $\overline{\Delta\lambda ET}$ per month of the year at PA2. The colorbar indicates years from 2000 to 2022.

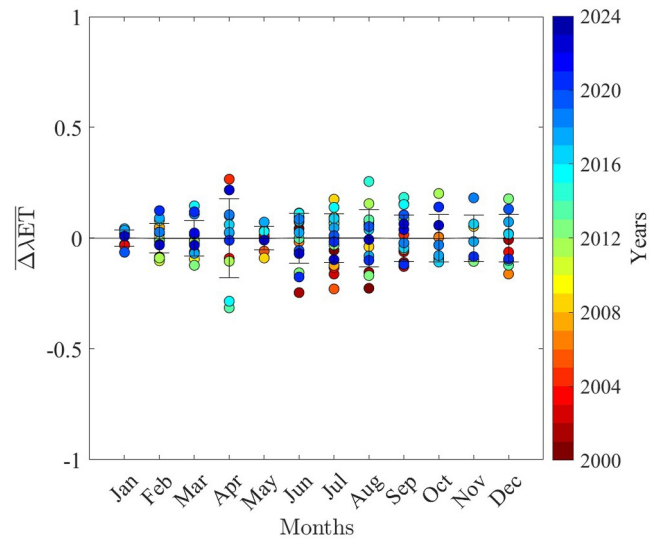


Figure C3. $\overline{\Delta\lambda ET}$ per month of the year at PA3. The colorbar indicates years from 2000 to 2022.

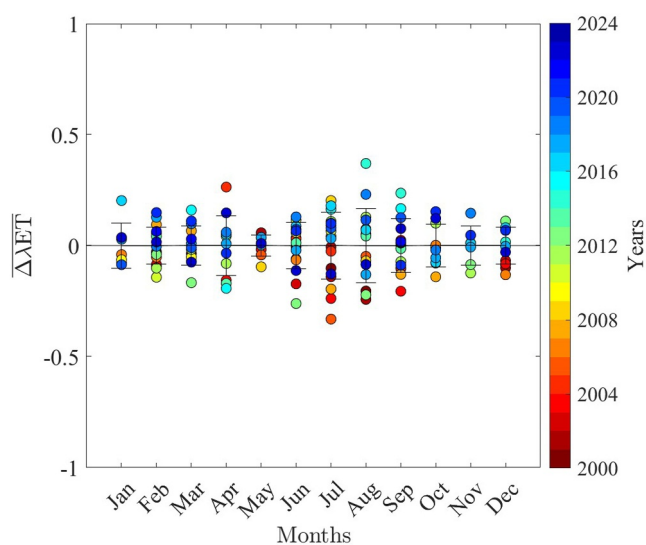


Figure C4. $\overline{\Delta\lambda ET}$ per month of the year at PA4. The colorbar indicates years from 2000 to 2022.

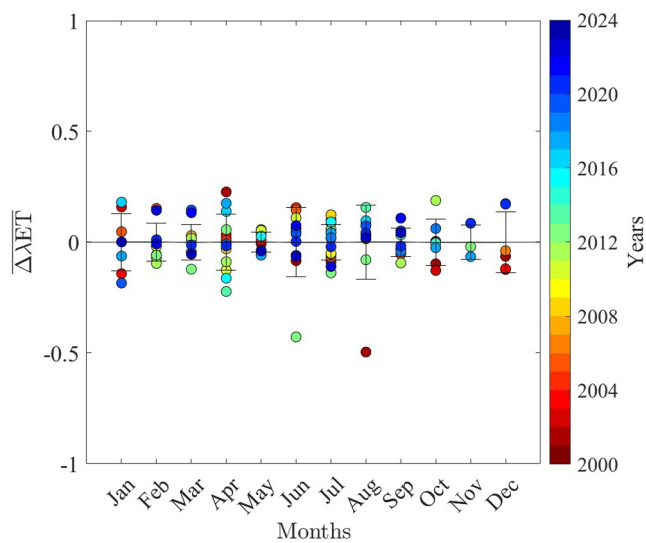


Figure C5. $\overline{\Delta\lambda ET}$ per month of the year at PA5. The colorbar indicates years from 2000 to 2022.

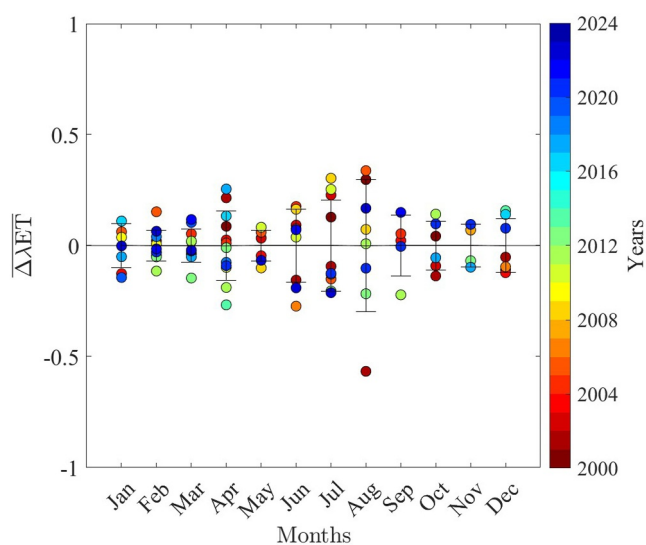


Figure C6. $\overline{\Delta\lambda ET}$ per month of the year at PA6. The colorbar indicates years from 2000 to 2022.

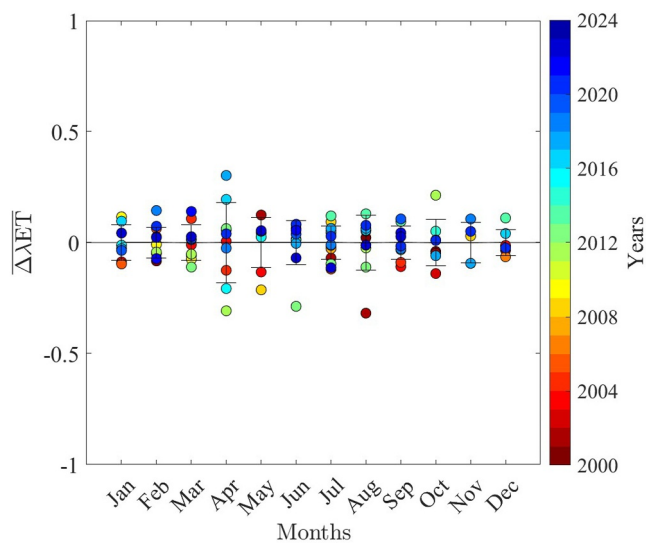


Figure C7. $\overline{\Delta\lambda ET}$ per month of the year at PA7. The colorbar indicates years from 2000 to 2022.

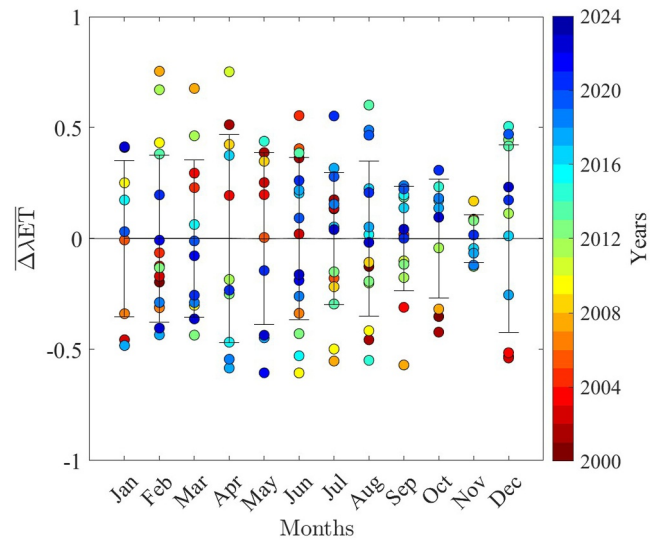


Figure C8. $\overline{\Delta\lambda ET}$ per month of the year at PA8. The colorbar indicates years from 2000 to 2022.

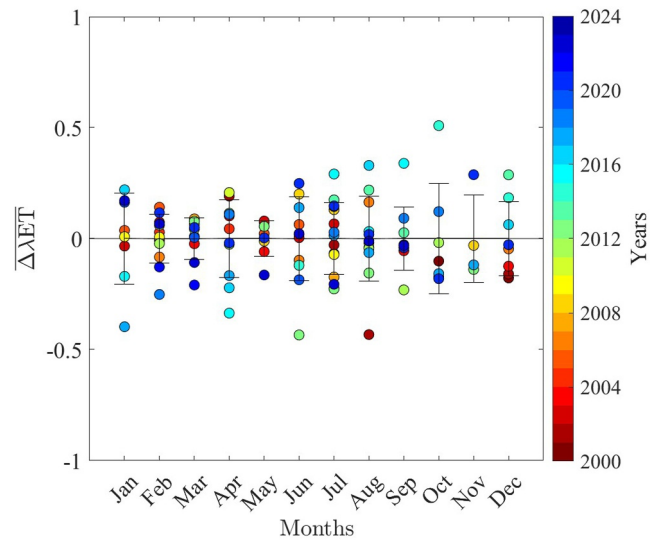


Figure C9. $\overline{\Delta\lambda ET}$ per month of the year at PA9. The colorbar indicates years from 2000 to 2022.

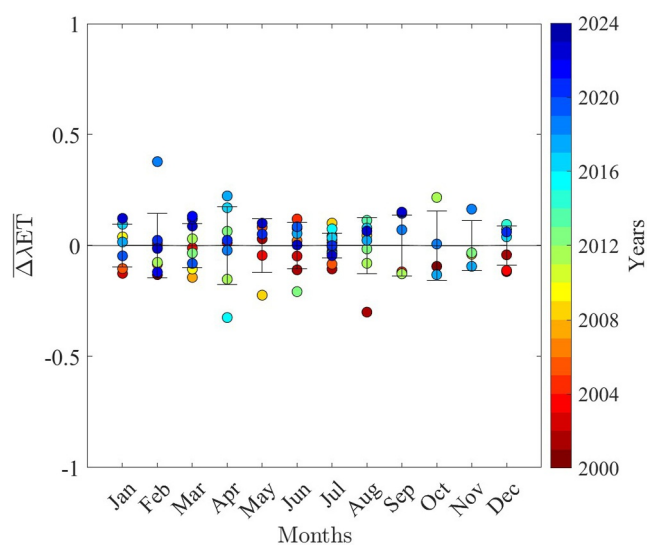


Figure C10. $\overline{\Delta\lambda ET}$ per month of the year at PA10. The colorbar indicates years from 2000 to 2022.

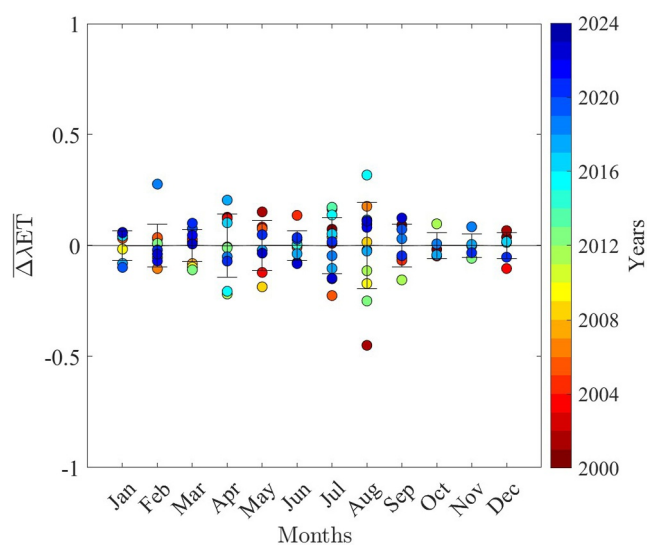


Figure C11. $\overline{\Delta\lambda ET}$ per month of the year at PA11. The colorbar indicates years from 2000 to 2022.

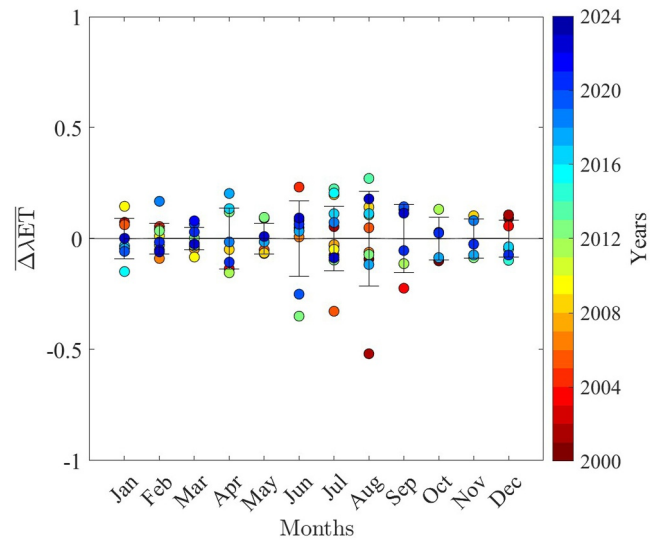


Figure C12. $\overline{\Delta\lambda ET}$ per month of the year at PA12. The colorbar indicates years from 2000 to 2022.

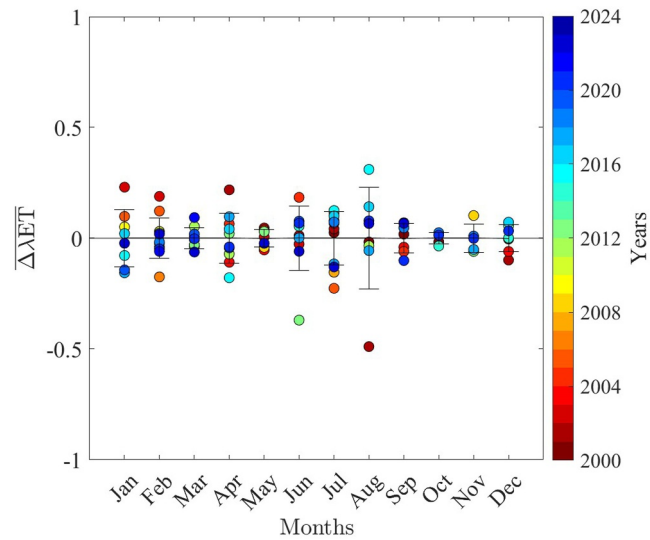


Figure C13. $\overline{\Delta\lambda ET}$ per month of the year at PA13. The colorbar indicates years from 2000 to 2022.

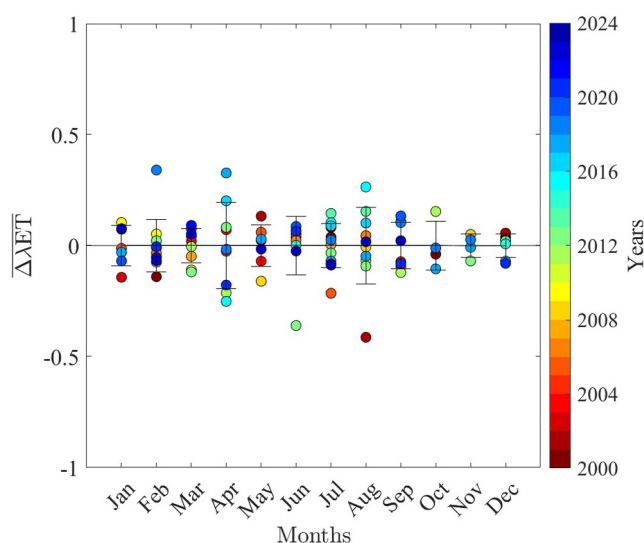


Figure C14. $\overline{\Delta\lambda ET}$ per month of the year at PA14. The colorbar indicates years from 2000 to 2022.

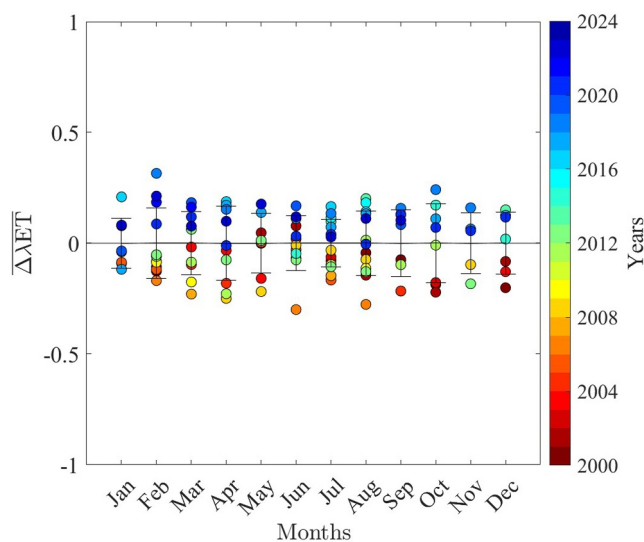


Figure C15. $\overline{\Delta\lambda ET}$ per month of the year at PA15. The colorbar indicates years from 2000 to 2022.

Appendix D: Species Composition in the PAs

In Table D1, we non-exhaustively report the plant species present in the PAs. Our list is based on previous surveys by the Lazio Region (Parks.it, 2024; Regione Lazio, 2024; Road2Rome.it, 2024; WWF Italia ETS, 2024). The naming order in the Table is related to the most abundant species in each PA.

Table D1

List of the Major Species Per Protected Area (PA)

PA	Observed species
PA1	<i>Quercus cerris</i> L., <i>Quercus pubescens</i> Willd., <i>Quercus ilex</i> L., <i>Acer</i> L., <i>Carpinus</i> L., <i>Cornus domestica</i> (L.) Spach <i>Fraxinus ornus</i> L., <i>Quercus robur</i> L., <i>Ilex aquifolium</i> L., <i>Castanea</i> Mill., <i>Acer monspessulanum</i> L., <i>Arbutus unedo</i> L. <i>Phillyrea latifolia</i> L., <i>Viburnum tinus</i> L., <i>Pinus nigra</i> J.F.Arnold, <i>Pinus halepensis</i> Mill., <i>Pinus pinaster</i> Aiton, <i>Olea europaea</i> L.
PA2	<i>Quercus cerris</i> L., <i>Quercus ilex</i> L., <i>Fagus sylvatica</i> L., <i>Ulmus</i> L., <i>Acer pseudoplatanus</i> L., <i>Fraxinus ornus</i> L.
PA3	<i>Quercus cerris</i> L., <i>Quercus pubescens</i> Willd., <i>Quercus ilex</i> L., <i>Quercus</i> × <i>crenata</i> Lam., <i>Acer monspessulanum</i> L., <i>Acer campestre</i> L. <i>Acer opalus</i> subsp. <i>obtusatum</i> (Waldst and Kit. ex Wild.) Gams., <i>Fraxinus ornus</i> L., <i>Ostrya carpinifolia</i> Scop. <i>Carpinus betulus</i> L., <i>Celtis australis</i> L., <i>Fagus sylvatica</i> L. <i>Ulmus minor</i> Mill., <i>Ulmus glabra</i> Huds., <i>Corylus avellana</i> L., <i>Sorbus torminalis</i> (L.) Crantz, <i>Sorbus domestica</i> L., <i>Sambucus nigra</i> L. <i>Mespilus germanica</i> L., <i>Pyrus communis</i> L. subsp. <i>pyraster</i> (L.) Ehrh., <i>Prunus spinosa</i> L., <i>Cornus mas</i> L., <i>Cornus sanguinea</i> L., <i>Crataegus monogyna</i> Jacq. <i>Crataegus oxyacantha</i> L., <i>Ilex aquifolium</i> L., <i>Euonymus europaeus</i> L., <i>Phillyrea latifolia</i> L., <i>Cytisus scoparius</i> (L.) Link, <i>Spartium junceum</i> L. <i>Colutea arborescens</i> L., <i>Clematis vitalba</i> L., <i>Hedera elix</i> L., <i>Loranthus europaeus</i> Jacq., <i>Helleborus foetidus</i> L., <i>Helleborus bocconeii</i> Ten. <i>Romulea bulbocodium</i> (L.) Sebast. and Mauri, <i>Crocus biflorus</i> Mill., <i>Primula vulgaris</i> Huds <i>Scilla bifolia</i> L., <i>Anemone appennina</i> L., <i>Anemonoides nemorosa</i> L. Holub. <i>Cyclamen repandum</i> Sm. subsp. <i>repandum</i> , <i>Viola reichenbachiana</i> Jord. ex Boreau, <i>Ranunculus ficaria</i> L. <i>Ranunculus lanuginosus</i> L., <i>Ranunculus velutinus</i> Ten., <i>Aristolochia rotunda</i> L. <i>Aristolochia pallida</i> Willd., <i>Lunaria annua</i> L., <i>Mercurialis perennis</i> L., <i>Tamus communis</i> L., <i>Bryonia dioica</i> Jacq., <i>Rubbia peregrina</i> L. <i>Fumaria officinalis</i> L., <i>Fumaria capreolata</i> L. subsp. <i>capreolata</i> , <i>Chelidonium majus</i> L. <i>Hypericum perforatum</i> L., <i>Hypericum perforatum</i> L., <i>Anchusella cretica</i> (Mill.) Bigazzi E. Nardi and Selvi <i>Achillea millefolium</i> L., <i>Vicia lathyroides</i> L., <i>Vicia melanopos</i> Sibth. and Sm., <i>Ornithogalum umbellatum</i> L., <i>Ornithogalum pyrenaicum</i> L., <i>Allium pendulinum</i> Ten. <i>Centaurium erythraea</i> Rafn., <i>Centaurium pulchellum</i> (Sw.) Hayek ex Hand.-Mazz., Stadlm., Janch. and Faltis subsp. <i>pulchellum</i> <i>Linaria purpurea</i> (L.) Mill., <i>Buglossoides purpureo-caerulea</i> (L.) I.M. Johnston, <i>Helycrysum italicum</i> (Roth) G. Don, <i>Ajuga reptans</i> L. <i>Ajuga chamaepitys</i> (L.) Schreb. subsp. <i>chamaepitys</i> , <i>Origanum vulgare</i> L., <i>Teucrium chamaedrys</i> L. <i>Opopanax chironium</i> (L.) W.D.J.Koch, <i>Phyllitis scolopendrium</i> (L.) Newman, <i>Adiantum capillus-veneris</i> L. <i>Asplenium trichomanes</i> L., <i>Corydalis cava</i> (L.) Schweigg. and Körte subsp. <i>cava</i> , <i>Sanicula europaea</i> L. <i>Barbarea verna</i> (Mill.) Asch., <i>Cardamine heptaphylla</i> (Vill.) O.E.Schulz, <i>Veronica scutellata</i> L. <i>Ophioglossum vulgatum</i> L., <i>Platanthera chlorantha</i> (Custer) Rchb., <i>Orchis tridentata</i> Scop. <i>Spiranthes spiralis</i> (L.) Chevall., <i>Dactylorhiza maculata</i> (L.) Soó, <i>Orchis morio</i> L. <i>Orchis papilionacea</i> L., <i>Serapias vomeracea</i> (Burm.f.) Briq., <i>Anacamptis pyramidalis</i> (L.) L. C.M. Richard <i>Himantoglossum hircinum</i> (L.) Spreng. subsp. <i>adriaticum</i> (H. Baumann) H. Sund., <i>Neottia nidus-avis</i> (L.) L.C.M. Richard, <i>Limodorum abortivum</i> (L.) Sw.

Table D1
Continued

PA	Observed species
	<i>Anacamptis coriophora</i> (L.) R.M.Bateman, Pridgeon and M.W.Chase subsp. <i>fragrans</i> (Pollini) Sudre <i>Ophrys bertolonii</i> Moretti, <i>Serapias lingua</i> L., <i>Orchis provincialis</i> Balb. ex Lam. and DC.
PA4	Same as PA3
PA5	<i>Quercus cerris</i> L., <i>Cornus mas</i> L., <i>Quercus ilex</i> L., <i>Fraxinus ornus</i> L., <i>Lobaria pulmonaria</i> (L.) Hoffm., <i>Usnea</i> Dill. ex Adans.
PA6	<i>Quercus cerris</i> L., <i>Quercus pubescens</i> Willd., <i>Quercus ilex</i> L., <i>Cistus</i> sp., <i>Celtis australis</i> L., <i>Alnus glutinosa</i> (L.) Gaertn. <i>Sambucus nigra</i> L., <i>Ulmus minor</i> Mill., <i>Ficus carica</i> L., <i>Pistacia terebinthus</i> L., <i>Hedera helix</i> L., <i>Sedum</i> L. <i>Helichrysum</i> Mill., <i>Linum usitatissimum</i> L., <i>Romulea</i> , <i>Scilla autumnalis</i> L.
PA7	<i>Quercus cerris</i> L., <i>Fagus sylvatica</i> L., <i>Quercus ilex</i> L., <i>Quercus frainetto</i> Ten., <i>Quercus robur</i> L., <i>Acer monspessulanum</i> L. <i>Carpinus betulus</i> L., <i>Ruscus aculeatus</i> L.
PA8	<i>Cornus mas</i> L., <i>Crataegus monogyna</i> Jacq., <i>Euonymus europaeus</i> L., <i>Fraxinus ornus</i> L., <i>Lonicera</i> L., <i>Prunus spinosa</i> <i>Quercus cerris</i> L., <i>Quercus ilex</i> L., <i>Quercus suber</i> L., <i>Rosa canina</i> L., <i>Populus</i> L., <i>Alnus</i> Mill., <i>Salix</i> L.
PA9	<i>Quercus pubescens</i> Willd., <i>Erica arborea</i> L., <i>Phillyrea latifolia</i> L., <i>Arbutus unedo</i> L., <i>Cistus</i> L., <i>Prunus spinosa</i> <i>Corylus</i> L., <i>Ulmus</i> L., <i>Fraxinus ornus</i> L., <i>Ligustrum</i> L., <i>Ruscus aculeatus</i> L., <i>Viburnum tinus</i> L., <i>Spiranthes spiralis</i> (L.) Chevall., <i>Orchis purpurea</i> Huds., <i>Serapias lingua</i> L., <i>Dactylorhiza romana</i> (Sebast.) Soó, <i>Anemone</i> L., <i>Cyclamen</i> L.
PA10	<i>Fagus</i> L., <i>Acer</i> L., <i>Quercus cerris</i> L., <i>Castanea</i> Mill., <i>Ilex Tourn.</i> ex L., <i>Ruscus aculeatus</i> L., <i>Daphne laureola</i> L., <i>Polypodiopsida</i> Ritgen, <i>Narcissus</i> L., <i>Scilla</i> L., <i>Anemone</i> (L.), <i>Cyclamen</i> L. <i>Lilium</i> Tourn. ex L., <i>Orchidaceae</i> Juss.
PA11	<i>Salix</i> L., <i>Populus</i> L., <i>Quercus robur</i> L., <i>Quercus cerris</i> L., <i>Quercus pubescens</i> Willd., <i>Carpinus</i> L., <i>Quercus suber</i> L., <i>Quercus ilex</i> L.
PA12	<i>Quercus pubescens</i> Willd., <i>Quercus cerris</i> L., <i>Fraxinus ornus</i> L., <i>Acer monspessulanum</i> L., <i>Acer campestre</i> L., <i>Crataegus monogyna</i> Jacq. <i>Lonicera</i> L., <i>Euonymus europaeus</i> L., <i>Asparagus acutifolius</i> L., <i>Fraxinus</i> L., <i>Ulmus</i> L., <i>Fagus</i> L. <i>Corylus</i> L., <i>Alnus glutinosa</i> (L.) Gaertn., <i>Populus nigra</i> L., <i>Salix alba</i> L., <i>Quercus ilex</i> L., <i>Celtis occidentalis</i> L. <i>Ficus carica</i> L.
PA13	<i>Cornus</i> L., <i>Ligustrum</i> L., <i>Cytisus scoparius</i> (L.) Link, <i>Carpinus</i> L., <i>Quercus pubescens</i> Willd., <i>Fraxinus ornus</i> L. <i>Ruscus aculeatus</i> L., <i>Rubia tinctorum</i> L., <i>Cyclamen</i> L., <i>Quercus cerris</i> L., <i>Ulmus</i> L., <i>Quercus robur</i> L., <i>Corylus avellana</i> L., <i>Acer</i> L.
PA14	<i>Quercus pubescens</i> Willd., <i>Quercus cerris</i> L., <i>Castanea</i> Mill., <i>Fagus</i> L., <i>Quercus ilex</i> L., <i>Laurus nobilis</i> L. <i>Viburnum tinus</i> L., <i>Ostrya carpinifolia</i> Scop., <i>Fraxinus ornus</i> L., <i>Ulmus minor</i> Mill., <i>Celtis australis</i> L., <i>Prunus spinosa</i> L. <i>Crataegus monogyna</i> Jacq., <i>Cornus mas</i> L., <i>Cytisus scoparius</i> (L.) Link, <i>Spartium junceum</i> L.
PA15	<i>Fagus</i> L., <i>Agrostis</i> L.

Note. The naming order is related to the abundance of the species.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The energy fluxes, temperature, and NDVI data used for forest water-availability estimation in the study are available at Zenodo via (Tauro, 2025).

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