

Article

Climate-Smart Framework for Olive Yield Estimation: Integrating Soil Properties, Thermal Time, and Remote Sensing NDVI Time Series

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Abstract

Olive groves in Mediterranean regions are being increasingly exposed to drought and heat extremes, intensifying the interannual yield variability. This study presents an integrated smart-farming framework that links soil context, climate forcing and satellite-observed canopy dynamics to enhance the interpretability and transferability of yield indicators at the parcel scale in southern Spain. Using SoilGrids root-zone properties and the Sentinel-2 time series of the normalized difference vegetation index (NDVI), we first classified parcels into three edaphic clusters. The canopy development was then expressed in thermal time using growing degree days (GDD), enabling phenology-aligned comparisons across campaigns. Two robust patterns emerged: (i) the cumulative NDVI up to 520 GDD showed a consistent negative association with both the biomass and the oil yield, suggesting an early-season vegetation trade-off and carry-over effects typical of perennial systems, and (ii) the rainfall accumulated during a thermally defined window (120–480 GDD) strongly estimated the yield in the subsequent year ($R^2 = 0.83\text{--}0.97$ across soil clusters). By anchoring both vegetation and precipitation indicators to physiologically meaningful thermal milestones, the proposed framework avoids arbitrary calendar windows and enhances the interpretability, cross-year comparability, and scalability. Under projected increases in drought frequency and heat extremes, such hydro-thermal scaling approaches offer a robust basis for early yield forecasting, cooperative-level production planning, and adaptive management in Mediterranean olive systems.

Keywords: olive yield estimation; Sentinel-2 NDVI time series; thermal time (growing degree days); hydro-thermal indicators; soil properties; precision agriculture



Academic Editors: Thanos Balafoutis and Evangelos Anastasiou

Received: 27 February 2026

Revised: 23 March 2026

Accepted: 26 March 2026

Published: 30 March 2026

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1. Introduction

Olive groves are a key perennial high-value crop in Mediterranean agriculture and a strategic component of rural economies, particularly in Spain. In recent years, however, recurrent droughts, heat extremes, and stronger interannual climatic variability have intensified the production instability across the Mediterranean basin, recognized as a hotspot by The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report [1]. Recent modelling studies further indicate that rising temperatures can substantially alter

olive oil accumulation dynamics and reduce the expected oil yield under future climate scenarios, reinforcing the vulnerability of olive production systems to heat extremes in southern Spain [2,3].

From a physiological perspective, olive yield formation is tightly linked to phenological timing (dormancy release, flowering, fruit set and fruit growth) and to hydro-thermal conditions [4]. Thermal-time metrics, commonly expressed as growing degree days (GDD), are widely used to align phenological progress across seasons with different thermal regimes [5]. However, olive systems are perennial and exhibit carry-over effects across consecutive campaigns [6], so environmental conditions influencing reserve dynamics and reproductive development can affect yield beyond a single calendar season. In addition, observed phenological responses are not spatially uniform; landscape factors such as the altitude and exposure can shift flowering timing, underlining that olive grove responses emerge from interactions among climate forcing and site conditions [2].

Remote sensing (RS) provides repeated, spatially explicit observations of canopy dynamics that complement field records and enable monitoring at operational scales. A comprehensive review of two decades of RS applications in olive growing highlights the rapid maturation of the field, driven by open-access satellite missions (notably Sentinel), and identifies the normalized difference vegetation index (NDVI) as the most widely used vegetation indicator in olive-focused studies [7]. Among current open-access missions, Sentinel-2 is particularly suitable for agricultural applications at the parcel scale due to its 10–20 m spatial resolution, the five-day revisit frequency of the Sentinel-2A/2B constellation, and the MultiSpectral Instrument (MSI) spectral configuration (13 bands from visible to shortwave infrared, including red-edge bands) [8–10]. These characteristics support frequent and spatially detailed vegetation monitoring, including the normalized difference vegetation index (NDVI), while also improving the sensitivity to the canopy biophysical status through red-edge information [10].

In olive systems, Sentinel-2 time series have already enabled operational smart-farming products based on multi-temporal vegetation signals, such as high-resolution mapping [11]. Nevertheless, RS-based yield inference in woody crops remains challenging because the observed signal can be affected by mixed pixels, soil background reflectance, inter-row vegetation, pruning impacts, and heterogeneous management. These limitations help explain why reported NDVI–yield relationships can be strong in some settings, yet weaker or unstable in others [7]. To improve the phenological inference and robustness, a growing line of work integrates RS indicators with meteorological information; for example, machine-learning approaches have shown that phenology predictions can benefit from combining a climate re-analysis and satellite-derived signals [11,12]. Beyond phenology, integrative modelling studies have demonstrated the potential of combining RS with ancillary data to reproduce the interannual variability in olive yield at regional scales [13].

To address these limitations, recent smart farming research has increasingly relied on integrated, multi-source frameworks that combine satellite time series with weather data (and, when available, soil or management information) to improve the phenological alignment, interpretability, and yield prediction. Data platforms such as Google Earth Engine facilitate reproducible workflows by enabling standardized access to multi-temporal Sentinel and Landsat archives and by supporting scalable feature extraction and modelling across large areas. Multi-source yield forecasting studies have shown that combining satellite indicators with meteorological forcing can improve pre-harvest yield estimation and interpretability [14–16]. In parallel, olive-focused work has demonstrated that integrating climate forcing and satellite information improves phenological predictions and supports decision-support applications [12]. Furthermore, multi-source RS approaches are rapidly expanding in Mediterranean olive systems to estimate biophysical variables such

as biomass, highlighting the potential of data fusion frameworks to characterize orchard functioning at scale [17].

A key dimension often underrepresented in scalable yield frameworks is the soil context. Soil properties regulate the plant-available water storage, drainage, nutrient buffering (e.g., cation exchange capacity, CEC), organic matter status (e.g., soil organic carbon, SOC) and pH-mediated availability, thereby conditioning canopy dynamics and yield responses to drought and heat. Process-based ecohydrological modelling supports the central role of soil moisture dynamics in determining olive yield variability beyond precipitation totals alone [18]. However, detailed soil surveys are rarely available at an operational scale. Global digital soil mapping products such as SoilGrids provide a reproducible alternative by delivering spatial estimates of root-zone soil properties at standardized depths with a quantified uncertainty [19,20]. This enables the systematic inclusion of the soil context in integrated RS–climate frameworks, particularly where local soil sampling is sparse.

Building on these advances, we developed a unified and transferable climate-smart framework that connects all these variables by (i) capturing the soil context via unsupervised clustering of key root-zone properties (texture, CEC, SOC, and pH) to delineate edaphic response groups; (ii) representing canopy development along a phenological axis by normalizing the cumulative NDVI with respect to the cumulative GDD, thereby enhancing the comparability across years compared to calendar-based timing; and (iii) characterizing precipitation within thermally defined GDD intervals to represent hydro-climatic forcing during phases that are critical for multi-season yield formation.

2. Materials and Methods

The methodological workflow (Figure 1) proceeded in the following order: (i) compilation and preprocessing of soil, climate, remote sensing, and field records; (ii) unsupervised clustering based on soil descriptors to define edaphic contexts for the full parcel set; (iii) selection of a yield-linked subset (single-parcel growers) to ensure an unambiguous linkage between parcel-level predictors and production outcomes; and (iv) construction of thermal-time phenological indicators and yield-related analyses stratified by soil cluster.

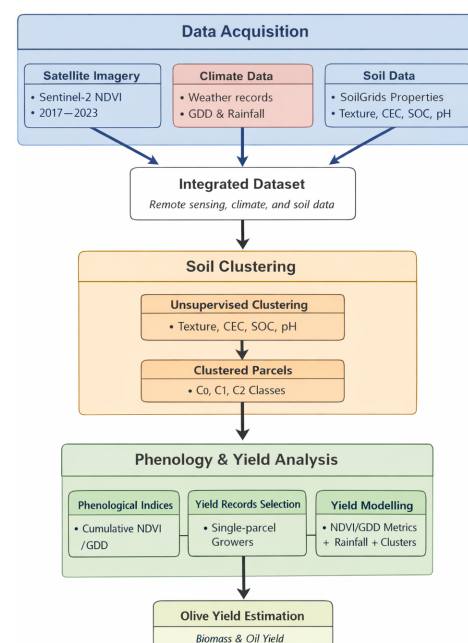


Figure 1. Workflow of the proposed climate-smart framework integrating soil, climate and Sentinel-2 remote sensing data for parcel-scale olive yield analyses.

2.1. Study Area

The study was conducted in olive groves located in the province of Córdoba (Andalusia, southern Spain), a representative Mediterranean olive-growing region characterized by dry winters and hot summers. The analysis unit was the cadastral parcel (hereafter, parcel), allowing for the integration of field records with spatially explicit environmental features. Figure 2 shows the spatial distribution of these parcel geometries that were used to compute centroids and to support spatial extraction of remote sensing and soil information.

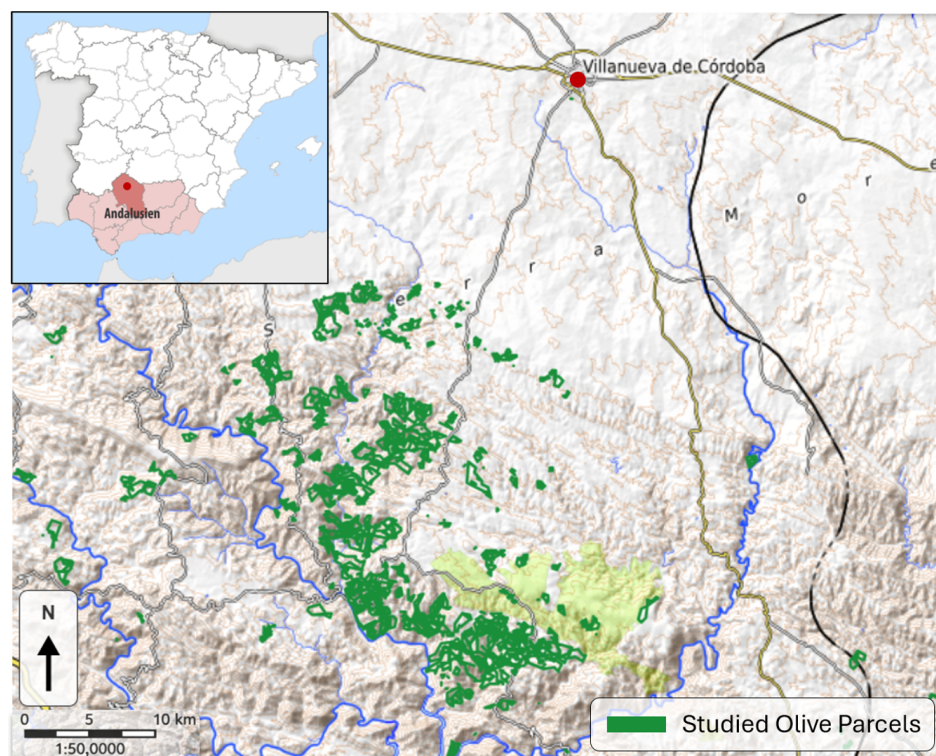


Figure 2. Location of the study area (Córdoba Province, Spain) and spatial distribution of the olive grove geometries included in the dataset.

We compiled a parcel-level dataset including 1141 olive parcels managed by 221 farmers. Annual production records were available at the grower level (i.e., aggregated across all parcels owned by each grower). To enable parcel-level analyses without introducing allocation assumptions, we restricted the soil–production assessment to a subset of farmers managing a single parcel. This yielded a final sample of 24 parcels for which grower-level production can be unambiguously attributed to the corresponding parcel. Table 1 summarizes relevant information on the study area.

Table 1. Study area description.

Item	Description
Location	Córdoba Province, Andalusia (southern Spain)
Climate	Mediterranean; hot dry summers and milder winters
Mean elevation (m)	~650
Mean annual temperature (°C)	16.1
Mean annual precipitation (mm)	358.1
Number of parcels/growers	1141 parcels; 221 growers
Study period	2017–2023

2.2. Data Collection and Preprocessing

The proposed framework relies on multiple data streams (parcel boundaries, satellite observations, climate forcing, soil descriptors, and yield records). An overview of the sources and the main information of the data is provided in Table 2.

Table 2. Data sources, formats, temporal coverage, and preprocessing steps.

Component	Source/Repository	Resolution/Format	Period Used	Variables	Processing (Tools/Key Steps)
Parcel boundaries	Cadastral parcel geometries	Vector polygons (GIS)	Static	Parcel geometry, area (ha), tree counts	Centroids for soil extraction; parcel zonal statistics in GEE
Remote sensing	Sentinel-2 surface reflectance S2_SR_HARMONIZED (GEE)	10–20 m; 5-day revisit; raster	2017–2023	NDVI (B8, B4)	Cloud filter CLOUDY_PIXEL_PERCENTAGE < 30%; weekly maximum NDVI composite; parcel aggregation (GEE Python 3.12 API)
Climate forcing	SIAR (MAPA) via WebSIAR API	Station records; CSV/JSON	2017–2023	Weekly mean temperature; weekly cumulative precipitation	Weekly aggregation; GDD with $T_{base} = 5^{\circ}\text{C}$, $T_{ceil} = 35^{\circ}\text{C}$; cumulative sums (Python)
Soil context	SoilGrids 2.0 (ISRIC) via REST API	~250 m grid; JSON	Static	CEC, SOC, clay, sand, phh2o	Extract at centroids; thickness-weighted mean 0–100 cm; z-score standardization; median imputation
Yield/oil metrics	Mill records	Tabular (CSV/Excel)	2016–2024	Biomass (kg), oil yield (kg)	Normalize to kg/ha; select single-parcel growers for one-to-one linkage

2.2.1. Field Records: Production and Oil Metrics

Annual grower records provided the parcel identifier, tree numbers, cultivated area (ha), total production (kg grower^{-1}), and oil-related metrics reported by campaign year (year when the product was harvested). The total production was normalized by area to compute the production per hectare (ha):

$$\text{Prod}_{ha,y} = \frac{\text{Prod}_{grower,y}}{\text{Area}_{ha}}, \quad (1)$$

where y denotes the campaign year reported for the mill records.

2.2.2. Remote Sensing: Sentinel-2 NDVI Time Series

Vegetation dynamics were characterized using the normalized difference vegetation index (NDVI) derived from Sentinel-2 surface reflectance imagery, specifically the S2_SR_HARMONIZED collection, accessed through the Google Earth Engine (GEE) Python API. The NDVI was computed using the following standard formula with the near-infrared ($B8$) and red ($B4$) bands:

$$\text{NDVI} = \frac{B8 - B4}{B8 + B4}, \quad (2)$$

where $B8$ and $B4$ are the near-infrared and red bands, respectively.

Images were spatially filtered to each parcel geometry and screened using the Sentinel-2 metadata cloudiness indicator, retaining scenes with a CLOUDY_PIXEL_PERCENTAGE < 30% [21]. To reduce residual cloud/shadow contamination while preserving the peak parcel signal, the NDVI was composited at a weekly resolution by selecting the maximum NDVI value within each calendar week for each parcel. This produced a weekly NDVI time series on a common temporal grid suitable for integration with climate indicators. The dataset covers the period from 2017 to 2023, ensuring a multi-seasonal perspective and aligned with data provided by growers.

2.2.3. Climate: Thermal Time and Precipitation

Weather data were obtained from the Agroclimatic Information System for Irrigation (SIAR, Spanish Ministry of Agriculture; MAPA) via the WebSIAR API. Daily temperature and precipitation records were extracted and aggregated to weekly values to match the temporal support of the NDVI composites. The weekly mean temperature ($T_{\text{mean}}(t)$) was used to compute the growing degree days (GDD) using a linear formulation with a base temperature and an upper temperature ceiling. Specifically, temperatures were truncated as:

$$T^*(t) = \min(T_{\text{mean}}(t), T_{\text{ceil}}), \quad (3)$$

with $T_{\text{ceil}} = 35^\circ\text{C}$. Weekly GDD increments were then calculated relative to a base temperature of $T_{\text{base}} = 5^\circ\text{C}$, consistent with previous olive phenology studies [22]:

$$\text{GDD}_{\text{inc}}(t) = \max(0, T^*(t) - T_{\text{base}}), \quad (4)$$

and accumulated over time:

$$\text{GDD}_{\text{cum}}(t) = \sum_{\tau \leq t} \text{GDD}_{\text{inc}}(\tau), \quad (5)$$

where t indexes weeks.

In addition, precipitation was used to support the interpretation of the NDVI temporal dynamics and interannual variability. The daily precipitation was aggregated to weekly totals ($P_{\text{week}}(t)$) and aligned to the same weekly calendar used for the NDVI and GDD.

Due to all the parcels being located within the same local climatic domain, the resulting temperature and precipitation series were assumed to be representative of the entire parcel set; therefore, the climate forcing (temperature, precipitation, and derived GDD) was considered common to all parcels and soil clusters.

2.2.4. Soil Descriptors

Spatial soil variability was characterized using SoilGrids (ISRIC) properties extracted at parcel centroids through the SoilGrids REST API. SoilGrids values were retrieved for the standard depth intervals and aggregated to a single root-zone descriptor using a thickness-weighted mean over 0–100 cm, in order to represent the effective soil profile influencing water and nutrient availability for olive trees [23]:

- cec: cation exchange capacity (nutrient retention potential), in $\text{cmol}_c \text{ kg}^{-1}$;
- soc: soil organic carbon (organic matter proxy), in g kg^{-1} ;
- clay and sand: particle-size fractions (water-holding capacity, drainage, and nutrient dynamics), in g kg^{-1} ;
- phh2o: soil pH in water (nutrient availability), unitless (pH scale).

These variables defined the feature space for the soil-based cluster analysis.

2.3. Unsupervised Machine Learning Model

Parcels were classified into edaphic groups using K-means clustering on the standardized soil feature space. Missing soil values were imputed using the median of each variable, and all features were z-score-standardized prior to clustering. The number of clusters (k) was explored over a range (e.g., $k = 2\text{--}6$) using the within-cluster dispersion and silhouette-based separation. Cluster labels were used for stratified analyses and for the construction of cluster-specific NDVI–GDD accumulation trajectories.

2.4. Phenological Window Definition

Two temporal definitions were used, reflecting different goals: (i) the phenological interpretation of the NDVI–GDD coupling and (ii) predictor construction.

Phenological windows for NDVI–GDD interpretation.

To examine how parcel development aligns with olive phenology, NDVI–GDD accumulation curves were analyzed and trajectories were computed from $\text{Mar}(y)$ to $\text{Feb}(y + 1)$.

Accumulation window for predictor construction.

All thermal-time and NDVI predictors were computed within a fixed extended window designed to capture carry-over effects from the preceding season while remaining consistent with the period most relevant to yield formation. For each harvest campaign year y , the accumulation window was defined as:

$$\text{Window}_{\text{pred}}(y) = \text{Mar}(y) \rightarrow \text{Feb}(y + 1), \quad (6)$$

where Mar and Feb denote March and February, respectively. To assess the robustness, we explored alternative accumulation windows (e.g., March–October, January–December and April–February variants) and found that the main qualitative relationships and cluster-level patterns were preserved. We therefore retained the March–February phenological-year window as the primary definition because it is biologically grounded both in olive phenology and in management, providing a consistent reference across campaigns. This window integrates (i) a preconditioning phase in year (y) and (ii) the main parcel-development period in year y leading to harvest, consistent with the multi-season reproductive cycle of olives [6].

NDVI–GDD Predictors

To link the parcel dynamics with thermal forcing in an interpretable and phenology-aware way, we expressed parcel development using the cumulative NDVI (NDVI_{cum}) as a function of the cumulative growing degree days (GDD_{cum}) within each campaign window (Section 2.4).

Notably, thermal-time approaches based on growing degree days have been widely used to characterize olive thermal requirements and to map spatiotemporal suitability patterns at the regional scale [24].

2.5. Statistical Analysis

To verify that the soil-based clusters represented statistically distinct edaphic groups, we tested for differences among the clusters in each SoilGrids descriptor (*cec*, *clay*, *sand*, *phh2o*, *soc*) using a one-way analysis of variance (ANOVA). Prior to the one-way ANOVA, residual normality and homogeneity of variances across clusters were assessed (Shapiro–Wilk and Levene tests, respectively); when the assumptions were deemed acceptable, post hoc pairwise differences were evaluated using Tukey’s HSD ($\alpha = 0.05$). When the omnibus ANOVA was significant, pairwise comparisons were assessed with Tukey’s honestly significant difference (HSD) test, controlling the family-wise error rate (FWER) at $\alpha = 0.05$. All statistical tests were two-sided.

To assess whether soil clusters modify the NDVI–yield relationship, we fitted ANCOVA models, including an interaction between a thermal-time-based NDVI accumulation indicator and soil cluster, for both biomass and oil yield. The interaction term tested for slope differences among the clusters, whereas the cluster main effect captured baseline yield shifts. Pairwise post hoc contrasts were Holm-corrected ($\alpha = 0.05$).

All the predictors and outcomes were computed at the parcel–year level and, when required for visualization, summarized as cluster-by-year statistics. Associations between predictors and outcomes were quantified using the Pearson and Spearman correlations, complemented by linear regression fits for visualization and an effect-direction assessment.

3. Results

3.1. Soil-Based Clustering

The unsupervised soil-based clustering (K-means, $k = 3$) classified the 1141 olive parcels into three edaphic groups with clearly differentiated distributions across the selected root-zone soil descriptors (0–100 cm aggregation): the cation exchange capacity (cec), texture fractions (clay, sand), soil organic carbon (soc) and pH in water (phh2o) (Figure 3). Overall, the three clusters represent contrasting soil functioning contexts that are expected to modulate water availability and nutrient retention, and therefore, the olive’s response to climatic conditions.

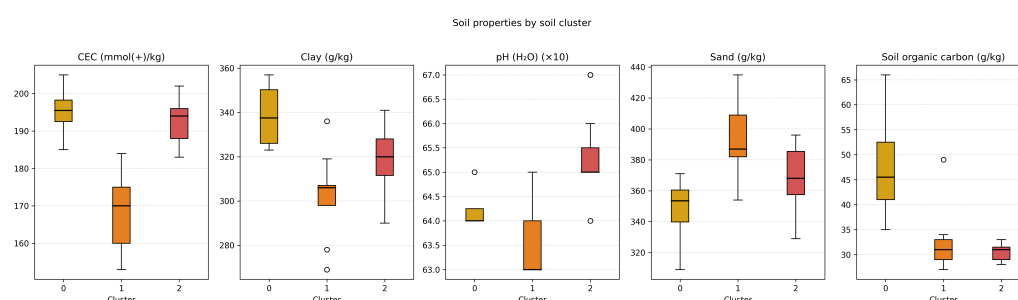


Figure 3. Distribution of SoilGrids-derived soil properties across the three edaphic clusters (K-means, $k = 3$, $n = 1141$). Colors denote clusters. Boxplots show median, interquartile range, whiskers ($1.5 \times \text{IQR}$), and outliers (circles) for CEC, clay, phh2o, sand, and SOC.

To verify that the soil clusters represent statistically distinct edaphic groups, we tested the differences in each soil descriptor using a one-way ANOVA followed by Tukey’s HSD post hoc comparison ($\alpha = 0.05$). All five descriptors differed significantly among the clusters (CEC, clay, sand, $\text{pH}_{\text{H}_2\text{O}}$ and SOC; $p \ll 0.001$ for all variables), and Tukey’s test indicated significant pairwise differences between all cluster pairs for each descriptor (Table 3).

Table 3. One-way ANOVA results for SoilGrids descriptors across soil clusters. Tukey’s HSD ($\alpha = 0.05$) indicated significant differences for all pairwise comparisons in all variables.

Variable	ANOVA p
cec	1.115×10^{-22}
clay	4.071×10^{-165}
sand	7.408×10^{-174}
phh2o	3.080×10^{-75}
soc	7.389×10^{-217}

This soil-based clustering assigned the 1141 parcels to three edaphic groups, with $n = 365$ parcels in Cluster 0, $n = 286$ in Cluster 1, and $n = 490$ in Cluster 2.

Edaphic Profile of Each Cluster

Cluster 0 was characterized by the highest clay content together with a high cec, and it also showed a markedly higher soc than the other clusters. In parallel, Cluster 0 exhibited the lowest sand fraction, which is consistent with finer-textured soils with a greater water-holding capacity and nutrient buffering potential.

Cluster 1 showed the lowest cec and clay levels and the highest sand fraction, indicating coarser-textured soils with a reduced nutrient retention capacity and potentially lower plant-available water. Cluster 1 also tended to present the lowest (phh2o) among the three groups.

Cluster 2 represented an intermediate textural condition, with clay and sand distributions between those of Clusters 0 and 1 and a relatively high cec. Notably, Cluster 2 displayed the highest phh2o values, suggesting a comparatively more alkaline soil environment, while the soc remained low and tightly distributed, similar to Cluster 1.

Based on these patterns, the three clusters can be interpreted as: (i) a fine-textured, high-buffering and organic-matter-enriched group (Cluster 0), (ii) a coarse-textured, low-buffering group (Cluster 1), and (iii) an intermediate group with a comparatively higher pH (Cluster 2).

3.2. Olive Biomass and Oil Yield Across Soil Clusters

After defining the three edaphic clusters, we evaluated whether soil grouping was associated with differences in olive grove performance, using the olive biomass yield and olive oil yield per hectare as the outcome metrics. Due to production records being reported at the grower level, we restricted yield-based analyses to single-parcel growers (i.e., growers associated with one unique parcel in the dataset), ensuring a one-to-one linkage between the production outcomes and the corresponding grove. This filtering yielded $n = 7$ groves in Cluster 0, $n = 7$ in Cluster 1, and $n = 10$ in Cluster 2 for the yield comparisons and subsequent modelling steps.

3.2.1. Overall Comparison Across Clusters

When pooling all available years, the distributions of both the biomass yield and oil yield largely overlapped across the three soil clusters (Figure 4), with comparable medians. This aggregated view suggests that any soil-related signal is not expressed as a consistent shift in productivity across clusters when the interannual variability is ignored.

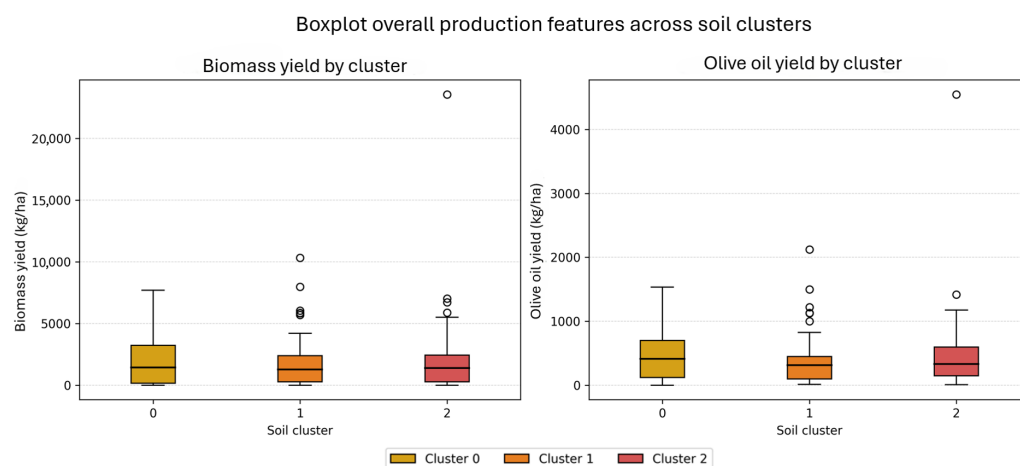


Figure 4. Distribution of olive biomass yield and olive oil yield per hectare (kg/ha) across soil clusters. Boxplots represent median, interquartile range, whiskers ($1.5 \times \text{IQR}$), and outliers (circles) by soil cluster.

3.2.2. Interannual Patterns Reveal Cluster-Dependent Differences

Given the strong year-to-year variability typical of Mediterranean olive systems, we subsequently examined the biomass and oil yield by production year.

Year-stratified boxplots revealed a strong interannual signal in both biomass yield and oil yield (Figures 5 and 6), with depressed distributions in low-production seasons (notably

2020 and 2023) and markedly higher medians and upper tails in productive years (e.g., 2017, 2019 and 2022). Beyond this dominant year effect, cluster-dependent differences emerged within specific campaigns. In several high-yield years, Cluster 2 tended to show higher medians and a wider dispersion (upper-tail values) than Clusters 0 and 1, suggesting that the coarser, lower-buffering soil group can exhibit a more heterogeneous, but occasionally higher-productivity, response. In contrast, differences among clusters were less evident during low-yield years.

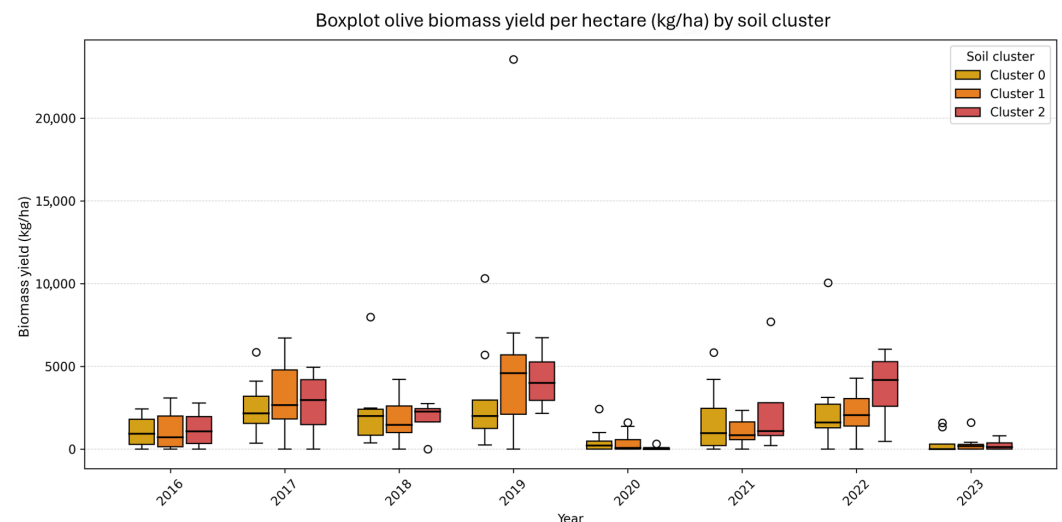


Figure 5. Annual distribution of olive biomass yield per hectare (kg/ha) by soil cluster. Boxplots show median, interquartile range, whiskers ($1.5 \times \text{IQR}$), and outliers (circles)

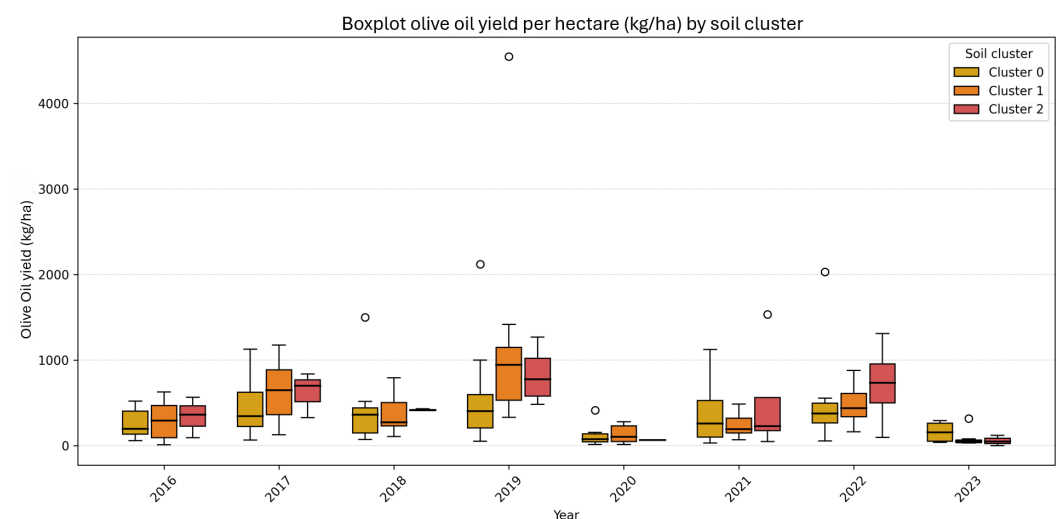


Figure 6. Annual distribution of olive oil yield per hectare (kg/ha) by soil cluster.

3.3. NDVI Temporal Dynamics by Soil Cluster: Links with Precipitation and Temperature

Building on the soil-based stratification, we examined whether the three edaphic groups exhibited differentiated canopy greenness dynamics through time and how these dynamics relate to seasonal hydro-climatic variability. Figures 7 and 8 summarize the weekly NDVI trajectories for 2017–2023 by soil cluster (median and interquartile range, IQR), overlaid with weekly precipitation totals and the weekly mean air temperature, respectively.

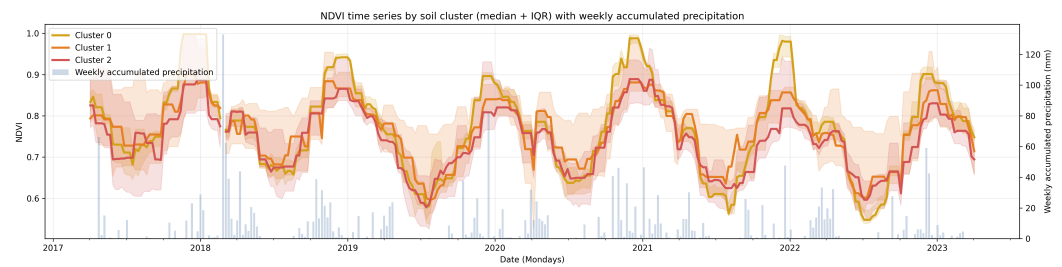


Figure 7. Weekly NDVI time series by soil cluster (median line) with the interquartile range (IQR; shaded band), together with weekly accumulated precipitation (bars) for 2017–2023.

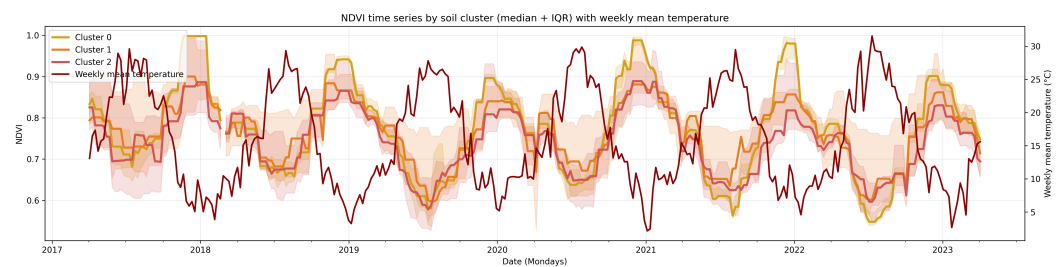


Figure 8. Weekly NDVI time series by soil cluster (median line) with the interquartile range (IQR; shaded band), together with weekly mean temperature (red line) for 2017–2023.

Across the study period, the three clusters shared a coherent seasonal NDVI cycle, but maintained persistent differences in both the NDVI level and dispersion. Cluster 1 generally exhibited higher median NDVI values over large portions of the annual cycle, while Cluster 2 tended to show lower medians, particularly during parts of the summer–early autumn period. Cluster 0 often displayed intermediate medians but, in several seasons, broader IQR bands, indicating higher within-cluster heterogeneity in canopy greenness. The persistence of these contrasts across multiple years suggests that the soil-based grouping captures stable differences in vegetation behaviour.

3.3.1. NDVI and Precipitation

Precipitation provided a clear context for the timing of NDVI recoveries and declines (Figure 7). An NDVI time series increase and rebound after low-NDVI phases frequently coincided with the onset of wetter periods, whereas prolonged intervals with low rainfall were associated with gradual NDVI declines and delayed recovery. Importantly, the amplitude and speed of these responses were not identical among clusters: in dry stretches, some clusters exhibited stronger reductions and wider dispersion, consistent with a different soil-mediated buffering capacity against water limitation.

3.3.2. NDVI and Temperature

The weekly mean temperature introduced an additional seasonal forcing (Figure 8). Higher temperatures typically coincided with the descending limb of the NDVI cycle and with periods of reduced NDVI stability, particularly when warm conditions overlapped with low precipitation (Figure 7). Conversely, cooler periods were associated with more stable NDVI trajectories and, when accompanied by rainfall, with stronger NDVI recovery. Together, these patterns support a coupled hydro-thermal control of canopy greenness, modulated by the soil context.

3.4. Thermal-Time Scaling of Parcel Dynamics: NDVI Accumulation Versus GDD

Although calendar-date NDVI trajectories are informative, the production results showed strong interannual variability and year-dependent contrasts among the soil clusters. Because phenological development is primarily driven by thermal accumulation,

comparing NDVI dynamics between campaigns using calendar time alone can be misleading when years differ in the rate of heat progression. Therefore, we reframed canopy development in thermal time by relating the cumulative NDVI (weekly NDVI accumulated over time) to the cumulative growing degree days (GDD; $T_{\text{base}} = 5^{\circ}\text{C}$). This representation enables consistent cross-year comparisons on a common phenological scale and supports the derivation of transferable indicators.

Cluster-Specific NDVI–GDD Accumulation Trajectories

Figure 9 summarizes the cumulative NDVI as a function of the cumulative GDD for each soil cluster across phenological years (March of year $y - 1$ to February of year y). In all clusters, the curves follow a monotonic and non-linear trajectory, indicating a coherent coupling between canopy greenness accumulation and thermal accumulation. Interannual variability is expressed as year-specific deviations around the mean curve (black line), implying that, for similar thermal forcing, the cumulative NDVI may still progress at different rates depending on the concurrent water availability and other environmental or management factors.

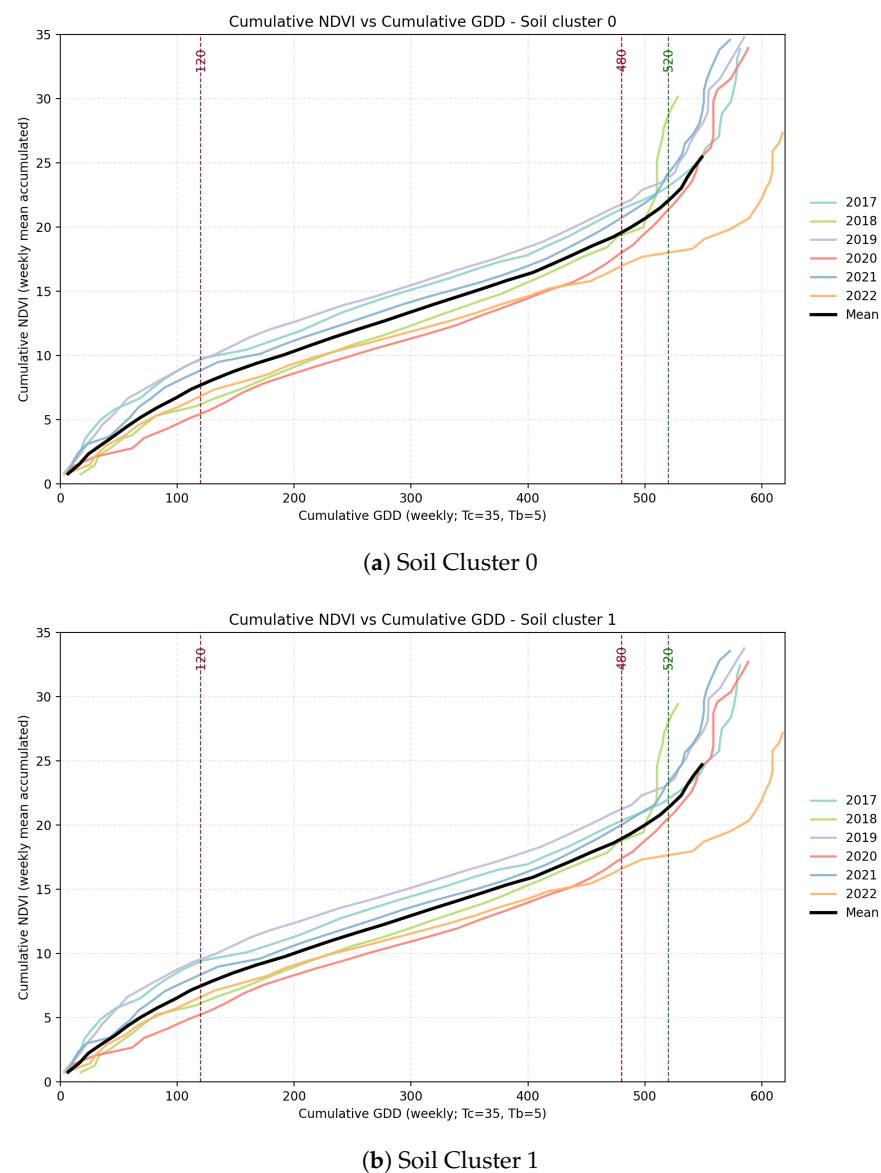


Figure 9. Cont.

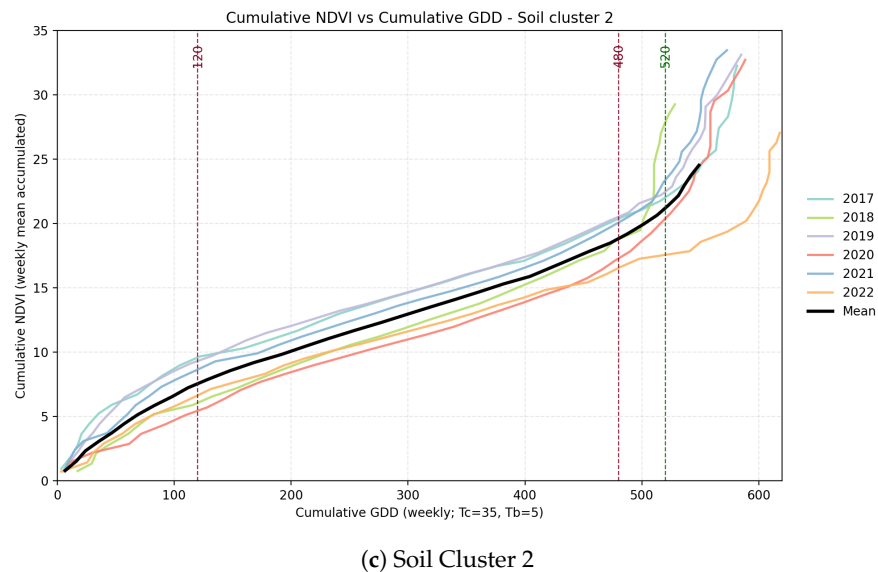


Figure 9. Cluster-specific thermal-time scaling of canopy development. Cumulative NDVI versus cumulative GDD across phenological years (March–February). Colored lines denote individual years and black line denotes mean trajectory. Vertical dashed lines indicate thermal milestones at 120, 480 and 520 GDD.

A consistent feature across clusters is the presence of slope changes along the thermal axis. From a mechanistic perspective, the local slope $d(\text{NDVI}_{\text{cum}})/d(\text{GDD}_{\text{cum}})$ provides an interpretable proxy for the canopy greenness accumulation rate per heat unit. Accordingly, three reference thermal milestones (120, 480 and 520 GDD; vertical dashed lines) were used to mark transitions in the mean trajectory and to define threshold-based indicators in the subsequent analyses. These milestones help quantify differences that are not always obvious by visual inspection of the full curves and provide a standardized basis to compare campaigns and soil clusters in a phenologically meaningful manner.

3.5. Ndzi Accumulation at 520 GDD as a Yield-Related Indicator

Motivated by the divergence of NDVI–GDD trajectories beyond ~ 520 GDD, we used the accumulated NDVI up to this thermal milestone ($\text{NDVI}_{\text{cum},520}$) as a standardized predictor to relate canopy development to production outcomes. The analysis was conducted on the subset of single-parcel growers to ensure a one-to-one link between parcel-level predictors and the reported yield.

3.5.1. Relationship with Olive Biomass Yield

Across clusters, the $\text{NDVI}_{\text{cum},520}$ showed a consistent negative association with the olive biomass yield (kg/ha) (Figure 10). Linear fits yielded similar slopes across soil groups, ranging from -255.03 to $-351.67 \text{ kg ha}^{-1}$ per unit increase in the $\text{NDVI}_{\text{cum},520}$, with an explained variance R^2 between 0.721 and 0.786. This indicates that the thermal-time normalized canopy accumulation at 520 GDD captures a substantial fraction of the interannual variability in the biomass yield within each soil cluster.

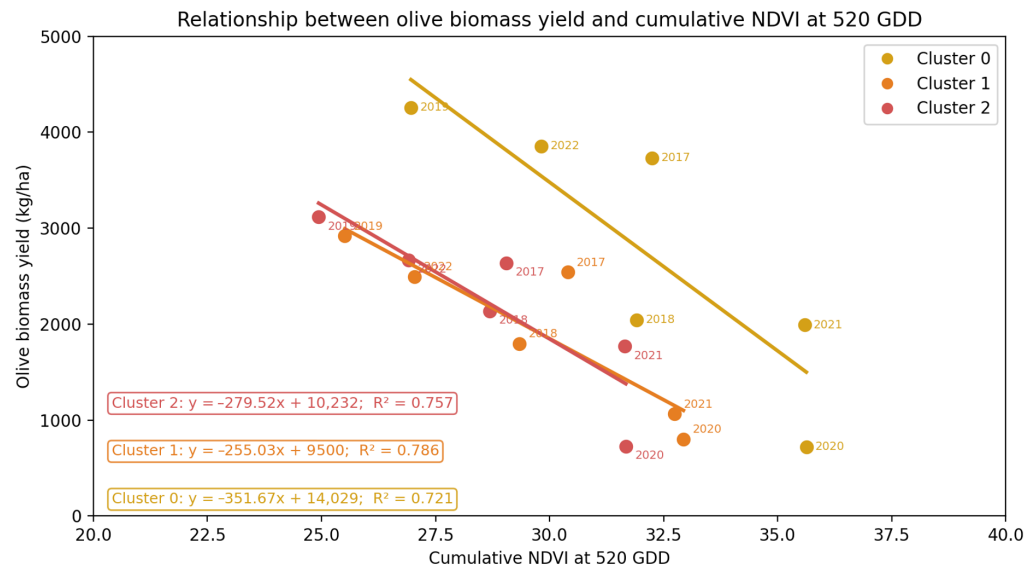


Figure 10. Relationship between olive biomass yield (kg/ha) and cumulative NDVI at 520 GDD ($NDVI_{cum,520}$) by soil cluster. Points correspond to annual cluster-level values; colored lines show cluster-specific linear fits; and annotations report fitted equations and R^2 .

3.5.2. Relationship with Olive Oil Yield

A comparable pattern was observed for olive oil yield (kg/ha), with the $NDVI_{cum,520}$ again displaying a negative relationship across clusters (Figure 11). The consistency of the direction of the association across soil contexts supports the use of the $NDVI_{cum,520}$ as a transferable indicator linking thermal-time-scaled canopy dynamics with economically relevant yield metrics.

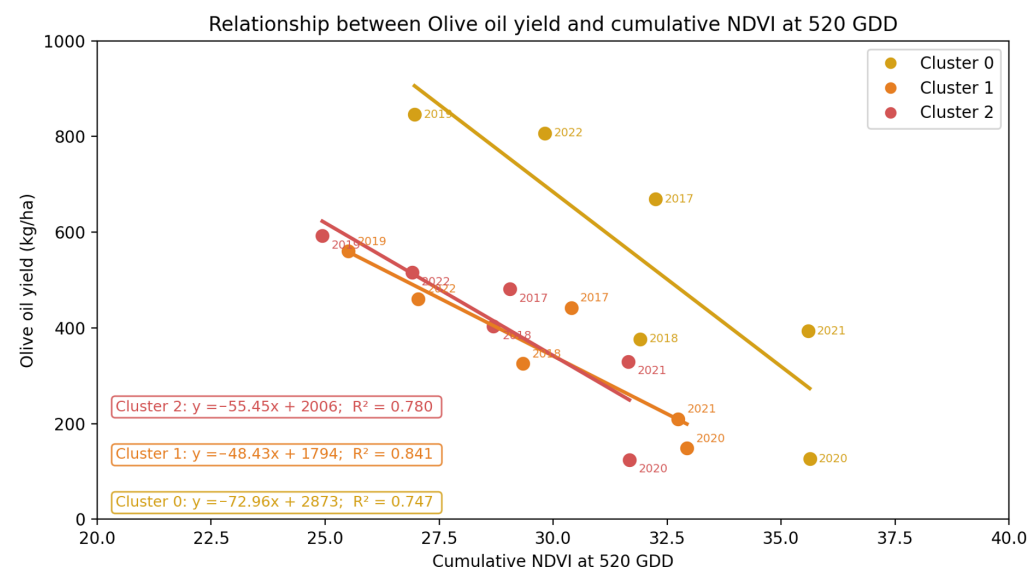


Figure 11. Relationship between olive oil yield (kg/ha) and cumulative NDVI at 520 GDD ($NDVI_{cum,520}$) by soil cluster. Points correspond to annual cluster-level values; colored lines show cluster-specific linear fits.

All clusters showed a consistent negative association between the $NDVI_{cum,520}$ and yield. The slope heterogeneity, shown by the ANCOVA, was not detected (interaction: oil $p = 0.544$; biomass $p = 0.710$), and pairwise tests confirmed no significant slope differences. In contrast, the baseline yield differed by soil cluster ($p < 0.01$); Cluster 0 presented higher baseline oil and biomass yields than Clusters 1 and 2 (Holm-adjusted $p < 0.005$).

3.6. Precipitation Accumulation from 110 to 520 GDD as a Yield-Related Indicator

To complement the NDVI–GDD indicators, we evaluated whether water availability during a key thermal window was associated with the yield outcomes. Specifically, we computed the cumulative precipitation during the 120–480 GDD interval in year t and related it to the olive biomass yield and olive oil yield in the subsequent campaign ($t + 1$).

3.6.1. Biomass Yield Response to Rainfall (120–480 GDD)

The biomass yield in year $t + 1$ increased with rainfall accumulated between 120 and 480 GDD in year t , showing a non-linear response across soil clusters (Figure 12). Cluster-specific quadratic models explained a large fraction of the interannual variability ($R^2 = 0.83$ for Clusters 1 and 2, and $R^2 = 0.96$ for Cluster 0). The fitted curves suggest diminishing marginal gains at higher rainfall totals, with Cluster 0 reaching the highest biomass levels under wetter conditions and Clusters 1–2 showing lower asymptotes.

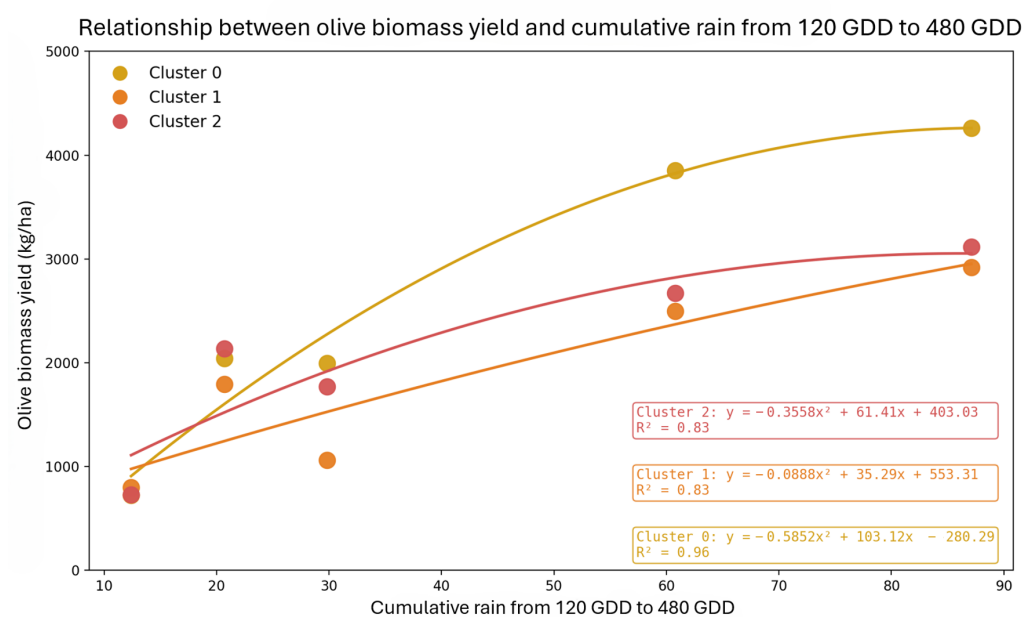


Figure 12. Relationship between olive biomass yield in year $t + 1$ (kg/ha) and rainfall accumulated during the 120–480 GDD window in year t (mm), shown by soil cluster. Curves represent cluster-specific quadratic fits; annotations report fitted equations and R^2 .

3.6.2. Oil Yield Response to Rainfall (120–480 GDD)

The olive oil yield in year $t + 1$ exhibited a similarly positive and concave relationship with rainfall in the 120–480 GDD window (Figure 13). The model fits were consistently high across clusters ($R^2 = 0.83$ – 0.87 for Clusters 1–2 and $R^2 = 0.97$ for Cluster 0). As for biomass, the response indicated diminishing returns at higher rainfall, and Cluster 0 attained higher oil yields under wet conditions compared with the other clusters, consistent with a stronger water-mediated productivity potential in this soil group.

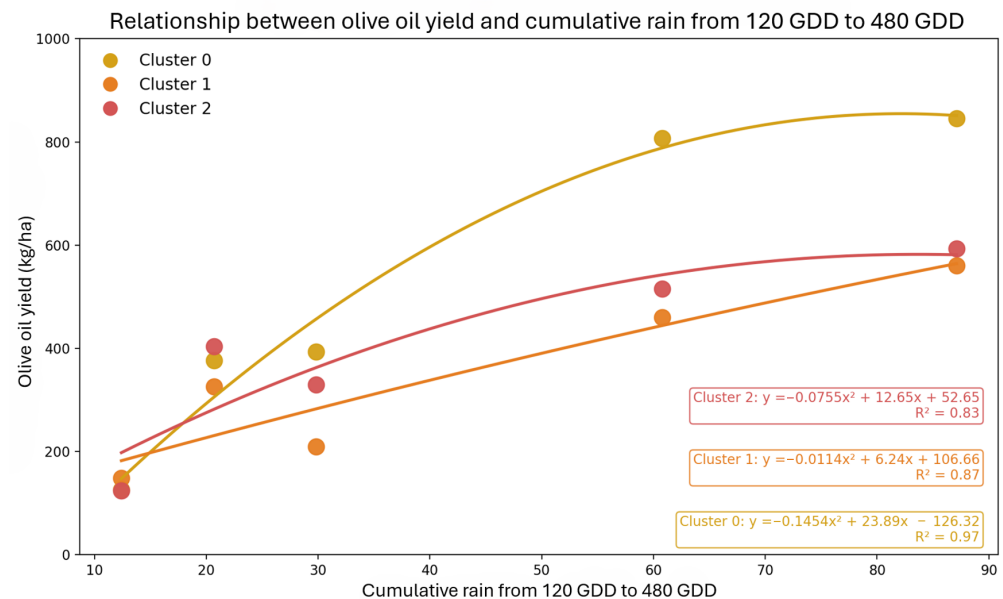


Figure 13. Relationship between olive oil yield in year $t + 1$ (kg/ha) and rainfall accumulated during the 120–480 GDD window in year t (mm), shown by soil cluster. Curves represent cluster-specific quadratic fits; annotations report fitted equations and R^2 .

4. Discussion

4.1. Soil as a Context-Dependent Regulator of Hydro-Thermal Response

The soil-based clustering revealed persistent differences in the NDVI dynamics (Figures 5–7), despite largely overlapping pooled yield distributions (Figure 2). This indicates that soil properties do not impose a fixed productivity ranking, but rather modulate how olive groves respond to interannual climatic variability.

Cluster 0, defined by a finer texture (higher clay), a higher cec and a clearly higher soc (Figure 3), showed generally higher NDVI medians across seasons. This pattern is consistent with a greater buffering capacity against short-term water stress, as fine-textured soils and a higher organic matter content increase plant-available water and improve nutrient retention in Mediterranean olive groves [18,23]. Process-based ecohydrological modelling has further demonstrated that olive yield variability is strongly controlled by soil moisture dynamics rather than precipitation totals alone [18].

In contrast, Cluster 1 (coarser, sandier soils with a lower cec and lower soc) exhibited lower NDVI medians during dry phases and, in some campaigns, a wider dispersion, pointing to a higher climatic sensitivity. Such patterns align with theoretical expectations: coarse soils may respond rapidly to rainfall inputs, but experience stronger and more rapid depletion of plant-available water under prolonged drought. Such conditional soil effects are consistent with projections of increasing hydro-climatic variability in Mediterranean regions [1].

Cluster 2, with an intermediate texture and a comparatively higher pH (phh2o), generally showed NDVI medians that were comparable to or lower than those of the other clusters, depending on the campaign (Figures 5–7). This indicates that the pH-related edaphic context may shape vegetation dynamics in ways that are not expressed simply as higher canopy greenness, and that additional factors (e.g., nutrient constraints, management, or local water redistribution) may contribute to the observed trajectories.

Importantly, the emergence of clearer soil-dependent yield differences in specific years (Figures 3 and 4) supports the interpretation that edaphic effects become more evident under climatic extremes rather than under average conditions.

4.2. Thermal-Time Normalization Improves Phenological Coherence

Expressing canopy development in thermal time (NDVI_{cum} versus GDD_{cum}; Figure 7) provides a phenologically meaningful framework that reduces distortions caused by early or delayed warming seasons. Olive development is strongly regulated by chilling and heat accumulation [2,5], and calendar-based comparisons may obscure the stage alignment between years [24]. This emphasis on thermal-time alignment is consistent with recent evidence showing that temperature is a primary driver of olive oil accumulation patterns and is expected to shift the timing and magnitude of oil content under warming scenarios [3].

The identification of slope transitions around 120, 480 and 520 GDD suggests that canopy accumulation per unit heat changes across phenological phases. The local derivative $d(\text{NDVI}_{\text{cum}})/d(\text{GDD}_{\text{cum}})$ can be interpreted as a proxy for the canopy expansion efficiency per thermal unit. Similar heat-normalized RS–climate integration approaches have improved phenological predictions and transferability in Mediterranean systems [12], providing robust thermal scaling indicators such as the NDVI_{cum,520}.

4.3. Early Canopy Accumulation (NDVI_{cum,520}) and Yield Trade-Offs

A consistent negative relationship was observed between the NDVI accumulated up to 520 GDD and both the biomass and oil yield (Figures 8 and 9). Although the NDVI is frequently positively associated with productivity in annual crops, perennial woody systems such as olives exhibit more complex source–sink dynamics. Several physiological mechanisms may explain this inverse relationship: (i) Vegetative–reproductive competition: Early vigorous vegetative growth can compete with reproductive organ development for assimilates and water, particularly under Mediterranean water limitations. Olive trees are known to exhibit strong allocation trade-offs that influence fruit set and alternate bearing patterns [6,25]. (ii) Phenological asynchrony under early warmth: Rapid canopy expansion under early heat accumulation may not coincide with adequate soil moisture reserves, predisposing trees to stress during the flowering and fruit set stages, which are highly sensitive to water deficits [26,27]. (iii) Carry-over effects and compensatory growth: High early NDVI accumulation may reflect vegetative compensation following a low-yield year, consistent with biennial tendencies reported in olive systems [28].

The stability of slopes across soil clusters (e.g., $R^2 \approx 0.72\text{--}0.79$ for biomass) supports the interpretation that the negative NDVI_{cum,520}–yield association reflects a general physiological mechanism like vegetative–reproductive competition and carry-over effects.

At the same time, significant intercept differences among the clusters indicate that soils modulate the overall yield level for a given early-season canopy status [18]. In practice, this means that soils influence the capacity to convert similar canopy development into harvestable output, consistent with differences in the buffering capacity against hydro-climatic stress [29] (plant-available water, effective rooting depth, and nutrient retention). This consistency across edaphic contexts suggests that thermal-time normalized canopy accumulation may serve as a transferable early indicator.

4.4. Rainfall Between 120 and 480 GDD as a Strong Predictor of Next-Year Yield

A major contribution of this revised analysis is the strong positive and concave relationship between rainfall accumulated during the 120–480 GDD window in year t and yield in year $t + 1$ (Figures 10 and 11). This thermally defined window likely overlaps with critical developmental processes, including (i) flower induction and differentiation, (ii) early reproductive organ development, and (iii) accumulation of carbohydrate reserves to support the subsequent campaign. Olive reproductive development spans multiple seasons, and water availability during specific pre-flowering stages can strongly influence the subsequent fruit set and yield potential [5,6]. The high explanatory power observed

($R^2 = 0.83\text{--}0.97$) indicates that hydro-thermal conditions during this phenologically anchored window capture a substantial fraction of the interannual variability in both the biomass and oil yield.

The concave (quadratic) shape of the response suggests diminishing marginal returns of rainfall, consistent with ecohydrological theory: once soil moisture approaches physiological sufficiency, additional rainfall does not proportionally increase productivity [18]. Such saturation behaviour reflects the nonlinear relationship between soil water availability and plant physiological performance. This is particularly evident in Cluster 0, which reached higher asymptotic yield levels under wetter conditions, possibly reflecting a favorable balance between drainage and retention capacity that allows for efficient water use without prolonged wateloggging [30] or excessive evaporative losses.

Importantly, this non-linear response is also consistent with physiological evidence demonstrating that water deficits modify assimilate partitioning, alter the vegetative–reproductive balance, and influence subsequent yield formation through carry-over effects [25,31]. Under deficit conditions, reductions in photosynthetic activity and altered carbon allocation may constrain the accumulation of reserves necessary for the following season, thereby affecting year $t + 1$ productivity.

Therefore, rainfall accumulated during the 120–480 GDD window in year t may not only alleviate short-term stress, but also determine the reserve dynamics and reproductive potential for the subsequent campaign, providing a mechanistic explanation for the strong lagged relationships observed in Figures 10 and 11. The fact that this rainfall–yield relationship operates with a one-year lag further reinforces the importance of climatic carry-over effects in perennial systems. Similar lagged climate–yield relationships have been reported in Mediterranean woody crops and regional modelling studies integrating remote sensing and environmental drivers [13], highlighting the multi-seasonal nature of yield determination in olive agroecosystems.

4.5. Integrating Hydro-Thermal Indicators for Smart Farming

The combined evidence indicates that olive yield variability emerges from the dynamic interaction among the soil buffering capacity, thermal progression, and water availability during phenologically critical GDD windows, with carry-over effects between consecutive campaigns. Rather than acting independently, these drivers operate as an interconnected hydro-thermal–edaphic system: the soil modulates water storage, thermal accumulation structures the phenological timing, and rainfall availability during key developmental phases influences both the immediate physiological performance and the subsequent reproductive potential.

By anchoring both NDVI accumulation and precipitation to clearly defined thermal milestones, the proposed framework avoids reliance on arbitrary calendar-based windows and instead adopts physiologically grounded thresholds aligned with olive developmental dynamics. This thermally normalized approach enhances cross-year comparability, improves mechanistic interpretability, and strengthens the scalability of yield-related indicators across heterogeneous olive grove conditions.

While recent studies have advanced drought monitoring in Iberian olive orchards using satellite vegetation indices and drought indicators, relatively few have integrated the soil context and thermal-time normalization to derive interpretable, transferable, yield-oriented indicators at the parcel scale [32]. The operational integration of SoilGrids root-zone descriptors [19], Sentinel-2 NDVI time series [7,21], and agroclimatic GDD metrics creates a reproducible and transferable decision-support structure that does not depend on dense in situ instrumentation.

In the context of projected increases in drought frequency and heat extremes across Mediterranean regions [1], and recent evidence of temperature- and drought-driven impacts on olive functioning [3,32], such hydro-thermal scaling approaches may become increasingly essential for early-season yield outlooks, cooperative-level production planning, and adaptive olive grove management strategies under climate uncertainty.

5. Conclusions

This study presents an integrated smart farming framework that combines soil descriptors, thermal-time metrics, satellite-derived canopy dynamics, and precipitation accumulation within phenologically defined windows to improve the interpretability of olive yield variability under Mediterranean conditions.

The results demonstrate that soil properties act as context-dependent modulators of hydro-thermal responses rather than as fixed productivity determinants. When the yield data were aggregated across years, soil clusters showed overlapping distributions; however, under specific climatic regimes, edaphic differences became more evident, highlighting the conditional nature of soil effects in perennial systems.

Thermal-time normalization proved essential for aligning canopy development across campaigns. Expressing the NDVI accumulation as a function of the GDD enabled the identification of phenologically meaningful thresholds and the construction of transferable indicators. In particular, the cumulative NDVI at 520 GDD showed a consistent negative relationship with both the biomass and oil yield, suggesting that early vegetative accumulation may reflect vegetative–reproductive trade-offs and carry-over dynamics inherent to olive physiology.

A key finding is the strong positive and concave relationship between rainfall accumulated during the 120–480 GDD window in year t and the yield in year $t + 1$. This thermally anchored precipitation metric captured a substantial fraction of the interannual variability, supporting the hypothesis that water availability during critical developmental phases influences the reserve accumulation and subsequent reproductive potential. The observed one-year lag reinforces the importance of multi-seasonal carry-over effects in perennial crops.

Methodologically, anchoring both vegetation and precipitation metrics to thermal milestones avoids arbitrary calendar-based windows and enhances physiological coherence, cross-year comparability, and scalability. The integration of SoilGrids root-zone information, Sentinel-2 NDVI time series, and agroclimatic GDD indicators provides a reproducible and transferable decision-support framework that can be implemented without intensive field instrumentation.

Under projected increases in the drought frequency and heat extremes in Mediterranean regions, hydro-thermal scaling approaches such as the one proposed here may become increasingly important for early yield forecasting, cooperative-level production planning, and adaptive olive grove management aimed at strengthening the resilience to climate variability.

Author Contributions: Conceptualization, R.G.-C., A.M.T. and J.B.; methodology, A.M.T.; validation, A.M.T., R.G.-C. and J.B.; formal analysis, R.G.-C.; investigation, R.G.-C. and A.M.T.; resources, J.B.; data curation, R.G.-C.; writing—original draft preparation, R.G.-C. and A.M.T.; writing—review and editing, R.G.-C., A.M.T. and J.B.; visualization, R.G.-C.; supervision, A.M.T.; funding acquisition, J.B. All authors have read and agreed to the published version of the manuscript.

Funding: The authors acknowledge the support from Project No. DIN2021-011913 and PID2021-122711NB-C21 of the Spanish Ministry of Science and Innovation.

Data Availability Statement: The dataset supporting the results of this study is openly available in the Zenodo repository at <https://doi.org/10.5281/zenodo.18891490>.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ANCOVA	Analysis of covariance
ANOVA	Analysis of variance
CEC	Cation exchange capacity
FWER	Family-wise error rate
GDD	Growing degree days
GEE	Google Earth Engine
GDD _{cum}	Cumulative growing degree days
GDD _{inc}	Weekly growing degree day increment
HSD	Honestly significant difference
IQR	Interquartile range
ISRIC	International Soil Reference and Information Centre
MAPA	Spanish Ministry of Agriculture, Fisheries and Food
NDVI	Normalized difference vegetation index
NDVI _{cum}	Cumulative NDVI
NDVI _{cum,520}	Cumulative NDVI at 520 GDD
pH _{H2O}	Soil pH in water
RS	Remote sensing
SIAR	Agroclimatic Information System for Irrigation (Spain)
SOC	Soil organic carbon

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