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Validation of SWAT+ Hydrological Model Using Remote Sensing-Based Evapotranspiration Data

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Abstract. This study evaluates the performance of the SWAT+ (Soil and Water Assessment Tool Plus) model in simulating evapotranspiration (ET) in the Tordera River Basin (Catalonia, Spain), a Mediterranean catchment with semi-arid conditions and complex topography, where accurate ET estimation is essential for sustainable water management.

Model simulations (2003–2022) were validated against satellite-derived ET from the MODIS (Moderate Resolution Imaging Spectroradiometer) MOD16A2GF product, providing spatially distributed long-term reference data. Data processing, visualization, and statistical analyses were conducted using GIS and remote sensing tools (MiraMon) and R programming.

MODIS-derived ET showed significant spatial and seasonal variability, revealing discrepancies with SWAT+ simulations and supporting improved validation protocols within the AquaINFRA project.

Submission Type. Analysis

BoK Concepts. [GC2] Spatial simulation modelling; [IP] Image processing and analysis; [DM] Data modelling and management.

Keywords. SWAT+, GIS, evapotranspiration, remote sensing, hydrological modeling, Tordera River Basin, MODIS

1 Introduction

Evapotranspiration (ET) is a key component of the hydrological cycle and water balance, especially in semi-arid and complex terrains. Its accurate estimation is essential for water resource management, yet ground measurements are often limited by sparse coverage and high costs.

In SWAT+ (https://swat.tamu.edu/), ET is simulated as part of water flux modeling, with vegetation playing a central role. Vegetation dynamics are represented using simplified formulations of Leaf Area Index (LAI) based on thermal units and photoperiod (Parajuli, P. B., Jayakody, P., & Ouyang, Y., 2018).

Recent advances in remote sensing provide spatially distributed ET datasets that support the calibration and validation of hydrological models such as SWAT+ (Parajuli et al., 2022). For instance, Abiodun et al. (2018) compared MODIS- and SWAT-derived ET across complex terrain at multiple spatial scales. These approaches enable improved representation of spatial heterogeneity and temporal variability in evapotranspiration estimation under diverse climatic conditions.

This study evaluates SWAT+ performance in simulating ET in the Tordera River Basin, a Mediterranean watershed with heterogeneous topography and land use, by comparison with satellite-derived ET from the MOD16A2GF product using GIS-based analysis and statistical metrics.

This study contributes by (i) implementing an HRU-level ET validation framework for spatially explicit assessment across land-cover classes, (ii) introducing a structured soft-calibration workflow integrating MOD16A2GF data with sensitivity analysis (Sobol indices) and HRU-specific parameter adjustment, and (iii) providing a transferable evaluation approach for data-limited Mediterranean catchments.

2 Materials

2.1. Area of study

The Tordera RB (894 km²), located in northeastern Spain (**Figure 1**), is a Mediterranean watershed with complex topography, strong altitudinal gradients, and contrasting land use, with forested headwaters (81%) and intensively cultivated lowlands. It exhibits a torrential hydrological regime, with an average discharge of ~5 m³/s and episodic floods.

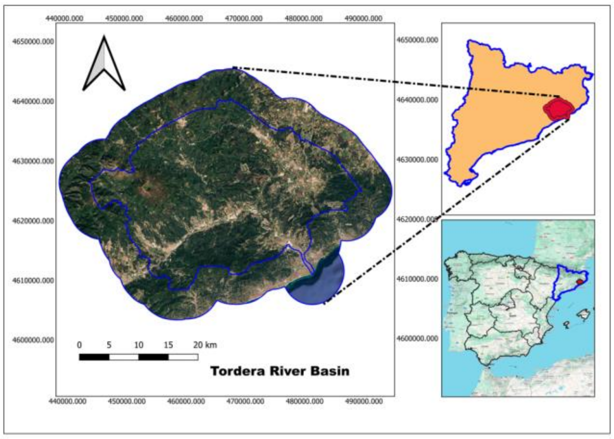

Figure 1. Study area map

Hydrological assessment was conducted using the SWAT+ model, delineating Hydrological Response Units (HRUs) based on land cover, soil type, and topography to represent spatial heterogeneity and ecohydrological processes. Eight land cover classes were defined (**Table 1**), and the two largest HRUs per class were selected to ensure spatial representativeness, forming the basis for evaluating evapotranspiration across dominant land uses.

2.2 MODIS dataset

ET data were obtained from the MODIS MOD16A2GF.061 product, providing 8-day composites at 500 m resolution for 2003–2022. The ET_500m variable was extracted and processed in the native MODIS Sinusoidal projection to ensure spatial consistency.

The product is based on a physically grounded algorithm derived from the Penman–Monteith equation, integrating meteorological and vegetation inputs (Mu et al., 2011, Running et al., 2017), and has been validated against ground-based measurements, including eddy covariance observations. Previous studies confirm its capability to represent basin-scale ET dynamics and spatial patterns (Velpuri et al., 2013).

However, MOD16A2GF ET is subject to uncertainties related to cloud contamination, spatial resolution, input data, and model assumptions. Its accuracy may vary across climatic and land-cover conditions (Velpuri et al., 2013); therefore, it is treated as a reference dataset rather than absolute ground truth, and differences with SWAT+ simulations may reflect uncertainties in both datasets.

No.	Code	Description	No. HRUs	Total Area(km²)
1	FRSD	Deciduous Forest	2630	11733.00
2	FRSE	Evergreen Forest	1045	2582.43
3	FRST	Mixed Forest	346	675.96
4	AGRL	Agricultural Land	801	1953.24
5	AGRR	Agricultural Residual (Row Crops)	140	225.32
6	ORCD	Orchards / Fruit Trees	61	117.24
7	PAST	Pastures / Grasslands	29	41.20
8	RNGB	Rangeland / Grass / Barren Lands	417	1023.50

Table 1. Land Use and Land Cover Classes in the Tordera River Basin with Corresponding HRUs

2.3 SWAT+ input data

For watershed and HRU delineation, the required input data included a Digital Elevation Model (DEM), Land Use/Land Cover (LULC), soil type raster datasets, and meteorological information. The DEM was obtained from the Copernicus DEM at 30 m spatial resolution (European Space Agency, 2020), which provides essential information on terrain elevation, slope, and drainage patterns controlling surface runoff and water transport dynamics.

LULC data constitutes a critical input in the SWAT+ modeling framework, influencing key hydrological processes such as evapotranspiring, surface runoff, and infiltration. In this study, the LULC map was derived from the 2018 CORINE Land Cover (CLC) dataset (Copernicus Land Monitoring Service, 2018) and reclassified into eight hydrologically relevant categories using the SWAT+ lookup tables provided by WaterITech (Gassman et al., 2018), ensuring consistency between land cover classes and model parameterization.

Soil type determinates hydrodynamics in the different soil layers. Soil type from Digital SoiL OpenLand Map (DSOLMap) was used in the model (López-Ballesteros, et al. 2023) The integration of LULC with soil and slope layers resulted in 6259 HRUs.

For SWAT+ model execution it has been integrated Meteorological data from the Spanish and Catalan Meteorological Services (AEMET and SMC) between the years 2000 and 2022, and the SWAT+ Spanish Weather Generator (Senent_Aparicio, et al. 2021).

3 Methodology

This study integrates remote sensing, spatial analysis methodologies, geospatial processing, and physically based hydrological modeling to evaluate ET simulation in the Tordera RB. The methodological framework (**Figure 2**) consisted of six structured phases including data acquisition, preprocessing, spatial analysis, model calibration, and comparative evaluation.

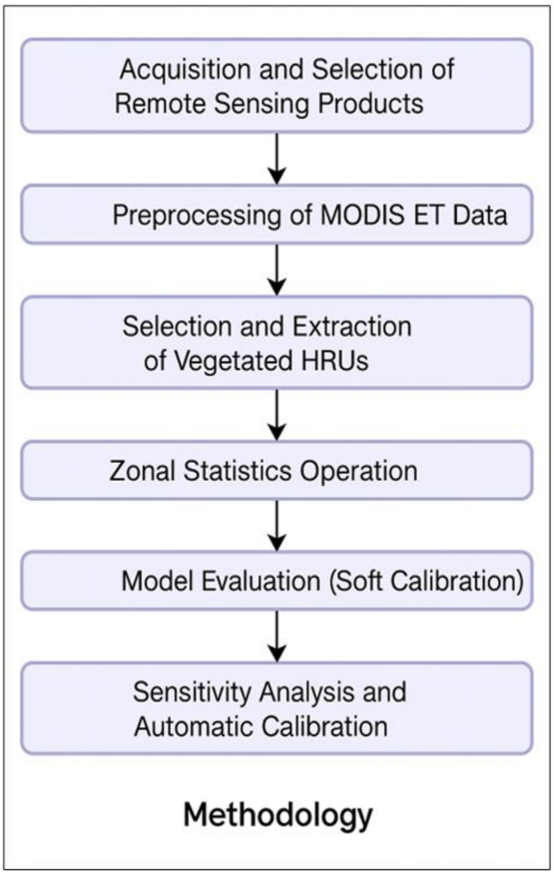

Figure 2. Schematic overview of the methodology

3.1 Remote Sensing Data Acquisition

The MODIS Terra evapotranspiration product (MOD16A2GF) was selected due to its 500 m spatial resolution and 8-day temporal composites. The 2003–2022 dataset enabled long-term evaluation of ET dynamics and model performance. Data were downloaded from the USGS EarthExplorer platform (https://earthexplorer.usgs.gov).

3.2 MODIS ET Preprocessing

A standardized preprocessing workflow was applied to MODIS evapotranspiration ET data to ensure quality and compatibility with GIS, R and SWAT+ environments, including:

- **Quality control and masking:**

Invalid and non-vegetated pixels (e.g., water bodies, urban areas) were removed using MOD16A2GF fill values and QA flags and reclassified as NODATA.

- **Monthly aggregation and reprojection:**

MODIS 8-day products were aggregated to monthly values using the MiraMon Raster Calculator (https://www.miramon.cat/Index_eng.htm). For 8-days periods spanning two months, values were weighed proportionally according to the number of days falling within each month. All NODATA values were consistently excluded during temporal aggregation, and only valid pixels were retained to avoid bias in ET estimates. MODIS products were reprojected to UTM Zone 31N ETRS89 (EPSG:25831).

3.3 Selection and Extraction of Vegetated HRUs

From over 6000 HRUs, 16 vegetated units were selected, corresponding to the two largest HRUs for each of the eight dominant land-cover classes (FRSD, FRSE, FRST, AGRL, AGRR, ORCD, PAST, RNGB), identified as "-1" (largest) and "-2" (second largest) (**Figure 3**). This selection represents a methodological simplification and accounts for approximately 12% of the vegetated area of the watershed.

This approach ensures statistical stability and reduces noise associated with small and heterogeneous units, while enabling more robust comparison with satellite-derived ET from the MOD16A2GF at 500 m resolution. However, it may limit the representation of smaller units; therefore, results should be interpreted as indicative of dominant land-cover behavior rather than full basin generalization.

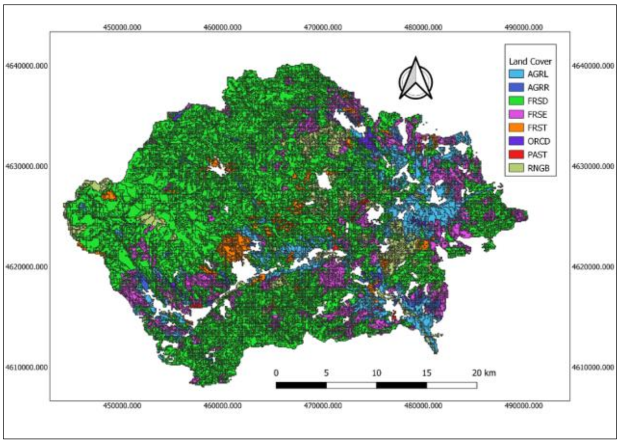

Figure 3. Land use and land cover classes

3.4 Spatial Integration of MODIS ET with HRUs

Zonal statistics were applied to overlay MODIS ET rasters with HRU polygons. For each HRU, mean, median, and standard deviation were computed from intersecting pixels. Pixels located along HRU boundaries were included and assigned using a centroid-based criterion, whereby each pixel was attributed exclusively to the HRU containing its centroid, avoiding duplication across adjacent units. This approach ensured spatial consistency while minimizing bias from boundary effects, enabling a reliable spatial link between satellite-derived ET and model units for subsequent comparison and evaluation of SWAT+ simulations.

3.5 SWAT+ Hydrological Modelling

SWAT+ was applied as a physically based, semi-distributed hydrological modeling framework to simulate evapotranspiration (ET) at the HRU level. The model represents ET as the combined effect of soil evaporation, plant transpiration, and canopy interception, driven by climatic inputs and regulated by vegetation dynamics, soil properties, and water availability.

Within this framework, SWAT+ was configured to simulate monthly ET (Penman-Monteith function) for 16 HRUs representing major land-cover types over the 2000–2014 period, with 3 warm-up days. The simulations were conducted as a preliminary step to assess model behavior and ensure proper configuration of land cover, soil, and climatic inputs prior to formal calibration.

3.5.1 Soft Calibration

A preliminary automatic soft calibration for water balance was conducted. Soft calibration adjusted model parameters to obtain annual average physically valid values. Based on available literature, it was set a Water Yield Ratio of 0.23 and a Baseflow Ratio of 0.08 (Pla et al., 2011). Assess SWAT+ performance prior to formal calibration by comparing basin level simulated annual average evapotranspiration (ET) with MODIS-derived from monthly ET for the period 2003–2014.

3.5.2 Sensitivity Analysis

Sensitivity analysis identified key parameters controlling ET at HRU level, including soil hydraulic properties, vegetation dynamics, and water balance components. Sensitivity analysis using the Sobol method (Sobol, 2001) was performed at the largest HRU of the watershed (Land Use Land Cover: FRSD, with a surface of 5,17km2), over the most common parameters for HRU , soil and river routing parameters (cn2, esco, epco, canmax, perco, lat_ttime, cen3_swf, awc, k, chk) with 2200 samples. With cn2, esco, canmax, perco, cn3_swf awc, and k identified as sensitive (1st order sensitivity indexes > 0.007).

3.5.3 Calibration

Automatic multi-site calibration of monthly ET at the HRU was performed for sensitive parameters using Latin-Hypercube Sampling Iterations (CALSI). HRU monthly MODIS-derived ET (mean value) for the selected HRU was introduced in the calibration as observed data.

Model performance compared to MODIS ET was quantified before and after calibration for each selected HRU using Kling-Gupta Efficiency (KGE) to measure the goodness-of-fit as it combines correlation (r), variability (α), and Bias (β) (Gulpa et al. 2009), and Root Mean Squared Error (RMSE) to measure the average magnitude of the error KGE and RMSE are defined in Equations (**1**) and (**2**), respectively:

$$\text{KGE} = 1 - \sqrt{+(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2} \quad (1)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(obs_i - sim_i)^2} \quad (2)$$

Where obs_i represents observed values (MODIS ET), sim_i simulated values (SWAT+ ET), and $\overline{obs}$ the mean of observed values. NSE and KGE range from −∞ to 1, with 1 indicating perfect match, and lower values indicating decreased fit between observed and simulated values. Computing performed with hydroGOF R package (Zambrano-Bigiarini, 2024).

Finally, the overall model improvement has been measured by comparing KGE and RMSE before and after calibration (Equations **3** and **4**):

$$\Delta KGE = KGE_{after} - KGE_{before} \quad (3)$$

$$RMSESS = \frac{RMSE_{before} - RMSE_{after}}{RMSE_{before}} \quad (4)$$

4 Results

4.1 Analysis of ET MODIS Values Across Land Cover Categories

4.1.1 Forest ET Dynamics (FRSD, FRST, FRSE)

MODIS-derived evapotranspiration during 2003–2014 showed strong seasonal dynamics across forested HRUs. Deciduous forests (FRSD) exhibited the highest monthly ET peaks, exceeding 120 mm month^{-1}, indicating high transpiration demand during summer months (June, July, August). Mixed forests (FRST) (**Figure 4**) recorded intermediate ET values ranging from ~20 to 120 mm month^{-1}, while evergreen forests (FRSE) showed the lowest and most stable ET levels (~20–100 mm month^{-1}).

4.1.2 ET in Agricultural and Managed Lands

Agricultural HRUs **(Figure 4)** exhibited clear seasonal variability in evapotranspiration. Non-irrigated croplands (AGRL) showed the lowest monthly mean ET (~37 mm month^{-1}), reflecting limited water availability. In contrast, irrigated croplands and orchards (ORCD) reached peak ET values exceeding 80 mm month^{-1}, driven by irrigation practices and crop characteristics. Irrigated agricultural units (AGRR) maintained moderate and relatively stable ET levels (~20 mm month^{-1}).

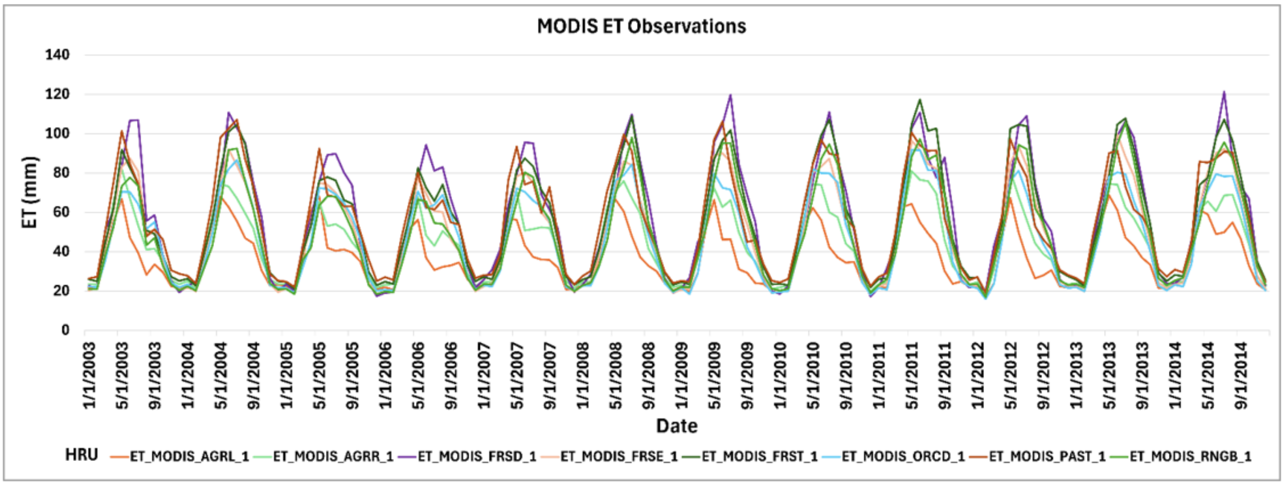

Figure 4. Temporal variation of monthly MODIS (ET) for selected HRUs.

4.1.3 ET in Pasture and Rangeland Areas

Pasture (PAST) and rangeland (RNGB) HRUs exhibited pronounced seasonal evapotranspiration patterns (2003–2022), with summer peaks often exceeding 90 mm/month.PAST_1 and RNGB_1 recorded the highest monthly mean ET (~56 and 49 mm/month), whereas the corresponding HRU_2 units showed lower values. RNGB consistently exceeded PAST in peak ET, reflecting differences in vegetation density and soil moisture availability.

4.2 SWAT+ Simulated ET After Calibration (2003–2014)

Following calibration, using MODIS ET values, monthly ET values simulated by SWAT+ improved in most of the major land-cover classes:

• **Forests (FRST, FRSD, FRSE):** mean monthly ET ranged 45–60 mm/month. Forest Deciduous and Mixed Forest showed the highest mean ET during summer seasons (peaking over 120mm/month), FRSD exhibited the greatest variability (SD ~ 45 mm), and Forest Evergreen presented lower, stable values (SD~30–35 mm/month).

• **Agricultural lands (AGRL, AGRR, ORCD):** Agriculture recorded the lowest monthly mean ET (~35mm/month), and the lowest monthly variability (SD~25 and 27mm/month). RangeLand showed intermediate ET and Orchards exhibited the highest monthly mean ET (~56mm/month) and also de highest variability (SD~45mm/month).

• **Pastures and rangelands (PAST, RNGB):** PAST displayed a mean monthly ET of 40–48 mm/month, while RNGB showed the lowest values (~37 mm/month).

4.3 Comparative Evaluation: MODIS vs SWAT+ ET

Comparison between MODIS-derived and SWAT+ simulated ET indicated land-cover-dependent discrepancies (**Table 2**):

• **Forests (FRSD, FRST, FRSE):** Forests (FRSD, FRST, FRSE): SWAT+ ET underestimated lows and overestimates the peaks showing a greater SD than MODIS (**Figure 5**). Larger deviations in Forest Deciduous likely reflect uncertainties in canopy interception and transpiration processes. A temporal shift is also evident in Forest Deciduous and Mixed, where simulations transition from overestimation (2003–2010) to underestimation (2011–2014),), which may also be attributed to the uneven temporal distribution of observed meteorological inputs, particularly radiation and wind speed, which are essential for the Penman–Monteith ET estimation function implemented in SWAT+. Despite these discrepancies, the KGE values for this land cover category are the highest in this test (KGE range 0.3–0.54).

• **Agricultural lands (AGRR, AGRL, ORCD):** Agriculture HRU showed different modeling behaviors with AGRL_2 obtaining and acceptable KGE of 0.54. This HRU is in good agreement for most of the year except the summer months where SWAT overestimates MODIS. Rangelands are in general with agreement with MODIS with KGE of 0.33 for AGRR_1. Orchards present important overestimation of the high ET during summer months producing negative KGEs.

• **Pastures and Natural Rangelands (PAST, RNGB):** Natural Rangelands in SWAT obtain acceptable KGE values of 0.68 and 0.49, regardless of general slight underestimation during the year and overestimation ET peaks in June.

Overall, SWAT+ model was able to model ET fluctuation patterns during the year, but with a tendency to overestimate ET extreme values.

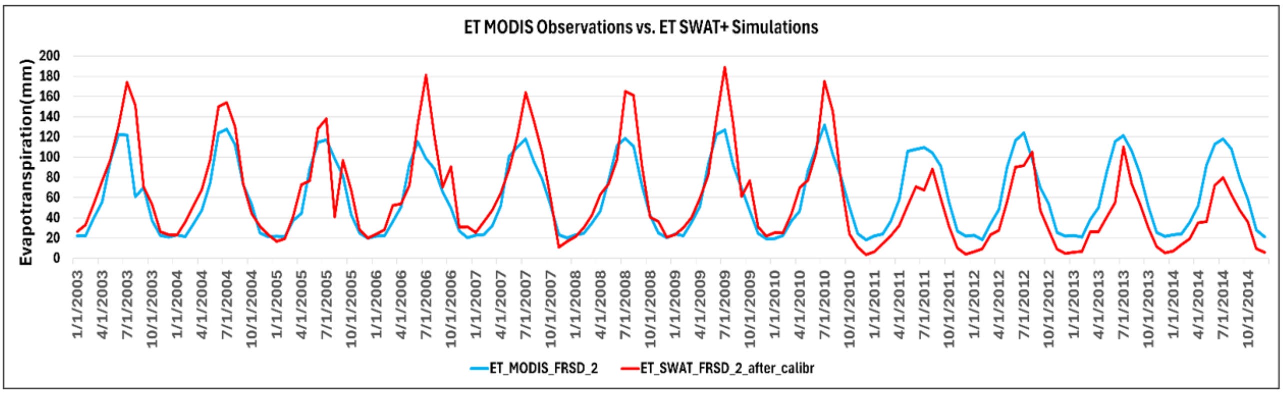

Figure 5. Comparison of (ET) MODIS observations and SWAT+ simulations for FRSD_2

4.4 Calibration Performance Evaluation

Calibration performance using MODIS ET showed a general improvement of the model ET estimations by reducing slightly ET overestimations during ET peaks in summer season, showing and improvement on model metrics for most cases (**Table 2**).

• Forests (FRSD_1, FRSE_2, and FRST_1): Moderate agreement (ΔKGE 0.11–0.18), combined with a decrease of RMSESS ≥ 13% indicating a reasonable representation of seasonal ET dynamics. The effect of calibration is illustrated for the deciduous forest HRU (FRSD_2), showing improvements in peak ET representation and overall temporal dynamics (**Figure 6**).

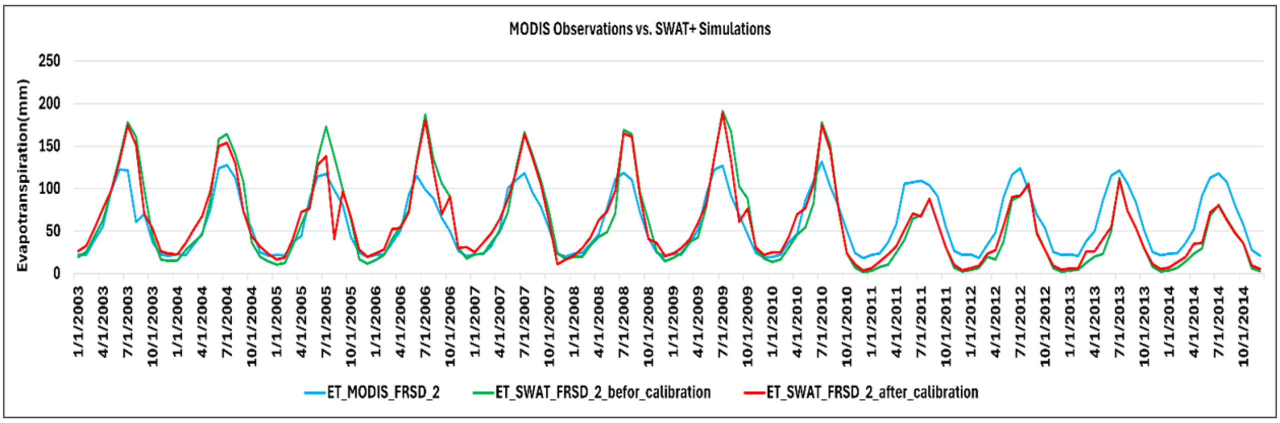

Figure 6. Comparison of (ET) MODIS observations with SWAT+ simulations before and after calibration for FRSD_2

• Agriculture and Managed lands: Moderate to strong improvement with ΔKGE of 0.17 to 0.5 and RMSESS between 14 to 20% in all studied HRUs except AGRL_2.

• Pastures and Natural Rangelands: a mixed response to calibration with moderate or no improvement in Pastures and slight improvement or worse for Natural Rangelands.

Overall, alignment with MODIS-derived ET improved, particularly in cultivated areas. But still in many cases KGE values are under 0.5 (generals are considered not satisfactory) and indicate that the model performs worse than the means of observations, reflecting structural limitations in representing vegetation dynamics, irrigation practices, and soil moisture processes. These discrepancies are further influenced by the absence of explicit irrigation representation in the model, as irrigated HRUs were simulated under rainfed conditions due to limited data on irrigation management (e.g., timing and volume).

These findings emphasize the need for improved parameterization of vegetation processes and water management to enhance SWAT+ ET simulations in heterogeneous Mediterranean environments.

5 Discussion

Comparison of MODIS-derived and SWAT+ simulated evapotranspiration (ET) across 16 HRUs revealed land-cover-dependent performance differences:

• **Forests:** Mixed forests (FRST_1) and Evergreen (FRSE_2) showed KGE ≥ 0.5 with evergreen forests (FRSE_2) achieved good accuracy with the lowest RMSE, whereas deciduous forests (FRSD_2) displayed lower accuracy with higher RMSE due to seasonal canopy dynamics.

• **Agriculture and Managed lands:** Orchards exhibited substantial overestimation, negative KGE and RMSE > 32. Agriculture AGRL_1, despite experiencing a strong improvement with the calibration, the KGE is still not satisfactory compared to AGRL_2 with a satisfactory KGE of 0.54 but not benefiting much further with the calibration.

• **RMSE** error analysis**:** Evergreen forests had better agreement (FRSE_2 RMSE 17.8 mm/month), while Orchards showed higher discrepancies (~32–27 mm/month), reflecting irrigation variability, and vegetation seasonality (**Table 2**)

		MODIS ET (mm)		SWAT Before Calibration ET (mm)				SWAT After Calibration ET (mm)						
Land Cover	HRU_ID	mean	Sd	mean	Sd	KGE	RMSE	mean	Sd	KGE	RMSE	ΔKGE	RMSESS	Model performance improvement
Forest (Deciduous)	FRSD_1	57.1	29.9	58.2	51.0	0.26	33.12	60.0	45.7	0.43	28.25	0.17	0.15	Moderate
	FRSD_2	60.4	36.7	45.0	39.9	0.42	41.61	46.1	37.3	0.39	41.64	-0.03	0.00	Worse
Forest (Evergreen)	FRSE_1	49.8	24.9	48.7	35.4	0.33	32.04	50.9	29.9	0.30	31.84	-0.03	0.01	Slight
	FRSE_2	52.3	24.3	43.6	38.3	0.40	20.36	45.3	35.9	0.50	17.80	0.10	0.13	Moderate
Forest (Mixed)	FRST_1	56.2	28.0	54.9	44.9	0.35	29.24	54.4	38.9	0.54	25.58	0.18	0.13	Moderate
	FRST_2	55.2	29.7	51.9	45.6	0.35	35.22	50.9	40.3	0.46	32.89	0.11	0.07	Slight
Agriculture	AGRL_1	36.7	14.6	41.4	28.9	-0.12	26.04	36.2	24.6	0.17	20.82	0.30	0.20	Strong
	AGRL_2	48.3	21.0	39.2	30.0	0.51	18.73	34.7	27.2	0.54	21.33	0.03	-0.14	Slight
Rangeland	AGRR_1	44.3	18.3	54.9	27.9	0.16	28.83	48.9	23.2	0.33	23.69	0.17	0.18	Moderate
	AGRR_2	45.0	17.4	49.6	35.8	-0.12	28.14	42.3	31.4	0.12	24.24	0.24	0.14	Moderate
Orchards	ORCD_1	46.9	22.7	58.9	53.8	-0.40	38.97	56.2	45.0	-0.03	32.58	0.37	0.16	Moderate
	ORCD_2	39.8	17.4	58.9	53.8	-1.16	45.23	56.2	45.0	-0.66	37.14	0.50	0.18	Moderate
Pastures	PAST_1	55.3	25.3	41.7	30.2	0.25	35.21	40.8	29.7	0.23	35.67	-0.02	-0.01	No change
	PAST_2	42.9	18.9	51.5	40.3	-0.16	26.65	48.3	37.1	0.02	23.76	0.18	0.11	Moderate
Natural Rangeland	RNGB_1	49.3	25.0	38.3	29.9	0.66	19.51	36.9	27.3	0.68	19.95	0.02	-0.02	Slight
	RNGB_2	45.3	23.5	34.6	29.8	0.53	24.20	36.9	30.7	0.49	25.37	-0.04	-0.05	Worse

Table 2: Monthly Mean ET values and Standard deviation for ET MODIS, and SWAT model before and after calibration at the selected HRUs. Objective functions NSE, KGE and RMSE results before and after calibration, and model improvement evaluation as Strong (ΔKGE ≥ 0.2 and RMSESS ≥ 0.2), Moderate (ΔKGE ≥ 0.1 and RMSESS ≥ 0.1), Slight (ΔKGE > 0 or RMSESS > 0), and Worse (ΔKGE < 0 and RMSESS < 0).

However, irrigation processes are not explicitly represented in the SWAT+ configuration used in this study, which likely contributes to discrepancies in agricultural HRUs, particularly in orchards and croplands.

A key limitation is the use of MODIS-derived ET as validation data, which is subject to uncertainties related to cloud contamination, spatial resolution (500 m), and model assumptions (Velpuri et al., 2013). These factors may affect ET accuracy in heterogeneous regions; therefore, discrepancies between SWAT+ and MODIS should be interpreted cautiously, considering uncertainties in both datasets.

Overall, SWAT+ performs best in evergreen and mixed forests, and selected Natural Rangelands, with agricultural performance is influenced by irrigation and management practices. Improving land-use representation and refining vegetation, irrigation, and soil parameterization remain essential. Future work should extend validation to a larger set of HRUs to improve spatial representativeness and reduce sampling bias.

6 Conclusion

This study combined MODIS-derived ET data (2003–2014) with SWAT+ simulations (2003–2014) to assess evapotranspiration dynamics across land cover types in the Tordera RB, a Mediterranean watershed. Key findings include:

- **Forests** ETs are reasonably well captured by SWAT, with best model performance in evergreen forests (FRSE_2; RMSE = 17.80 mm; KGE = 0.50), followed by Deciduous and mixed forests (FRSD_1, FRST_1) with moderate accuracy, and higher RMSE in some units.
- **Agricultural and Managed lands** showed a strong to moderate improvement thanks to the calibration suggesting MODIS provides a high-value calibration information in managed systems.
- **Orchard's** calibration obtained large improvements in RMSE (up to 18%), KGE improved substantially but remains low or negative, suggesting calibration improved the magnitude of simulated ET but temporal dynamics remain poorly represented, likely due to management practices not explicitly represented in the model.
- **Natural Rangelands** had already relatively good performance before calibration (KGE ~0.5-0.7), calibration providing limited added value.

Calibration using MODIS ET values enhances ET simulation, particularly those with poor pre-calibration performance. Improved KGE in most of the HRUs, indicate a better representation of temporal dynamics and variability, and a reduction of RMSE in most cases indicating a ET magnitude improved with reductions between 10 -20% specially in Managed Land. Nevertheless, some HRU showed a slight negative response suggesting that MODIS ET is a useful but not universally optimal calibration target. These results highlight the need to refine vegetation and irrigation parameterization and to assess calibration transferability.

The proposed process-based framework integrates satellite observations with physically based evapotranspiration modeling to robustly evaluate ecohydrological processes. It also supports water resource management and decision-making by enabling assessment of evapotranspiration dynamics across land-use types and management scenarios, including irrigation and land-use change.

7 Data and Software Availability

The datasets used in this study, including the 2018 CORINE Land Cover, Copernicus DEM (30 m), soil maps, and MODIS MOD16A2GF evapotranspiration products, are publicly available through the respective platforms:

https://land.copernicus.eu/pan-european/corine-land-cover , https://spacedata.copernicus.eu/ , https://earthexplorer.usgs.gov

The spatial analyses, statistical calculations and remote sensing processes were carried on by open or free software: QGIS, MiraMon and R. The hydrological models by SWAT, a free and open-source software.

8 Declaration of Generative AI in Writing

The authors acknowledge the use of generative artificial intelligence tools during the preparation of this manuscript. These tools were employed exclusively to support language refinement and improve clarity of expression. All scientific content, data analysis, interpretations, and conclusions were developed independently by the authors without AI-generated contributions.

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