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Topography-Constrained Correction of MOD16A2 PET for Estimating and Mapping ET_0

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Abstract

Reference evapotranspiration (ET_0) is essential for irrigation management, but its spatial estimation is limited by sparse meteorological observations. Satellite products such as MOD16 potential evapotranspiration (PET) provide spatial continuity, yet they are not directly comparable to FAO-56 ET_0 due to structural differences in model parameterization. This study proposes a topography-constrained framework to convert MOD16 PET into FAO-consistent ET_0 . The approach was tested in two heterogeneous regions of northern Italy (Piemonte and Veneto) using ground-based ET_0 derived from the FAO Penman–Monteith equation (2010–2022). PET– ET_0 transformation coefficients, estimated via station-wise linear regression, showed no significant temporal drift over the study period and strong spatial structure. Among the tested topographic predictors, elevation was retained as the main topographic proxy for modelling the spatial variability of the correction coefficients. The locally calibrated correction reduced the systematic overestimation of raw MOD16 PET and improved agreement with station-based ET_0 in both regions. Its performance was comparable to an IDW interpolation benchmark, although IDW slightly outperformed the topography-based model in Piemonte. A cross-region test showed that the correction reduced MOD16 PET errors when transferred between Piemonte and Veneto, but residual bias remained. The proposed framework should therefore be interpreted as a parsimonious regional topographic correction approach that requires local calibration and validation before application to other areas.

Keywords: MOD16; PET; ET_0 ; reference evapotranspiration; topographic correction; elevation; remote sensing; multivariate regression; data-scarce regions



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1. Introduction

In recent years, the Italian climate has shown increasing irregularity in weather patterns, with periods of intense rainfall alternating with prolonged droughts [1]. This variability imposes significant pressure on the agricultural sector, which often lacks the tools to anticipate the effects of such fluctuations on water availability and crop conditions [2,3]. Although particularly evident in Italy, similar patterns of hydro-climatic variability affect many Mediterranean and semi-arid regions, highlighting the need for reliable indicators to support irrigation planning and water resource management.

Reference evapotranspiration (ET_0) quantifies the atmospheric evaporative demand over a standardized reference surface and provides the climatic baseline for irrigation planning and crop water requirement assessment. The FAO-56 Penman–Monteith formulation, widely recommended for its physically based structure and climatic consistency, has become the international standard [4]. ET_0 depends solely on meteorological variables—solar radiation, air temperature, humidity, and wind speed—making it independent of crop type and transferable across agricultural systems.

Despite its theoretical robustness, generating spatially explicit ET_0 information is challenging. Ground station networks are often sparse or unevenly distributed, limiting the production of high-resolution maps suitable for operational irrigation management [2]. Remote sensing products can help overcome these limitations by providing spatially continuous and temporally consistent observations of key land surface variables, including vegetation conditions, soil properties, and surface fluxes, over large areas [5–7]. Among these, the MOD16 product derived from MODIS provides global potential evapotranspiration (PET) estimates using a Penman–Monteith framework. However, MOD16 PET is parameterized for biome-specific surface conditions and does not represent the standardized FAO reference surface [8]. Consequently, PET and ET_0 are not directly interchangeable. Differences in aerodynamic resistance and surface conductance parameterization [9] imply that PET may systematically deviate from FAO-consistent ET_0 , which is defined for a standardized grass surface with fixed surface resistance and aerodynamic properties [4].

Because of these structural differences, several strategies have been proposed to bridge satellite PET and ground-based ET_0 . However, only a limited number of studies have explicitly investigated the conversion or projection of MOD16 PET into reference evapotranspiration. A previous study [10] estimated monthly FAO-PM ET_0 across Brazil using MOD16 PET together with climatic covariates and machine-learning regression models. The results showed that MOD16 PET generally overestimated FAO-PM ET_0 , but also retained useful predictive information and could support spatial ET_0 modelling after recalibration. Another study [11] combined MOD16 PET with ground-based ET_0 estimates in New Zealand using monthly linear fitting and uncertainty propagation, interpreting MOD16 as a spatial support rather than as a direct substitute for locally adopted ET_0 estimates. At regional scale, empirical calibration strategies have also been explored. In northwestern Italy [8], MOD16 PET was linearly calibrated against station-based ET_0 , substantially reducing systematic bias during the irrigation season. Terrain-aware interpolation provides an additional methodological reference for spatial ET_0 /PET mapping. A previous study [12] interpolated daily PET across New Zealand using a trivariate thin-plate smoothing spline based on latitude, longitude and elevation. The results showed that elevation-constrained interpolation can provide useful gridded PET estimates, although accuracy decreases in high-elevation areas where station density is limited. This highlights both the relevance of topographic information for PET/ ET_0 spatialization and the dependence of interpolation-based approaches on station-network structure.

The novelty of the present study is therefore not the station-level linear calibration of MOD16 PET alone, which was already explored in northwestern Italy [8], but the spatial parameterization of the PET– ET_0 correction coefficients using topographic information. This allows station-specific PET– ET_0 relationships to be translated into spatially continuous correction surfaces. The spatial distribution of the linear correction coefficients in the previous study suggested structured patterns associated with elevation gradients and terrain variability. This association is physically plausible because topography is linked to near-surface temperature, pressure, radiation exposure and wind regimes, all of which contribute to atmospheric evaporative demand [4]. In this study, elevation is therefore treated as a topographic proxy rather than as a single causal driver of the PET– ET_0 discrepancy.

Taken together, existing approaches reveal a methodological trade-off. Machine learning frameworks maximize predictive skill but require numerous predictors and advanced computation. Spatial interpolation methods are operationally simple and effective when station networks are dense, but their performance depends strongly on station distribution and may not explicitly represent terrain-driven controls. Physically based high-resolution ET_0 modeling would require spatially explicit fields of radiation, temperature, humidity, and wind, which are often unavailable or uncertain at fine scales. A framework that preserves computational efficiency while introducing physically meaningful spatial controls on the PET- ET_0 correction therefore remains needed.

In this context, the present study proposes a topography-constrained empirical correction framework to transform MOD16 PET into FAO-consistent ET_0 at 500 m resolution using only satellite-derived PET and DEM-based predictors. By explicitly incorporating terrain-related variability, the model characterizes the spatial organization of PET- ET_0 discrepancies rather than treating them as uniform statistical deviations. The objective is to develop a minimally parameterized, operationally applicable framework capable of generating high-resolution ET_0 estimates suitable for irrigation management in heterogeneous agricultural landscapes. The presented framework can be applied to other regions, provided that it is recalibrated and validated locally before application.

2. Materials and Methods

2.1. Study Area

The study considers two agricultural regions of northern Italy, Veneto and Piemonte, located respectively in the eastern and western sectors of the Po Plain (Figure 1). They cover approximately 18,400 km² and 25,400 km², respectively, and were selected because they combine intensive agricultural activity with strong climatic and physiographic gradients, providing suitable conditions for testing the PET- ET_0 relationship across heterogeneous environments.

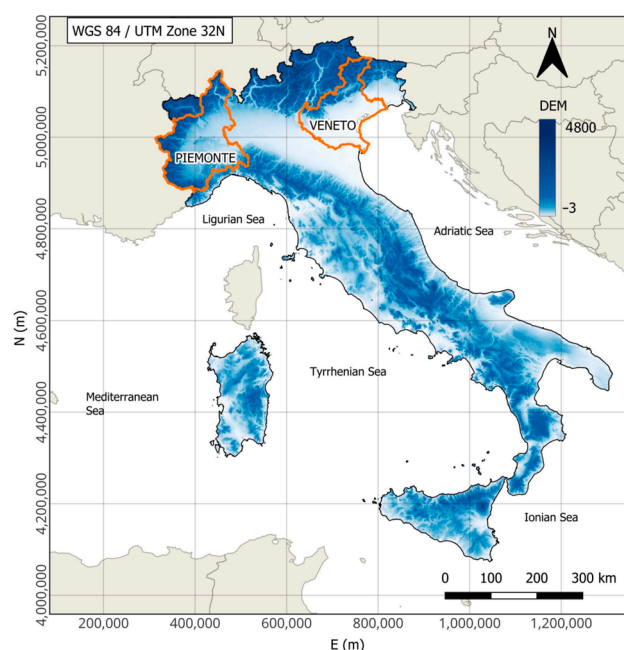


Figure 1. Geographic setting of the study area. The map shows the Digital Elevation Model (DEM) of Italy, with the regions of Piemonte and Veneto, which are the focus of the study, highlighted in orange. Coordinates are expressed in the projected coordinate reference system UTM Zone 32N (WGS84).

Both regions are characterized by marked elevation variability. Based on the TINITALY DEM [13], elevation ranges from sea level along the Adriatic coast and the Po Delta to 3343 m a.s.l. at Marmolada in Veneto, and to approximately 4560 m a.s.l. in the Monte Rosa massif in Piemonte. According to the ISTAT altimetric-zone classification, Veneto is predominantly flat, with 56.4% plain, 14.4% hill and 29.1% mountain areas, whereas Piemonte is more upland, with 27% plain, 30% hill and 43% mountain areas. The retained meteorological stations therefore cover a broad plain–hill–mountain gradient.

Climatic conditions vary substantially with elevation and distance from the reliefs. In Veneto, mean annual precipitation is approximately 1127 mm over the 1991–2020 reference period, ranging from less than 600 mm in the southern plain to more than 2000 mm in the Belluno Dolomites [14]. In Piemonte, annual precipitation ranges from more than 1600 mm in the northern reliefs and Lake Maggiore area to less than 700 mm in the Alessandria plain [15]. These gradients in elevation, rainfall and temperature are directly relevant to atmospheric evaporative demand and may influence the spatial behaviour of both MOD16 PET and station-based FAO-56 ET_0 .

Agriculture is mainly concentrated in the lowland sectors of both regions. Veneto is dominated by arable crops, vineyards and irrigated summer crops, while Piemonte includes maize, rice, vineyards and fruit orchards [16,17]. Irrigation is particularly relevant in the Veneto high plain, where permeable gravelly soils increase summer water demand, and in Piemonte, where rice is traditionally grown under flooded conditions and maize is widely irrigated. These agricultural and irrigation settings provide the operational context for ET_0 mapping and may contribute to local differences between satellite-derived PET estimates over vegetated pixels and station-based reference ET_0 .

2.2. Available Data

2.2.1. MODIS Data

In this study, the MOD16A2GF dataset derived from NASA's MODIS sensor was used to compare potential evapotranspiration (PET) estimates with ground-based observations. The MOD16 algorithm, originally developed by [18] and subsequently refined by [9], is based on the Penman–Monteith conceptual framework [19] and integrates meteorological reanalysis data with MODIS-derived variables, including vegetation characteristics, albedo, and land-cover information.

The MOD16A2GF product provides global PET estimates at 500 m spatial resolution and an 8-day temporal scale. Since MOD16A2 version 6.1 does not include data prior to 2023, the MODIS Science Team recommends the use of the gap-filled MOD16A2GF dataset for the 2000–2023 period. This product improves spatial continuity by interpolating LAI/FPAR values in pixels failing quality checks and is released once the complete annual set of M*D15A2H products becomes available [20]. In this work, 8-day PET data from the MOD16A2GF collection 6.1 were used.

MOD16A2GF provides PET estimates only for vegetated surface; pixels corresponding to non-vegetated land-cover classes are assigned fill values. Consequently, some meteorological stations located within non-vegetated pixels, as described in Section 2.2.3, were excluded from the analysis.

The Google Earth Engine platform [21] was used to retrieve the 8-day PET time series for the study period (1 January 2010–31 December 2022). Single-pixel PET values were extracted at the locations of the selected meteorological stations to match each ground-based ET_0 observation with the corresponding MOD16A2GF grid cell. This choice preserves consistency with the native 500 m MOD16 spatial resolution, although it may introduce some representativeness uncertainty because station measurements are point-based, whereas MOD16 PET represents the average conditions within a 500 m pixel. MOD16A2GF PET

values are provided as 8-day totals and were multiplied by the product scale factor of 0.1 to obtain PET in $\text{kg m}^{-2} \text{ 8-day}^{-1}$, equivalent to mm 8-day^{-1} . Stations located in non-vegetated MOD16A2GF pixels were excluded because PET is returned as a fill value at these locations. Apart from this exclusion, no additional ET_QC-based filtering or temporal gap filling of MOD16A2GF PET values was applied.

2.2.2. Elevation Data

For the topographic characterization of the study area, the TINITALY Digital Elevation Model [13], developed by the Italian National Institute of Geophysics and Volcanology (INGV), Rome, Italy, was used at its native 10 m spatial resolution. The DEM was employed to derive the main morphometric parameters, specifically slope and aspect, which were subsequently used in the analysis of topographic controls. Elevation, slope and aspect were extracted at the meteorological station locations and used as candidate topographic predictors.

2.2.3. Ground Reference Data

Ground reference data were obtained from the regional agrometeorological networks operated by ARPA Piemonte [22] and ARPA Veneto [23]. The initial networks included 336 stations in Piemonte and 206 stations in Veneto. The stations were progressively screened according to three criteria: availability of the meteorological variables required for FAO-56 Penman–Monteith ET_0 computation, temporal completeness over the 2010–2022 period, and availability of MOD16A2GF PET values at the station location. Specifically, retained stations were equipped with sensors measuring air temperature, relative humidity, wind speed and incoming solar radiation, together with metadata on station elevation and geographic coordinates. The number of stations retained and removed at each filtering step is reported in Table 1.

Table 1. Station filtering summary for Piemonte and Veneto. The table reports the initial number of stations, the main filtering steps, and the final datasets.

Filtering Step	Piemonte	Veneto
Initial station network	336	206
With needed sensor and continuous records	37	99
Removed (non-vegetated MOD16A2GF pixel)	−9	−9
Retained for the analysis	28	90

Stations located within MOD16A2GF non-vegetated pixels were excluded because PET is returned as a fill value and is therefore unavailable at these locations. These stations could not be used in the PET– ET_0 regression by construction. Most of the removed stations corresponded to urban or built-up locations, indicating that their exclusion was mainly related to MOD16A2GF pixel availability rather than to a deliberate removal of specific terrain conditions.

After filtering, the final dataset included 28 stations in Piemonte and 90 stations in Veneto. These were divided into independent training and validation subsets, with 23 training and 5 validation stations in Piemonte, and 72 training and 18 validation stations in Veneto. The spatial distribution of the retained training and validation stations is shown in Figure 2. The training and validation sets were selected to preserve a comparable altitudinal distribution in both subsets, as shown in Figure 3.

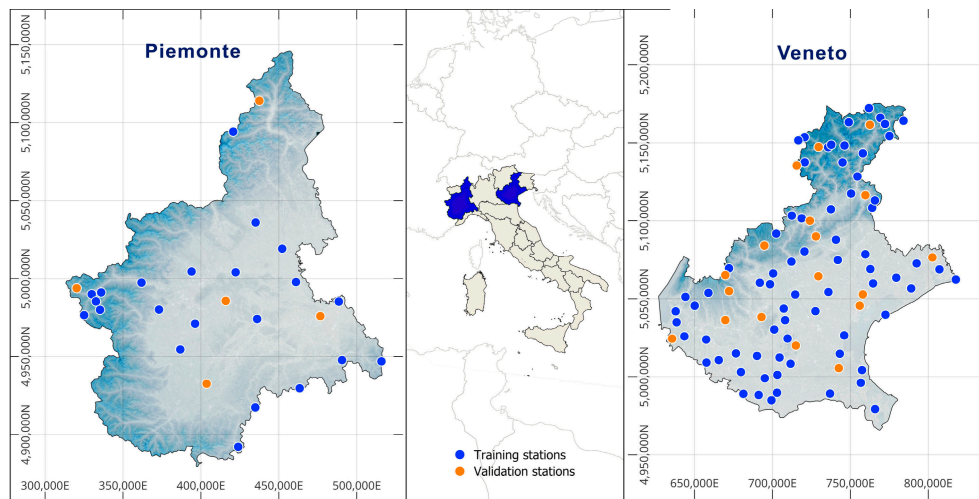


Figure 2. Spatial distribution of monitoring stations in the study areas: Piemonte (left) and Veneto (right). Blue points indicate the stations used for the model training phase (training stations), while orange points represent the stations used for independent validation (validation stations). Coordinate system: WGS84/UTM Zone 32N.

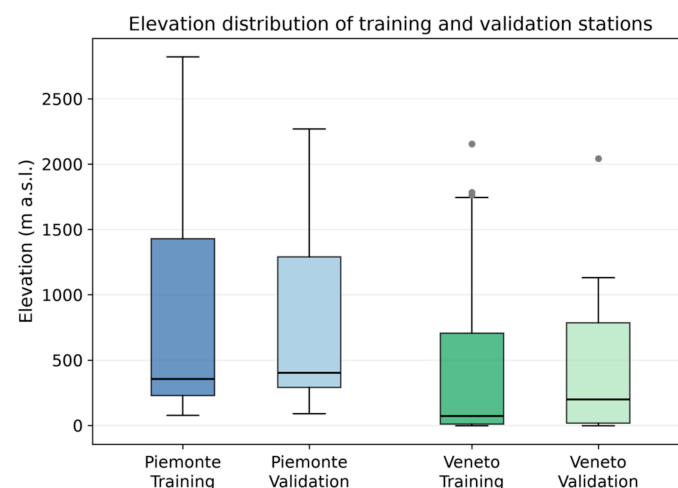


Figure 3. Elevation distribution of the retained meteorological stations used for model training and validation in Piemonte and Veneto. The boxplots, the horizontal bars are respectively (from the bottom to the top) 5th, 25th, 50th, 75th, 95th percentiles and points outside the whiskers indicate outliers.

2.3. Data Processing

2.3.1. ET_0 Computation

The computation of reference evapotranspiration using the FAO Penman–Monteith (FAO PM) equation requires station elevation, latitude, and longitude, together with standard meteorological variables: solar radiation, daily maximum and minimum air temperature, daily maximum and minimum relative humidity, and wind speed. All variables were measured at 2 m height or converted accordingly. As the ground stations were not equipped with barometers, atmospheric pressure was estimated following [4].

Ground-station data were filtered to retain observations within the reference period 2010–2022 and further restricted to the months from March to October, corresponding to the irrigation season under the climatic conditions of the study area. Once all required

input variables were obtained, daily ET_0 was calculated following the FAO-56 procedure and using the FAO Penman–Monteith equation (Equation (1)).

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (1)$$

where ET_0 is the reference evapotranspiration (mm day^{-1}), R_n is the net radiation at the crop surface ($\text{MJ m}^{-2} \text{ day}^{-1}$), G is the soil heat flux density ($\text{MJ m}^{-2} \text{ day}^{-1}$), T is the air temperature at 2 m height ($^{\circ}\text{C}$), u_2 is the wind speed at 2 m height (m s^{-1}), e_s is the saturation vapour pressure (kPa), e_a is the actual vapour pressure (kPa), $(e_s - e_a)$ is the saturation vapour pressure deficit (kPa), Δ is the slope of the vapour pressure curve ($\text{kPa } ^{\circ}\text{C}^{-1}$), and γ is the psychrometric constant ($\text{kPa } ^{\circ}\text{C}^{-1}$). Following the FAO-56 procedure for daily calculations, G was assumed equal to 0, because soil heat flux over a 24 h period is generally small relative to net radiation and is commonly neglected at the daily time step [4].

Reference evapotranspiration (ET_0) represents the evaporative demand of the atmosphere and corresponds to the evapotranspiration from a standardized reference surface, defined as a hypothetical, well-watered grass crop with a height of 0.12 m, a fixed surface resistance of 70 s m^{-1} , and an albedo of 0.23 [4]. As ET_0 depends solely on atmospheric conditions, it can be derived directly from meteorological data using the FAO Penman–Monteith method.

Daily ET_0 values were subsequently aggregated to an 8-day temporal resolution to match the MOD16A2GF product. Aggregation periods containing missing daily observations were excluded to ensure data consistency between station-based ET_0 and MOD16 PET. This filtering removed approximately 8% of the 8-day aggregation periods in Piemonte and 3% in Veneto.

2.3.2. PET vs. ET_0 Spatio-Temporal Comparison

In order to compare PET and ET_0 and explore the discrepancies, an ordinary least squares (OLS) analysis was performed according to Equation (2), modelling a linear relationship between annual PET time series and ET_0 one.

$$\widehat{ET_0}(x, y, t) = a(x, y, t) \cdot PET(x, y, t) + b(x, y, t) \quad (2)$$

where x and y denote spatial coordinates (here set in WGS84/UTM32N reference system) and t is the t -th year along the full PET- ET_0 time series. The OLS solution provides the coefficients a and b , i.e., linear gain and offset values per each meteorological station at t -th year. The model in Equation (2) allows to map ET_0 estimate (i.e., $\widehat{ET_0}$) using PET maps derived by MOD16A2 data.

The nominal number of observations per annual regression was therefore approximately 30–31 8-day periods, depending on the MOD16 compositing calendar and on the exclusion of aggregation periods with missing ground observations. To assess the robustness of the station-wise regressions, we recorded the number of valid observations, the coefficient of determination (R^2), the p -value of the slope coefficient for each station-year model.

To evaluate the temporal behaviour of the station-wise correction coefficients, boxplots of $a(x, y, t)$ and $b(x, y, t)$ per each t -th year in the considered period were computed. The boxplots were used to describe the yearly distribution of the coefficients, while linear trends fitted to the annual medians and interquartile ranges (IQRs) were used to test for systematic temporal drift in both Piemonte and Veneto.

Subsequently, the mean values of coefficients were computed involving all years creating the $\underline{a}(x, y)$ e $\underline{b}(x, y)$. These two maps represent the mean value of coefficients for each meteorological station summarizing the relationship between PET and ET_0 .

2.3.3. Modelling ET_0 -PET Transformation Coefficients

Since $\underline{a}(x, y)$ e $\underline{b}(x, y)$ spatially vary, a multivariate regression model was proposed to explore how local environmental conditions like topography can affect coefficients distribution. From DTM the longitude, the latitude, the altitude, the slope, the aspect and the north south index, i.e., $NSindex = 1 - \cos(\text{aspect})$, were computed and mapped. From these layers, the corresponding values at meteorological station location were sampled and involved in a multivariate linear regression (MLR) by using OLS relating topographic conditions as independent variables and $\underline{a}(x, y)$ e $\underline{b}(x, y)$ as dependent ones (Equations (3) and (4)).

$$Y = XB + E \quad (3)$$

$$\hat{B} = (X^t X)^{-1} X^t Y \quad (4)$$

where $Y \in \mathbb{R}^{n \times m}$ matrix containing n observation, i.e., number of available meteorological stations, and m is the number of dependent variables, i.e., $\underline{a}(x, y)$ e $\underline{b}(x, y)$. $E \in \mathbb{R}^{n \times m}$ matrix containing zero mean gaussian errors; $X \in \mathbb{R}^{n \times k}$ the design matrix, containing n observation and k independent variables, i.e., selected topographic features. Before computing Equations (3) and (4) a multicollinearity analysis by correlogram computation was performed over topographic features in order to select only not-collinear features in MLR.

Estimates from 4 were added in Equation (2) and a final model (FM) to estimate ET_0 from PET and topographic features was proposed in Equation (5).

$$\widehat{ET_0}(x, y) = [\sum_{j=1}^k c_j \cdot T_j(x, y) + d] \cdot PET(x, y) + [\sum_{j=1}^k e_j \cdot T_j(x, y) + f] \quad (5)$$

where c_j and e_j are coefficient of the j -th topographic feature; $T_j(x, y)$ is the value of j -th min-max normalized topographic feature at location (x, y) ; d and f are two offset values.

The FM coefficients i.e., c_j , e_j , d and f , were calibrated using training sets for Veneto and Piemonte regions separately. It is worth highlighting that FM is no longer dependent on meteorological station data but it depends only on topography making this model more generalizable.

2.3.4. Model Validation

Model performance was assessed through two complementary validation experiments: a local interpolation test and a cross-region extrapolation test.

First, the local interpolation performance of the proposed topography-based correction was evaluated separately for Piemonte and Veneto. In each region, the final model was calibrated using the regional training stations and then applied to the independent regional validation stations. This experiment was designed to quantify the accuracy of the elevation-based correction under local calibration conditions.

To provide a purely spatial interpolation benchmark, an inverse distance weighting (IDW) approach was also implemented. The multi-year mean station-wise correction coefficients $\underline{a}(x, y)$ and $\underline{b}(x, y)$, estimated at the training stations, were interpolated over each region using IDW. The interpolated coefficients were then extracted at the independent validation stations and applied to the MOD16 PET time series according to Equation (2). The local validation therefore compared three estimates at the same independent validation stations: raw MOD16 PET, the locally calibrated topography-based correction, and the IDW-

based correction. This experiment was used to assess whether the proposed elevation-based model provides a competitive alternative to a distance-based interpolation of empirical correction coefficients.

Second, a cross-region extrapolation test was performed to evaluate the model behaviour outside the calibration region. In this experiment, the model was calibrated using all retained stations from one region and then applied to all retained stations of the other region. Specifically, the Piemonte-calibrated model was applied to Veneto, and the Veneto-calibrated model was applied to Piemonte. This test was designed to assess whether the elevation-based correction captures a component of the PET-ET₀ relationship that can be transferred across neighbouring physiographic domains. Because this experiment evaluates extrapolation rather than local interpolation, the transferred models were compared primarily with raw MOD16 PET in the target region.

For all validation experiments, predicted ET₀ values were compared with station-based FAO-56 ET₀ using mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), mean error (Bias), and the coefficient of determination (r^2). Bias was calculated as predicted minus observed ET₀, so that positive values indicate overestimation and negative values indicate underestimation. The coefficient of determination was computed as the square of the Pearson correlation coefficient between predicted and observed ET₀.

Metrics were computed over the full validation period and were also summarized by year and by month to evaluate interannual and seasonal performance. In addition, 1:1 scatter plots of observed versus predicted ET₀ were produced to visually assess model agreement and possible deviations from linear behaviour.

3. Results

3.1. PET vs. ET₀ Spatio-Temporal Comparison

Before analysing the temporal behaviour of the correction coefficients, the robustness of the station-wise annual OLS regressions was assessed on the training set (Table 2). In both regions, the annual local regressions showed statistically significant slopes, supporting the use of a linear PET-ET₀ relationship at the station-year scale. These diagnostics should not be interpreted as predictive validation of the final topography-based model, because each regression was fitted locally using observed PET and ET₀ values. Rather, they confirm the suitability of the station-wise linear formulation used to derive the correction coefficients before modelling their spatial variability as a function of topography.

Table 2. Training-set diagnostics of the station-year PET-ET₀ regressions.

Region	N. of Regressions	N. Obs. Median (Range)	Median R ² (IQR)	Significant Slope (%)
Piemonte	260	28 (11–31)	0.92 (0.88–0.94)	100
Veneto	851	29 (13–31)	0.74 (0.67–0.79)	100

The annual boxplots of $a(x, y, t)$ and $b(x, y, t)$ for both study regions (Figure 4) show that the correction coefficients vary among years, particularly in terms of distribution width. However, no consistent directional change is evident over the 2010–2022 period. This visual pattern was confirmed by the linear trend analysis performed on the annual medians and interquartile ranges (IQRs) of both coefficients (Table 3). No statistically significant temporal trend was found for either $a(x, y, t)$ or $b(x, y, t)$ in Piemonte or Veneto. The only near-significant tendency was observed for the median of b in Veneto ($p = 0.09$), but it did not reach the $p < 0.05$ significance threshold.

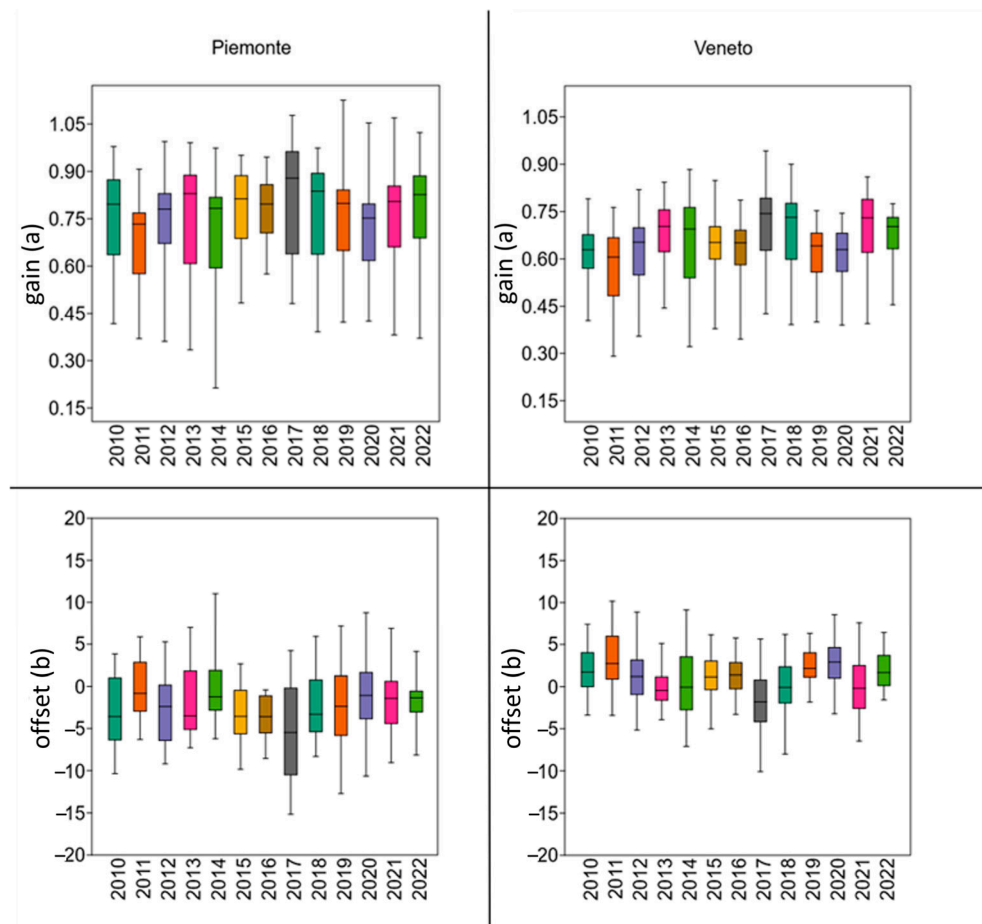


Figure 4. Annual boxplots of the gain coefficients (a) (x,y,t) (top row) and offset coefficients (b) (x,y,t) (bottom row) for the regions of Piemonte (left column) and Veneto (right column). The plots show the temporal distribution of values from 2010 to 2022, highlighting the internal spatial variability within each region for each year considered.

Table 3. Linear trend analysis of the annual medians and interquartile ranges (IQRs) of the station-wise PET-ET₀ correction coefficients $a(x,y,t)$ and $b(x,y,t)$ over the 2010–2022 period. Slopes are expressed per year. p -values refer to the significance of the linear trend.

Annual Statistic	Coeff.	Piemonte Slope	Piemonte R ²	Piemonte p -Value	Veneto Slope	Veneto R ²	Veneto p -Value
IQR	$a(x,y,t)$	−0.0006	0.002	0.89	−0.0028	0.089	0.32
IQR	$b(x,y,t)$	−0.1988	0.131	0.22	−0.0438	0.023	0.61
MEDIAN	$a(x,y,t)$	−0.0299	0.009	0.75	−0.0480	0.018	0.66
MEDIAN	$b(x,y,t)$	0.0020	0.042	0.51	0.0057	0.244	0.09

These results indicate that the station-wise correction coefficients are not strictly time-invariant, because their annual distributions vary in spread. However, the absence of significant temporal trends suggests that they do not exhibit a systematic temporal drift over the study period. Therefore, the multi-year mean coefficients $\bar{a}(x,y)$ and $\bar{b}(x,y)$ were used as long-term average correction parameters to represent the persistent PET-ET₀ relationship at each meteorological station, rather than as year-specific correction terms.

Figure 5 shows the spatial distribution of the coefficients $a(x,y)$ and $b(x,y)$ for the Piemonte and Veneto regions. In both regions, central areas display higher gain values (dark green), indicating that the model captures the main spatial variability of ET₀ derived from MOD16. Lower gain values (red and orange) are observed in the northern, western,

and southern parts of Piemonte, as well as in the mountainous areas of Veneto, likely due to complex topography and sparse vegetation. High-altitude zones are known to show larger differences between PET and ET_0 , suggesting that topography influences the relationship, rather than implying errors in MOD16 itself [10].

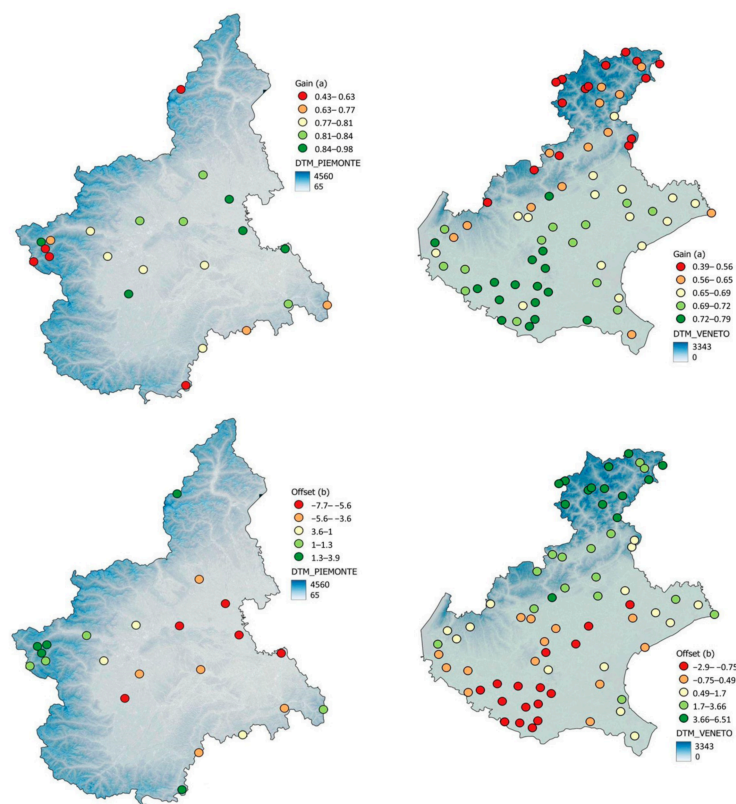


Figure 5. Distribution maps of parameters, gain (a) (**top**) and offset (b) (**bottom**) derived for the study stations in Piemonte (**left**) and Veneto (**right**). The color scale groups the values into classes. The background represents the Digital Terrain Model (DTM), with elevations expressed in meters above sea level.

The spatial distribution of offset coefficient values (Figure 5) reveals that in central plains and hilly areas (predominantly cultivated), PET tends to be higher than ET_0 (red and orange), indicating the need for larger correction coefficients to accurately estimate ET_0 from MOD16. These patterns reflect the combined influence of land cover, topography, and management practices on the relationship between PET and ET_0 .

3.2. Modelling ET_0 -PET Transformation Coefficients

Figure 6 presents the correlogram for Veneto (left panel) and Piemonte (right panel), illustrating the interdependencies between the coefficients a and b and the considered environmental variables. In both regions, a and b show a clear dependence on elevation, consistent with the patterns already observed in Section 3.1. Elevation is also strongly correlated with slope in both regions, and with latitude in Veneto, indicating redundancy among these variables.

To construct a robust multivariate model, all variables highly correlated with elevation were excluded, as well as those lacking a significant effect on a and b ($p > 0.05$), such as NS_index and latitude in Piemonte. Longitude exhibited a statistically significant effect in both regions, but its contribution was negligible and therefore omitted.

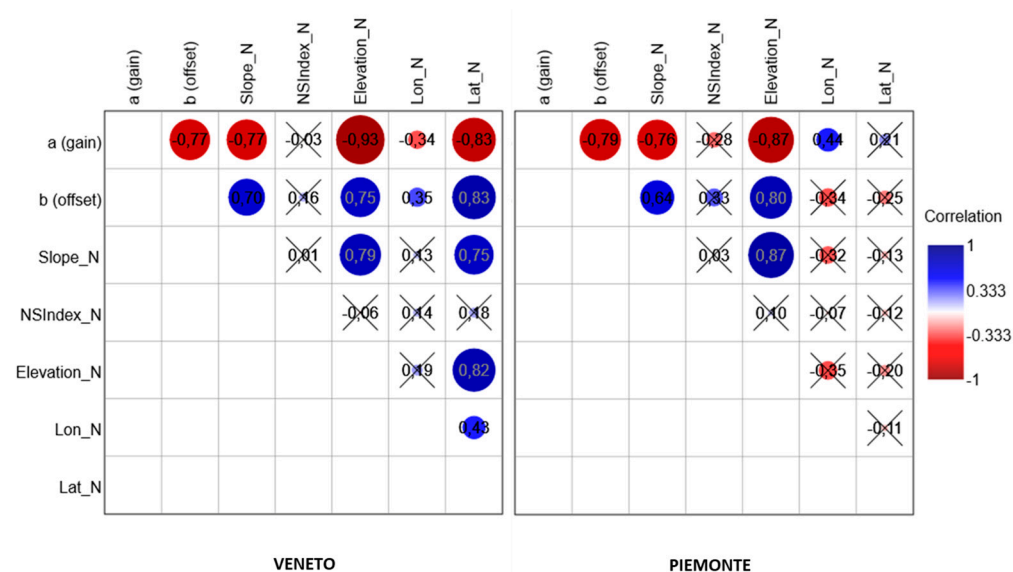


Figure 6. Pearson correlation matrices between the model coefficients (a, b) and the environmental predictors for the Veneto region (left) and the Piedmont region (right). Circles indicate the strength and direction of the correlations: blue represents positive correlations and red represents negative correlations. Circle size and color intensity are proportional to the correlation coefficient. Cells marked with an “X” indicate relationships that are not statistically significant ($p > 0.05$).

As a result, elevation remained the only relevant topographic predictor (T_j), and the final multivariate model (FM) linking a and b to elevation was developed based on this variable. The direct relationship between the multi-year mean correction coefficients and elevation is shown in Figure 7. In both regions, the multiplicative coefficient a decreases with increasing elevation, while the additive coefficient b increases. This pattern confirms the altitudinal structure already suggested by the spatial maps (Figure 5) and the correlation analysis (Figure 6). The relationship is stronger for a than for b , indicating that elevation is more strongly associated with the multiplicative component of the PET- ET_0 relationship, while the additive component retains a larger unexplained variability.

The coefficients of FM for Piemonte and Veneto are reported respectively in Tables 4 and 5.

Table 4. Estimated coefficients of the elevation-dependent ET_0 model for the Piemonte region (Equation (5)). The table reports the regression coefficients associated with the multiplicative and additive components of the model, along with standard errors (S.E.), t -statistics, p -values, and coefficients of determination (R^2).

	Coeff	S.E.	<i>t</i>	<i>p</i>	R^2
<i>c</i>	−0.39	0.05	7.98	1.21×10^{-7}	0.76
<i>d</i>	0.88	0.02			
<i>e</i>	9.65	1.59	6.06	6.30×10^{-6}	0.65
<i>f</i>	−5.21	0.66			
R^2			0.65		

c and e are coefficients associated with the topographic predictor (elevation) in the multiplicative and additive terms, respectively, while d and f are the corresponding intercepts. Statistical significance is reported only for regression-derived coefficients (c and e). R^2 values refer to the explanatory power of elevation for each component and to the overall model performance (bottom row).

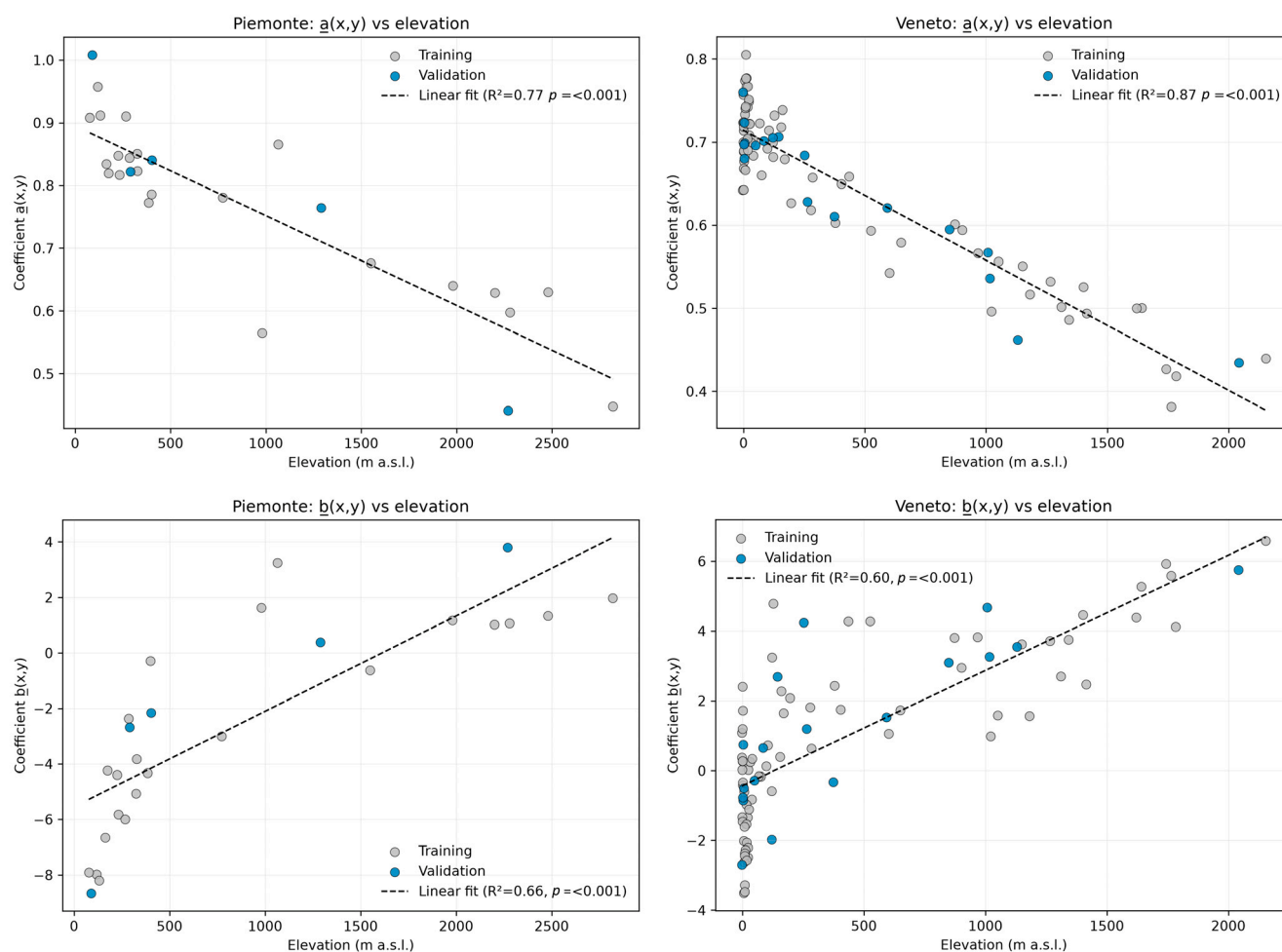


Figure 7. Relationship between station-wise PET-ET₀ correction coefficients and elevation in Piemonte and Veneto. Points represent multi-year mean coefficients; lines indicate the fitted elevation-based models.

Table 5. Estimated coefficients of the elevation-dependent ET₀ model for the Veneto region (Equation (5)). The table reports the regression coefficients associated with the multiplicative and additive components of the model, along with standard errors (S.E.), *t*-statistics, *p*-values, and coefficients of determination (R^2).

	Coeff	S.E.	<i>t</i>	<i>p</i>	R^2
<i>c</i>	−0.48	0.02	21.16	3.94×10^{-32}	0.86
<i>d</i>	0.71	0.01			
<i>e</i>	9.36	0.98	9.54	2.69×10^{-14}	0.57
<i>f</i>	0.00	0.22			
R^2			0.57		

c and *e* are coefficients associated with the topographic predictor (elevation) in the multiplicative and additive terms, respectively, while *d* and *f* are the corresponding intercepts. Statistical significance is reported only for regression-derived coefficients (*c* and *e*). R^2 values refer to the explanatory power of elevation for each component and to the overall model performance (bottom row).

The elevation-dependent formulation of ET₀ exhibits statistically robust and physically plausible behavior in both regions. The negative and highly significant coefficient *c* indicates a systematic decrease in the sensitivity of ET₀ to PET with increasing elevation, while the positive coefficient *e* reflects a compensating additive effect of elevation. The dependence of the PET sensitivity coefficient (*a*) on elevation is strongly supported by the data ($R^2 = 0.76$ in Piemonte and 0.86 in Veneto), whereas the elevation dependence of the intercept term

(b) shows moderate explanatory power ($R^2 = 0.65$ and 0.57 , respectively). These values describe how effectively elevation explains the spatial variability of the model parameters. The overall ET_0 model explains 65% of the variance in Piemonte and 57% in Veneto, confirming the relevance of an elevation-dependent parameterization, although part of the variability remains unexplained. The lower explanatory power observed in Veneto suggests a greater influence of local or climatic drivers not explicitly represented in the model.

3.3. Spatialization of Correction Coefficients

The spatialized correction coefficients obtained with the topography-based model and with IDW interpolation are shown in Figure 8. The two approaches reproduce comparable broad-scale spatial patterns, although their spatial behaviour differs. The IDW-based surfaces show more localized variations around the calibration stations, whereas the topography-based model produces smoother gradients aligned with the elevation structure of each region. In Piemonte, differences between the two spatialization methods are more evident in topographically complex areas and in sectors with lower station density. In Veneto, the two spatialization approaches show more similar patterns, consistent with the validation results reported in Section 3.4. Overall, the comparison highlights that IDW provides a local interpolation benchmark, while the topography-based model imposes an explicit terrain-related structure on the correction surfaces.

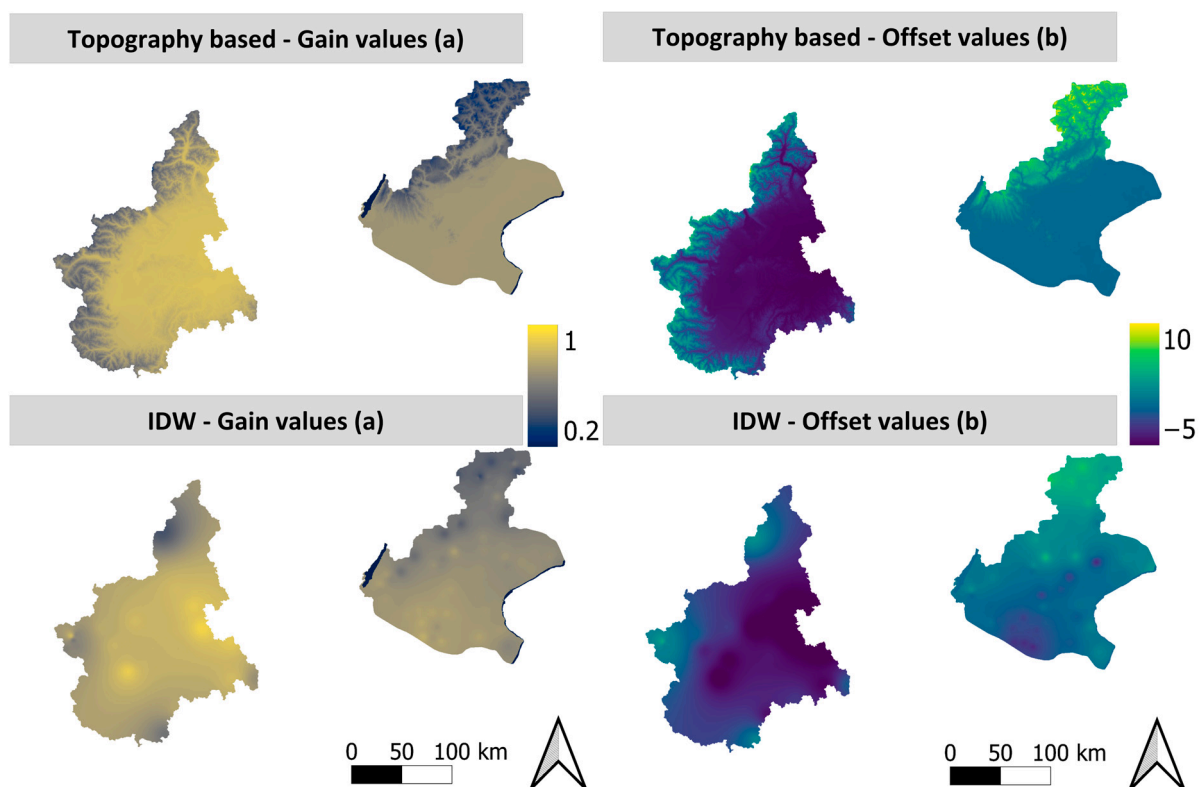


Figure 8. Spatialized PET- ET_0 correction coefficients obtained with the topography-based model and IDW interpolation for Piemonte and Veneto.

3.4. Model Validation

3.4.1. Local Interpolation Performance

Training performance was first evaluated for the locally calibrated topography-based models. The training-set RMSE and r^2 values were $4.09 \text{ mm } 8\text{-day}^{-1}$ and 0.85 in Piemonte, and $5.39 \text{ mm } 8\text{-day}^{-1}$ and 0.74 in Veneto, respectively. These values were used only to

describe model fit under calibration conditions, while the independent validation stations were used to assess predictive performance.

The independent local validation results are reported in Table 6 and visually summarized in Figure 9. In both regions, raw MOD16 PET showed a systematic overestimation of station-based FAO-56 ET_0 , as indicated by the positive Bias values and by the position of the point clouds above the 1:1 line. The locally calibrated topography-based correction substantially reduced this offset and decreased MAE, RMSE and MAPE relative to MOD16 PET.

Table 6. Independent local validation metrics for raw MOD16 PET, the locally calibrated topography-based ET_0 model, and the IDW-based correction. Metrics were computed on the independent validation stations. MAE, RMSE and Bias are expressed in mm 8-day^{−1}; MAPE is expressed as %.

Region	Product/Model	N	MAE	RMSE	MAPE (%)	Bias	r ²
PIEMONTE	MOD16 PET	1544	9.61	10.92	42.76	9.57	0.821
PIEMONTE	Topography-based ET_0	1544	3.33	4.19	14.45	−0.86	0.861
PIEMONTE	IDW-based ET_0	1544	3.12	3.99	12.83	−1.46	0.890
VENETO	MOD16 PET	6429	11.45	13.37	55.89	11.14	0.695
VENETO	Topography-based ET_0	6429	4.28	5.52	20.96	0.18	0.715
VENETO	IDW-based ET_0	6429	4.31	5.56	20.75	−0.23	0.711

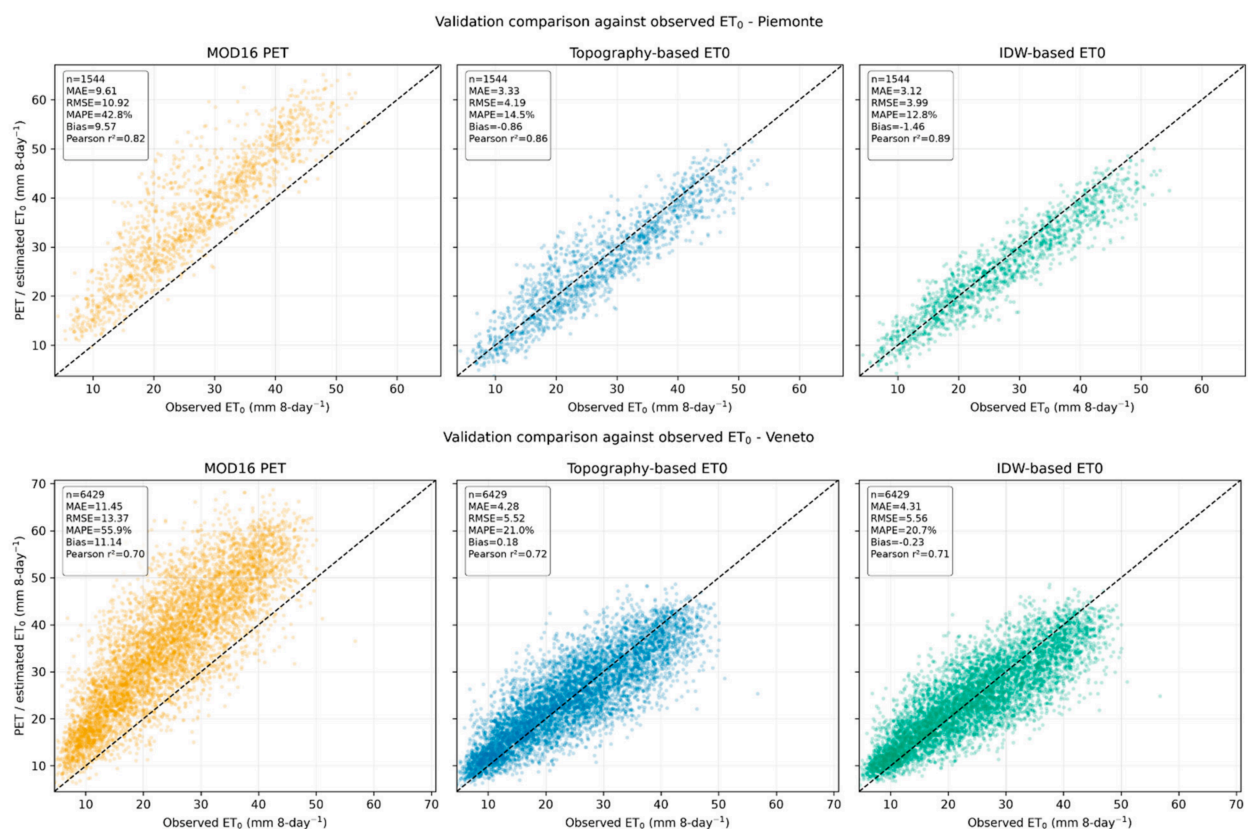


Figure 9. Observed versus estimated 8-day ET_0 for the independent local validation stations. Columns show raw MOD16 PET, the topography-based correction, and the IDW-based correction. The dashed line indicates the 1:1 relationship.

The IDW-based correction provided a local interpolation benchmark. In Piemonte, IDW showed slightly lower MAE, RMSE and MAPE and a higher r² than the topography-based model, although it produced a more negative Bias. In Veneto, the two corrected estimates showed very similar performance across all metrics. In the scatter plots, both

corrected products were more closely distributed around the 1:1 line than raw MOD16 PET, although some residual dispersion and partial compression of the ET_0 range remained.

Figures 10 and 11 show the MAPE distributions for raw MOD16 PET and for the topography-based corrected ET_0 estimates in Veneto and Piemonte, respectively. Monthly distributions are reported in Figures 10a and 11a, while annual distributions are shown in Figures 10b and 11b. In both regions, the annual MAPE distributions remained relatively stable over the 2010–2022 period, with consistently lower median values and reduced variability for the corrected estimates compared with raw MOD16 PET.

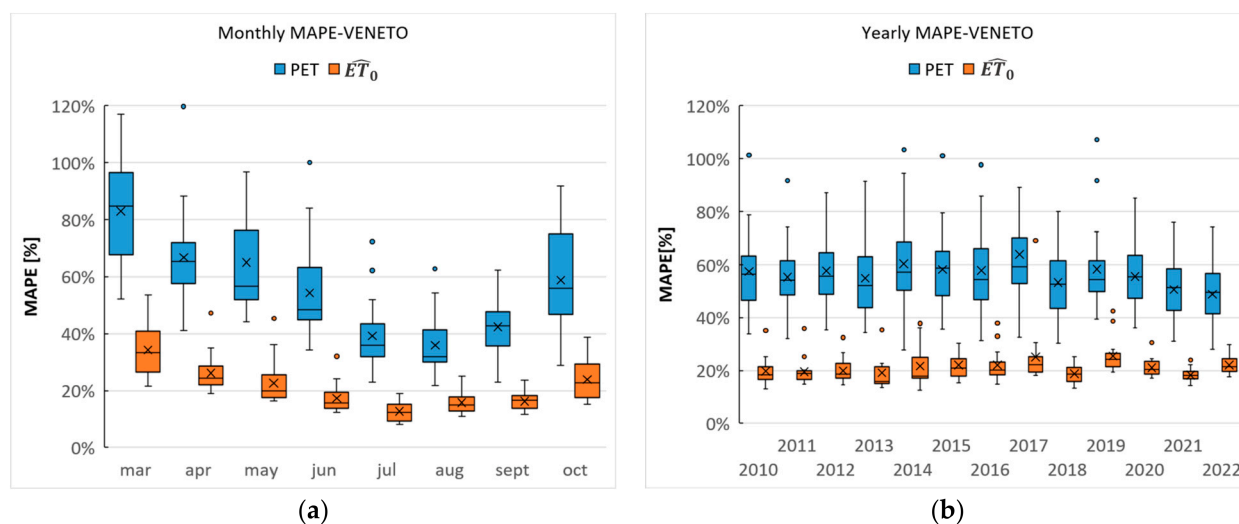


Figure 10. Monthly (a) and annual (b) MAPE for the Veneto region, comparing MOD16 PET and the topography-based corrected ET_0 estimates (2010–2022). The boxplots, the horizontal bars are respectively (from the bottom to the top) 5th, 25th, 50th, 75th, 95th percentiles and points outside the whiskers indicate outliers, while crosses indicate mean values.

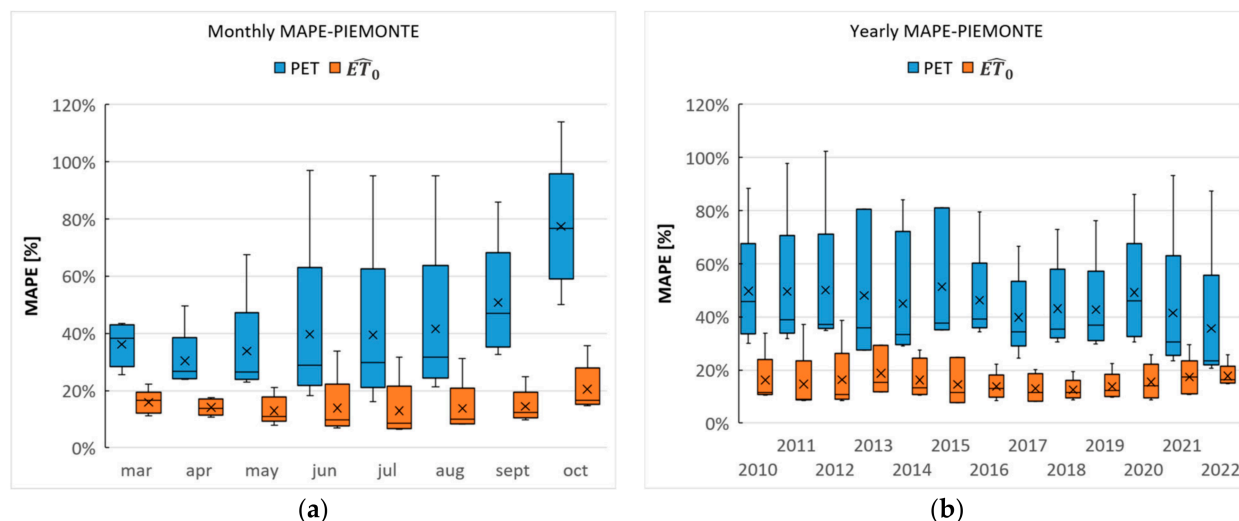


Figure 11. Monthly (a) and annual (b) MAPE for the Piemonte region, comparing MOD16 PET and topography-based corrected ET_0 estimates (2010–2022). The boxplots, the horizontal bars are respectively (from the bottom to the top) 5th, 25th, 50th, 75th, 95th percentiles and points outside the whiskers indicate outliers, while crosses indicate mean values.

At the monthly scale, higher MAPE values were observed at the beginning and end of the March–October period, particularly in March and October, whereas lower percentage errors occurred during the central summer months. This seasonal pattern reflects the

sensitivity of MAPE to low ET_0 values: when ET_0 is low, small absolute deviations can produce larger percentage errors. The corresponding annual and monthly MAE, RMSE and Bias distributions are reported in Figures A1–A6, while the complete validation metrics, including MAE, RMSE, Bias and r^2 , are summarized in Table 6.

3.4.2. Cross-Region Extrapolation Performance

A second validation experiment was conducted to assess cross-region extrapolation performance. In this test, the model was calibrated using all retained stations from one region and then applied to all retained stations of the other region. The transferred model was compared with raw MOD16 PET in the independent target region. The results are reported in Table 7 and shown in Figure 12. In both transfer directions, the model calibrated in one region improved MOD16 PET estimates in the other region, reducing MAE, RMSE, MAPE and absolute Bias. The scatter plots show that raw MOD16 PET values were mostly located above the 1:1 line, whereas the transferred-model estimates shifted closer to the observed ET_0 values. Residual bias remained after transfer: the Piemonte-to-Veneto transfer retained a positive Bias, while the Veneto-to-Piemonte transfer produced a negative Bias.

Table 7. Cross-region transfer metrics for raw MOD16 PET and the transferred topography-based model. The model was calibrated in one region and applied to all retained stations of the other region. MAE, RMSE and Bias are expressed in $\text{mm } 8\text{-day}^{-1}$; MAPE is expressed as %.

Target Region	Product/Model	Calibration Region	N	MAE	RMSE	MAPE (%)	Bias	r^2
Veneto	MOD16 PET	None	30,792	11.56	13.42	55.19	11.28	0.714
Veneto	Piemonte model on Veneto	Piemonte	30,792	4.65	6.07	21.88	1.26	0.732
Piemonte	MOD16 PET	None	8495	10.94	12.10	48.74	10.85	0.820
Piemonte	Veneto model on Piemonte	Veneto	8495	3.90	4.97	16.56	−1.88	0.830

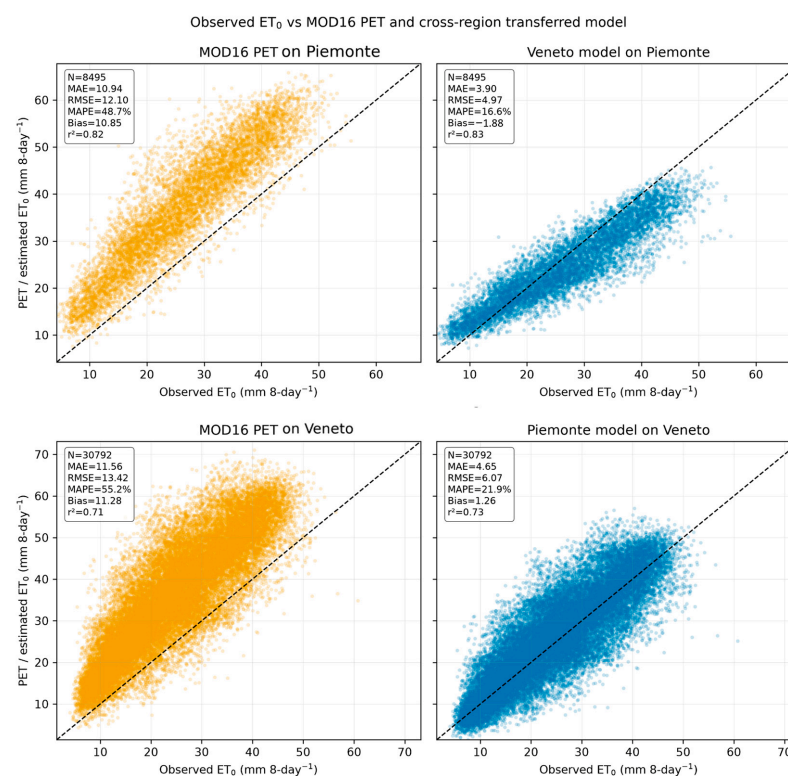


Figure 12. Cross-region transfer scatter plots. Panels compare observed FAO-56 ET_0 with raw MOD16 PET and with the transferred model. The dashed line indicates the 1:1 relationship.

4. Discussion

The station-year OLS diagnostics also suggest that the local PET-ET₀ relationship was less tightly constrained in Veneto than in Piemonte, as indicated by the lower R² distribution in the training regressions. This pattern is consistent with the lower explanatory power of the final elevation-based model in Veneto and suggests that additional sources of variability, not captured by elevation alone, may affect the PET-ET₀ relationship in this region. These may include coastal influences, local wind regimes, irrigation heterogeneity, land-cover variability and vegetation dynamics. The temporal analysis of the transformation coefficients showed that their annual distributions vary among years, particularly in terms of dispersion, but no statistically significant temporal drift was detected in either the annual medians or interquartile ranges over the 2010–2022 period. This result suggests that the relationship between MOD16 PET and meteorologically derived ET₀ is not controlled only by short-term interannual variability, but also reflects persistent spatial and modelling-related factors. Therefore, the use of multi-year mean correction coefficients is appropriate for representing long-term average PET-ET₀ discrepancies, although it should not be interpreted as evidence that the correction parameters are strictly time-invariant.

This interpretation is consistent with previous studies showing that MOD16 performance can be affected by algorithmic parameterizations, environmental constraints, land-cover representation and scale mismatch. Modified MOD16 formulations have improved ET estimates by revising aerodynamic resistance, stomatal constraints, soil evaporation schemes or soil-moisture constraints [24,25]. Similarly, validation studies against flux-tower observations have reported inconsistent MOD16 performance and attributed part of the uncertainty to land-cover classification, spatial scaling and algorithm limitations [26]. In this context, the proposed formulation can be interpreted as a regional bias-adjustment procedure that reconciles MOD16 PET with the FAO-56 definition of reference evapotranspiration used in agronomic applications.

Although multiple topographic descriptors were initially evaluated, elevation emerged as the only robust predictor retained in the final formulation. This does not imply that elevation alone directly controls reference evapotranspiration. Rather, elevation acts as a synthetic proxy for several terrain-related gradients, including temperature regime, radiation conditions, atmospheric coupling and landscape position. Other morphometric variables did not provide independent explanatory power once redundancy was accounted for. This result suggests that altitudinal gradients encapsulate the primary terrain-driven controls affecting the PET-ET₀ relationship, allowing the final model to remain parsimonious while retaining physical interpretability.

Higher elevations were associated with reduced sensitivity of ET₀ to PET and larger additive offsets, revealing a coherent spatial structure across both regions. This behaviour is consistent with the influence of terrain on near-surface temperature regimes, radiation balance, and atmospheric coupling processes, all of which indirectly modulate reference evapotranspiration. The emergence of elevation as the sole robust predictor reinforces the interpretation that PET-ET₀ discrepancies are spatially organized rather than random, and that their structure can be effectively captured through a physically meaningful gradient.

The local validation confirmed that raw MOD16 PET systematically overestimated station-based FAO-56 ET₀ in both regions. The locally calibrated topography-based correction substantially reduced MAE, RMSE, MAPE and Bias, indicating that the proposed formulation effectively mitigates the dominant systematic offset between MOD16 PET and ground-derived ET₀. The comparison with IDW further clarified the interpolation capability of the approach. IDW slightly outperformed the topography-based model in Piemonte and showed almost equivalent performance in Veneto. This indicates that, when a dense local calibration network is available, a purely distance-based interpolation of empirical

correction coefficients can be highly competitive. However, the elevation-dependent model achieved comparable accuracy while imposing an explicit terrain-related structure on the correction surfaces, rather than relying only on station proximity.

A scale-dependent bias pattern further emerges when contrasting absolute and relative error metrics. Consistent with previous observations [11], absolute overestimation by MOD16 PET increases during periods of high evaporative demand. However, when errors are expressed in relative terms (MAPE), proportional overestimation becomes larger under low ET_0 conditions. This apparent discrepancy reflects the mathematical properties of percentage-based metrics, whereby moderate absolute deviations correspond to larger relative errors when the reference variable is small. The distinction between absolute and relative bias is therefore crucial for interpretation, as it confirms that MOD16 PET deviations persist across the seasonal cycle, while their perceived magnitude depends on the chosen metric.

The present findings align with large-scale assessments [10], where substantial improvements in ET_0 estimation were achieved through regression-based recalibration of MOD16 PET. In that study, a multivariate linear regression, including radiation, precipitation, wind speed, elevation, and several bioclimatic variables, achieved high predictive performance. However, the objective was primarily predictive optimization through a high-dimensional predictor set. In contrast, our approach targets structural bias reduction using a single, physically interpretable topographic gradient identified as dominant. Despite the reduced dimensionality, the performance obtained is of comparable order of magnitude, highlighting the relevance of terrain-related gradients in explaining part of the PET– ET_0 discrepancies in the study regions.

The cross-region experiment showed that the elevation-based correction has partial extrapolation capability. When calibrated using all retained stations from one region and applied to the other, the model substantially improved raw MOD16 PET estimates in both transfer directions. However, residual bias remained: the Piemonte-to-Veneto transfer retained a positive bias, whereas the Veneto-to-Piemonte transfer produced a negative bias, indicating partial overcorrection. The similarity of the cross-region results suggests that the elevation-based correction captures a common PET– ET_0 structure across Piemonte and Veneto, indicating that a broader multi-region calibration may be feasible. However, this hypothesis was not tested here because the two regions were kept separate to allow an independent extrapolation test. Therefore, the proposed correction should not be interpreted as fully transferable without local constraints. Local or regional calibration remains preferable when suitable ground observations are available, while future work should directly compare pooled and region-specific calibration strategies.

Similarly, [11] emphasized that raw MOD16 PET provides a valuable first-order estimate but requires regional projection or calibration to conform to locally adopted ET_0 standards, especially in topographically heterogeneous areas. Our results reinforce this conclusion, demonstrating that a parsimonious elevation-dependent correction can effectively align satellite-derived PET with FAO-based ET_0 while preserving spatial consistency and minimizing data requirements. At the same time, the comparison with IDW and the cross-region test show that the method should be understood as a terrain-constrained regional correction framework, rather than as a universally transferable calibration.

Overall, converging evidence from climatically diverse regions supports a common interpretation: MOD16 PET encapsulates meaningful information on atmospheric evaporative demand but exhibits systematic structural biases that limit its direct use as a surrogate for FAO-56 reference evapotranspiration. The present study shows that these discrepancies can be substantially mitigated through a physically grounded, elevation-constrained correction scheme. The approach provides a potentially operational framework for regional ET_0

mapping that is useful for irrigation planning and water-balance assessment in complex landscapes, provided that its calibration domain, local station density and extrapolation limits are explicitly considered.

5. Conclusions

This study presents a regionally calibrated approach to derive reference evapotranspiration (ET_0) from MOD16 potential evapotranspiration (PET) products, with the aim of addressing the limited availability of spatially continuous ET_0 data for agricultural applications. The analysis showed that the station-wise PET- ET_0 correction coefficients varied among years, particularly in terms of dispersion, but did not exhibit statistically significant temporal trends over the 2010–2022 period. This supports the use of multi-year mean correction coefficients as long-term average parameters, although they should not be interpreted as strictly time-invariant. Within the set of tested topographic predictors, elevation emerged as the only robust variable retained in the final model. This does not imply that elevation alone directly controls reference evapotranspiration, but rather that it acts as a synthetic proxy for terrain-related gradients affecting the PET- ET_0 relationship. The elevation-dependent formulation reduced the systematic overestimation of raw MOD16 PET in both Piemonte and Veneto and decreased MAE, RMSE, MAPE and absolute bias relative to the uncorrected product. The comparison with IDW showed that a purely distance-based interpolation of empirical correction coefficients can be highly competitive under dense local calibration conditions, especially in Piemonte. However, the proposed topography-based model achieved comparable performance while providing an explicit terrain-constrained representation of the PET- ET_0 correction surfaces.

The cross-region experiment suggested that the elevation-based correction has partial extrapolation capability. When calibrated in one region and applied to the other, the model reduced the error of raw MOD16 PET estimates in both transfer directions. Nevertheless, residual bias remained, indicating that the correction should not be considered fully transferable without local constraints. Local or regional calibration therefore remains preferable when suitable ground observations are available in the target domain.

Despite these encouraging results, some limitations should be acknowledged. First, elevation acts as a synthetic proxy for multiple terrain-related gradients, but it cannot fully represent local variability associated with land use, irrigation practices, or mesoscale atmospheric processes. Second, the availability and spatial distribution of meteorological stations influence calibration quality, particularly in areas characterized by complex morphology or lower observational density. Third, the cross-region results indicate that extrapolation outside the calibration domain can reduce MOD16 PET errors, but may introduce residual positive or negative bias depending on the target region.

Future developments should evaluate whether additional variables derived from remote sensing, such as land surface temperature, vegetation indices, or radiative variables, can improve model performance while preserving operational simplicity. Moreover, approaches based on machine learning techniques may help capture non-linear relationships between PET and ET_0 , especially in areas where elevation alone does not sufficiently explain local variability. However, the present results indicate that a parsimonious elevation-constrained correction provides an interpretable baseline for regional ET_0 mapping.

Overall, MOD16 PET contains useful information on atmospheric evaporative demand, but it cannot be directly assumed to be equivalent to FAO-56 reference evapotranspiration. The proposed correction framework reduces this discrepancy and provides an operationally efficient approach for regional ET_0 estimation in topographically heterogeneous areas, provided that its calibration domain, station-network dependence and extrapolation limits are explicitly considered.

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

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Data Availability Statement: The data presented in this study are available from public repositories and institutional data portals. These data were derived from the following publicly available resources: MOD16A2GF data from NASA LP DAAC (<https://www.earthdata.nasa.gov/data/catalog/lpcloud-mod16a2gf-061>, accessed on 17 October 2025), agrometeorological observations from the ARPA Piemonte historical database (https://www.arpa.piemonte.it/rischi_naturali/snippets_arpa_graphs/map_meteoweb/?rete=stazione_meteorologica, accessed on 22 October 2025) and the ARPAV meteorological data portal (https://www.arpa.veneto.it/dati-ambientali/dati-storici/meteo-idro-nivo/ultimi_anni, accessed on 22 October 2025), and elevation data from the Tinitaly DEM dataset (<https://doi.org/10.13127/tinitaly/1.1>, accessed on 11 November 2025).

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

Appendix A

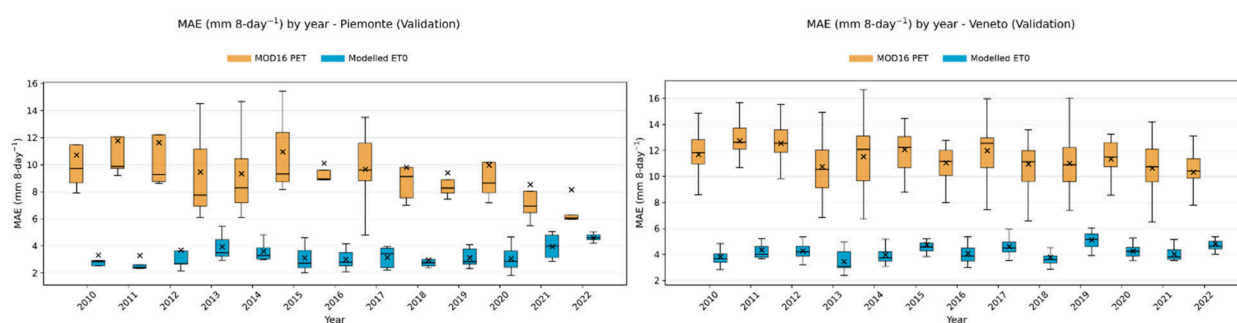


Figure A1. Annual MAE distributions for raw MOD16 PET and modelled ET_0 at the validation stations in Piemonte (**left**) and Veneto (**right**), 2010–2022. The boxplots, the horizontal bars are respectively (from the bottom to the top) 5th, 25th, 50th, 75th, 95th percentiles and points outside the whiskers indicate outliers, while crosses indicate mean values.

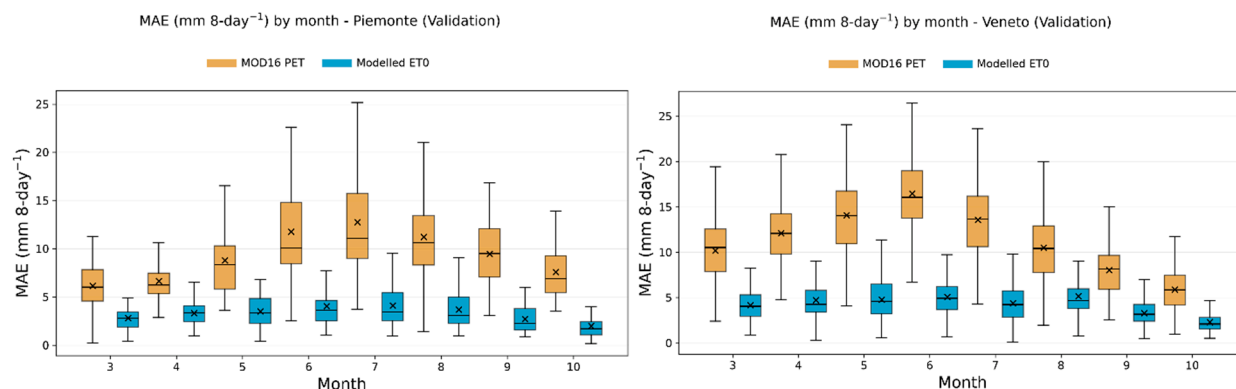


Figure A2. Monthly MAE distributions for raw MOD16 PET and modelled ET_0 at the validation stations in Piemonte (**left**) and Veneto (**right**), 2010–2022. The boxplots, the horizontal bars are respectively (from the bottom to the top) 5th, 25th, 50th, 75th, 95th percentiles and points outside the whiskers indicate outliers, while crosses indicate mean values.

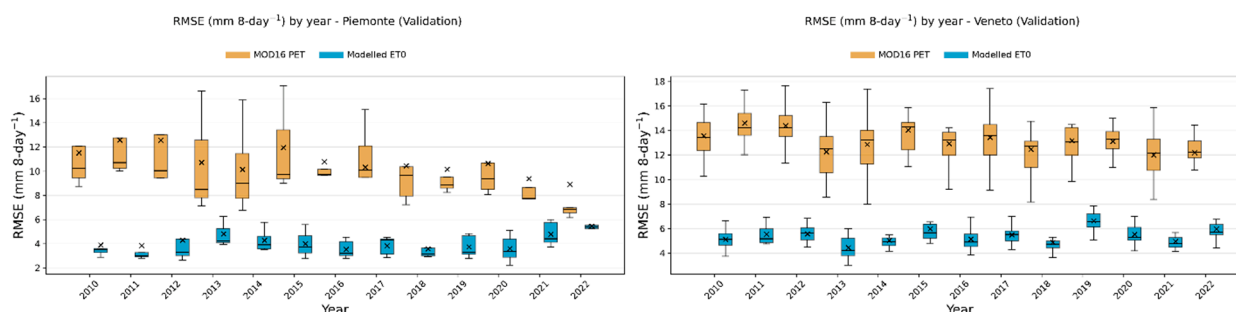


Figure A3. Annual RMSE distributions for raw MOD16 PET and modelled ET_0 at the validation stations in Piemonte (**left**) and Veneto (**right**), 2010–2022. The boxplots, the horizontal bars are respectively (from the bottom to the top) 5th, 25th, 50th, 75th, 95th percentiles and points outside the whiskers indicate outliers, while crosses indicate mean values.

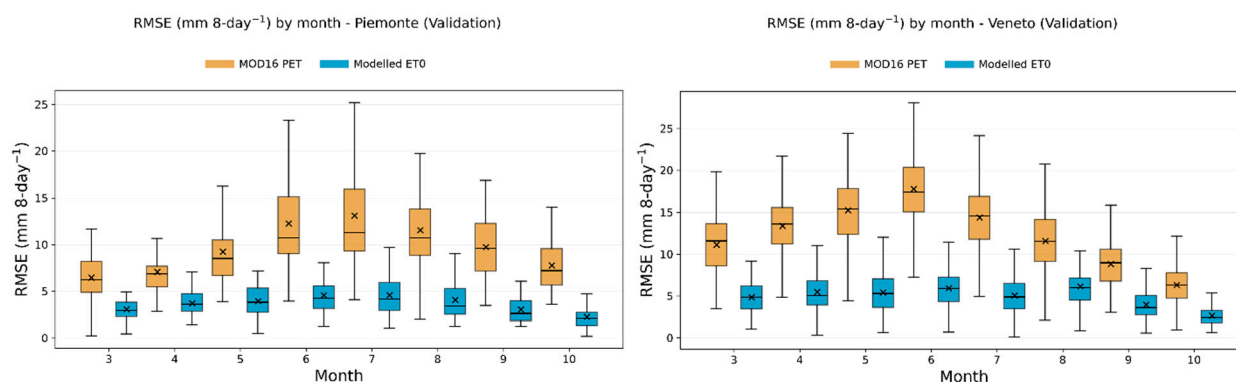


Figure A4. Monthly RMSE distributions for raw MOD16 PET and modelled ET_0 at the validation stations in Piemonte (**left**) and Veneto (**right**), 2010–2022. The boxplots, the horizontal bars are respectively (from the bottom to the top) 5th, 25th, 50th, 75th, 95th percentiles and points outside the whiskers indicate outliers, while crosses indicate mean values.

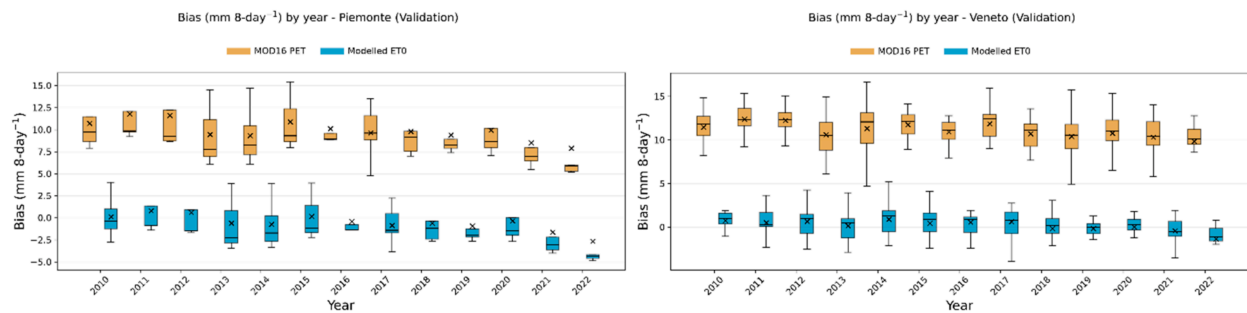


Figure A5. Annual Bias distributions for raw MOD16 PET and modelled ET_0 at the validation stations in Piemonte (**left**) and Veneto (**right**), 2010–2022. The boxplots, the horizontal bars are respectively (from the bottom to the top) 5th, 25th, 50th, 75th, 95th percentiles and points outside the whiskers indicate outliers, while crosses indicate mean values.

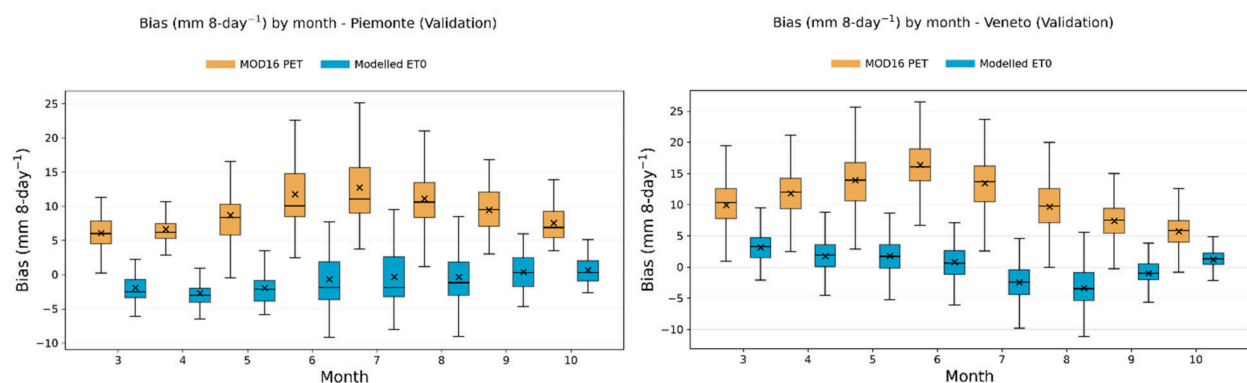


Figure A6. Monthly Bias distributions for raw MOD16 PET and modelled ET_0 at the validation stations in Piemonte (**left**) and Veneto (**right**), 2010–2022. The boxplots, the horizontal bars are respectively (from the bottom to the top) 5th, 25th, 50th, 75th, 95th percentiles and points outside the whiskers indicate outliers, while crosses indicate mean values.

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