Aligning Evapotranspiration from MOD16A2.061 Product to Ground Estimates in Piemonte (NW Italy): an analysis of temporal and spatial biases.

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Abstract

Evapotranspiration (ET), and in particular Reference Evapotranspiration (ET_0), is essential for agricultural planning, irrigation management, and water resource allocation—especially in regions facing water scarcity and limited observational data. While ground-based ET_0 is typically estimated using the FAO Penman-Monteith method, satellite-derived products such as MOD16 offer broader spatial coverage, although with conceptual and methodological differences. MOD16 provides Potential Evapotranspiration (PET) estimates, which, unlike ET_0, depend on local biome characteristics and are not standardized to a reference surface.
This study investigates whether the PET data from the MOD16A2GF product (version 6.1) can be adapted for ET_0 estimation in Piemonte (NW Italy), a region characterized by diverse climates and topographies. We compared PET data from 2010 to 2022 with ground-based ET_0 and applied a bias-correction method using linear regression models calibrated on local meteorological time series. The corrected dataset ($\widehat{ET}_0$) shows significantly improved agreement with ground-based ET_0, reducing the Mean Absolute Error from 10.06 mm/8 d to 2.48 mm/8 d, a 75% improvement. This correction proved robust across the region and particularly effective during the summer, when accurate ET_0 estimation is critical for crop irrigation.
Our results suggest that, with appropriate local calibration, MOD16A2GF PET data can serve as a practical surrogate for ET_0 in data-scarce environments. Future research should focus on exploring the impact of additional factors, such as altitude and land cover variability, to further refine the accuracy of satellite-derived ET_0 estimates and improve their applicability in diverse climatic and topographical conditions.

1. Introduction

Evapotranspiration (ET) plays a fundamental role in the Earth's water cycle, as it describes the process through which water moves from the soil and plant surfaces into the atmosphere via evaporation and transpiration. This process is vital for understanding the movement of water in ecosystems, and it is a key component in hydrological and agricultural models. Among the various types of evapotranspiration, Reference Evapotranspiration (ET_0) is particularly important. ET_0 represents the amount of water that would evaporate and transpire from a well-watered grass surface under standard environmental conditions. It is widely used to estimate crop water requirements, plan irrigation schedules, and manage water resources, especially in regions facing water scarcity (Allen et al., 1998).

Globally, agriculture accounts for nearly 70% of freshwater withdrawals, with most of that water used for irrigation (Hoekstra and Mekonnen 2012). As climate change leads to increased frequency and severity of droughts, improving water-use efficiency in agriculture has become more urgent (Liu et al., 2016). To achieve this, accurate and reliable methods for estimating evapotranspiration are essential, particularly in areas where ground-based meteorological data are sparse or unavailable. Estimating ET_0 is complex, as it depends on a variety of climatic factors, including temperature, solar radiation, humidity, and wind speed. Over the years, several models have been developed to estimate ET_0, ranging from empirical methods to physically based approaches. Among these, the Penman-Monteith equation, recommended by the Food and Agriculture Organization (FAO), is considered one of the most accurate and consistent methods across different climatic zones (Allen et al., 1998).

In recent decades, the availability of satellite data has opened new possibilities for estimating evapotranspiration over large spatial scales. One widely used product for estimating global evapotranspiration is MOD16, which is derived from NASA's MODIS satellite sensor. The Potential Evapotranspiration (PET) layer is one of the available ones. PET maps the estimate of the maximum possible evapotranspiration from a specific biome, assuming unlimited water availability. While PET can provide valuable insights into atmospheric demand for moisture over vast regions, it differs from ET_0 in several key ways. PET is influenced by different land covers (defining the local biome) and atmospheric variables, and does not account for specific crop types or phenology. In contrast, ET_0 is a standardized measure designed to reflect water loss from a uniform reference crop under ideal conditions. Thus, although PET and ET_0 are conceptually related, they are not interchangeable (Mu, Zhao, and Running 2011).

This distinction raises an important question for researchers and water managers: Can satellite-derived PET be used as a substitute for ET_0, especially in regions with limited ground-meteo stations? If not, is it possible to adjust or calibrate PET so that it aligns with ET_0 derived from traditional meteorological methods? These questions are at the core of the present study.

This work deepens a previous one for the same research group (Farbo et al. 2024) aims at evaluating whether PET data from the MOD16 product can be reliably used to map ET_0 in the context of agricultural water management. Specifically, we focus on the Piemonte region (NW Italy), a region with diverse climatic and

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topographical conditions. We compare PET values from the MOD16A2GF dataset with ground-based ET_0 estimates calculated using the FAO Penman-Monteith method. We explored a bias-correction approach based on local linear regressions, calibrated along measures time series, relating MOD16A2GF estimates with ground ones.

If successful, this method would provide a valuable tool for agricultural planning and water resource management in areas lacking sufficient observational infrastructure. Ultimately, our findings are expected to contribute to a better understanding of how remote sensing products can be adapted to meet practical needs in a changing climate, promoting more efficient and sustainable water use in agriculture.

2. Materials and methods

2.1 Study area

The Po River Basin, covering 23% of Italy's territory, is essential for Italian agriculture, contributing 35% of national agricultural production and 50% of its agricultural value. Spanning 2.7 million hectares, 59% of which is irrigated, the region's key crops include maize, rice, and forage, with irrigation largely reliant on canal systems managed by consortia, notably the Cavour Canal. Historically rich in water resources, the basin has faced increasing pressure from socio-economic demands, technological developments, and climate variability. Since 2003, recurring water shortages have emerged due to rising temperatures, prolonged dry spells, and increased demand, leading to significant agricultural losses and power disruptions, especially during drought years like 2003, 2007, and 2022. Furthermore, seawater intrusion into the Po River has posed additional challenges.

In this context, the Piemonte region stands out as a crucial area within the Po River Basin. As the region responsible for 45% of the irrigation water withdrawals in the entire basin, it plays a central role in agricultural water management. The region heavily relies on open canals (94%) and surface flooding techniques (52%) for irrigation. Given its importance, the region is particularly vulnerable to the impacts of recurrent droughts, making precise hydrological monitoring and efficient water resource management essential. Studying the Piemonte region is thus critical for understanding and addressing the broader challenges faced by the Po River Basin, especially as water scarcity continues to threaten agricultural production and regional stability.

2.2 Meteorological data

Meteorological data were retrieved from the ARPA Piemonte website. There are 337 ARPA monitoring stations across the Piemonte region. Only 61 out of these are fully equipped with a thermometer, hygrometer, anemometer, and radiometer, which are necessary to compute the reference evapotranspiration (paragraph 2.3). Since 22 stations present incomplete data time series, only 39 stations having complete recordings were used for this study (Figure 1). After removing the ones falling where no satellite estimates were available, only 28 stations remained for the study.

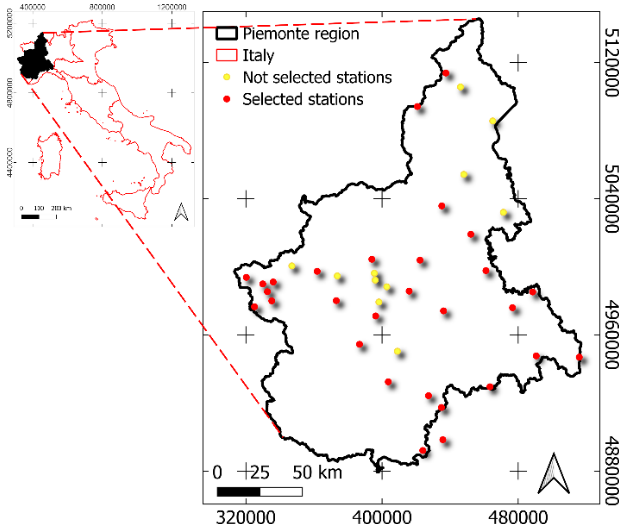

Figure 1. Spatial distribution of the fully equipped meteorological stations in the Piemonte region. Yellow dots = stations falling in positions without MOD16 estimates.

2.3 Calculation of ET_0 from Ground Measures

Data needed to compute the FAO Penman-Monteith (PM) equation are the elevation and the latitude of the location and the standard meteorological measure of solar radiation (sunshine), maximum and minimum daily air temperature, maximum and minimum daily relative humidity, and wind speed. To ensure the integrity of computations, meteorological measurements should be made at 2 m (or converted to that height). The ground stations are not equipped with barometers, so the atmospheric pressure was calculated as described by (Allen et al. 1998).
The ground data needed for the computation of the FAO PM formula were filtered for the reference period (1st January 2010 - 31th December 2022).
Once obtained the needed data the ET_0 was calculated using the FAO PM equation (Equation 1).

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

Where ET_0=reference evapotranspiration [mm day^{-1}],
Rn=net radiation [MJ m^{-2} day^{-1}],
G=soil heat flux density, set to 0 [MJ m^{-2} day^{-1}],
T=air temperature at 2 m height [°C],
u2=wind speed at 2 m height [m s^{-1}],
es=saturation vapour pressure [kPa],
ea=actual vapour pressure [kPa],
es-ea=saturation vapour pressure deficit [kPa],
Δ=slope vapour pressure curve [kPa °C^{-1}],
Γ=psychrometric constant [kPa °C^{-1}]

The reference crop evapotranspiration (ET_0) is a climatic parameter expressing the evaporation capacity of the atmosphere. It represents the evapotranspiration from the reference surface. This hypothetical reference surface is defined as: "The reference surface is a hypothetical grass reference crop with an assumed crop height of 0.12 m, a fixed surface resistance of 70 s m-1 and an albedo of 0.23"(Allen et al. 1998). The reference surface closely resembles an extensive surface of green, well-watered grass of uniform height, actively growing and completely shading the ground. The fixed surface resistance of 70 s m^{-1} implies a moderately dry soil surface resulting from about a weekly irrigation frequency. The only factors affecting ET_0 are meteorological measures. The FAO Penman-Monteith method is recommended for this calculation, though it requires many climatic parameters which may not always be available. Then, the obtained daily ET_0 values were aggregated based on the MOD16A2GF dates, obtaining an 8-day aggregated dataset. However, this aggregation can be problematic if one or more data points are missing within the 8-day period, so those periods were discarded.

2.4 The MOD16A2GF product

The MOD16A2GF product from the NASA MODIS sensor was tested against ground ET estimates. MOD16 product is a dataset that includes the global evapotranspiration (ET), latent heat flow (LE), potential ET (PET) and potential LE (PLE). The MOD16 product provides regular 500m x 500m land surface ET datasets for the 109.03 million km^2 global vegetated land areas at 8-day, monthly and annual intervals. The algorithm developed by Mu et al. 2007 and improved by Mu, Zhao, and Running 2011 used for the MOD16 data product collection is based on the logic of the Penman-Monteith equation (Monteith,1965), which includes inputs of daily meteorological reanalysis data along with MODIS remotely sensed data products such as vegetation property dynamics, albedo, and land cover. The MODIS input data required for the MOD16 algorithm includes global soil and land cover products (MOD12Q1), leaf area index (LAI), fraction of photosynthetically active radiation (FPAR-MOD15A2), and albedo (MCD43B2) (Mu, Zhao, and Running, 2013). According to the MODIS Science Team, the MOD16A2 6.1 product will not have data before 2023, and the gap-filled MOD16A2GF 6.1 product will be recommended for data from 2000 to 2023. The MODIS Science Team recommends the gap-filled product because it is expected to be superior. This is achieved by retrieving the FAL/FPAR values through interpolation for pixels that do not meet the quality screening criteria. The MOD16A2GF is not available in the current year because it is generated at the beginning of the following year, when the entire yearly 8-day M*D15A2H (LAI/FPAR product) is available. In this study, 8-days PET data from MOD16A2GF of collection 6.1 were used.

MOD16A2GF PET does not cover all land uses, only those with vegetation. Therefore, for other land uses, the pixel values in the images are filled with the following codes: Earth (bare soil and rock), 32767; water bodies, 32766; barren or sparse vegetation, 32765; permanent snow and ice, 32764; permanent wetlands, 32763; urban or built areas, 32762; unlisted, 32761. As a result, of the 39 stations shown in Figure 1, 11 stations were excluded due to falling into one of the non-vegetated categories, bringing the total number of stations used for the comparison to 28.

Google Earth Engine platform was used to retrieve the 8-day PET from the MOD16A2GF values for the study period (1st January 2010 - 31st December 2022) for all the points where ground stations were located. PET values were extracted at the locations of the 28 ARPA meteorological stations to ensure spatial consistency between the PET and ET_0 time series.

2.5 Modelling biases

The comparison between PET and ET_0 was achieved over time, through a I order linear regression (Equation 2), for each ground station located at (x,y). Firstly, this was done at a single-year level and then considering all years jointly for the entire reference period. Estimates of local gain – $\hat{a}(x,y)$ - and offset – $\hat{b}(x,y)$ - were obtained through an Ordinary Least Squares approach and applied to recover new timely unbiased PET values (hereinafter called $\widehat{ET}_0$).

$$\widehat{ET}_0 = \hat{a}(x,y) \cdot PET + \hat{b}(x,y) \tag{2}$$

2.6 Statistical analyses

Various metrics were calculated for each year within the reference periods to test improvement of estimates after bias removal. The following metrics were used: Pearson's Correlation Coefficient (r), Mean Absolute Error (MAE) and Mean Relative Error (MRE) as defined in eq. 4 and 5

$$MAE = \frac{1}{n}\sum\nolimits_{i-1}^{n} |S_i - G_i| \tag{3}$$

$$MRE = \frac{1}{n}\sum\nolimits_{i-1}^{n} \left(\frac{S_i - G_i}{G_i}\right) \tag{4}$$

Where S_i is the satellite value (PET or $\widehat{ET}_0$)) at time i
$\bar{S}$ is the average satellite value (PET or $\widehat{ET}_0$))
G_i is the ground measurement at time i
$\bar{G}$ is the average ground measurement
n is number of observations

3. Results and Discussion

Results are reported in the following figures. Namely, Figure 2 displays the yearly *r* values between ET_0 and PET, illustrating the variability of these values across the different meteorological stations. It can be noticed that the median *r* value remains consistent throughout the years, hovering around 0.96. Additionally, 50% of the values, between the upper and lower quartiles, fall within the range of 0.93–0.98. Although values show great variability, they do not drop below 0.90. This means that PET is well correlated with ET_0 at the annual scale in the time domain, and that this relationship remains stable over the years and consistent across different meteorological stations. These findings are in line with previous studies (Farbo et al. 2024; Mu et al. 2013).

Figure 3 shows the distribution of *r* values concerning the comparison of PET and ET_0 at monthly level throughout the years and for all the stations. Compared to annual values, monthly *r* values are generally lower. This is likely due to (i) the shortness of the investigated period (1 month) that makes differences in evapotranspiration values small; (ii) the limited number of observations available per month (about 3-4 observations for all the stations), which makes it harder to detect stable trends.

It is evident that the *r* values are particularly low in winter months, namely November, December, and January. This drop in correlation may have several explanations. One possible hypothesis is that evapotranspiration is naturally very low during this time due to climatic conditions (low temperatures, reduced solar radiation, etc.). Under such conditions, the MOD16 dataset may lack the sensitivity needed to capture small variations in ET_0, leading to reduced accuracy in the estimates. Another potential explanation could involve systematic errors in the MOD16 product during winter. For example, the presence of snow, frozen soil, or persistent cloud cover may interfere with the quality of the satellite data used in the calculations.

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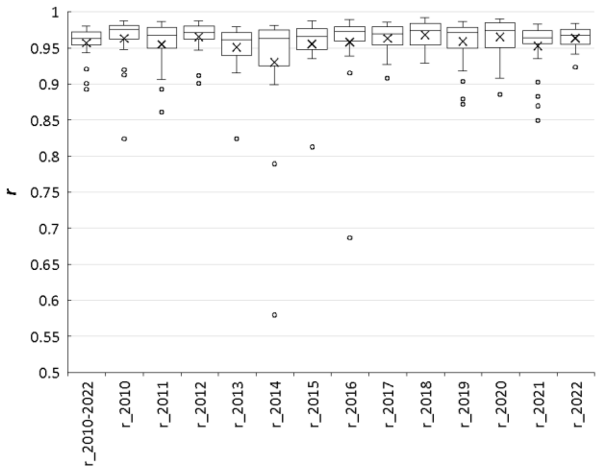

Figure 2. Box plot showing the distribution of the yearly Pearson's correlation coefficient (r) between PET and ground ET$_0$ estimates for the period 2010-2022 considered for all the meteorological stations.

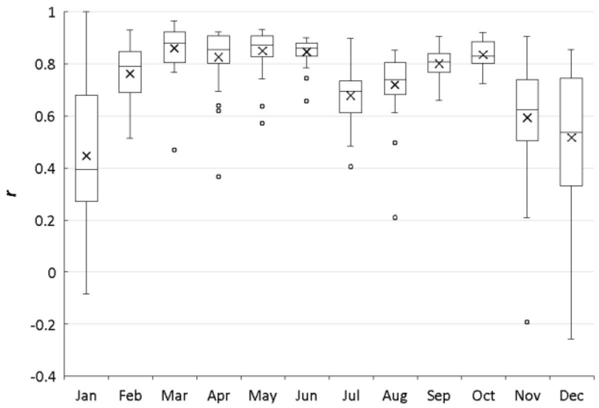

Figure 3. Box plot showing the monthly Pearson's correlation coefficient (r) between MOD16 PET and ground-based ET$_0$ estimates for the period 2010–2022. Each box represents the distribution of r values calculated across different meteorological stations and years for a given month.

In Figure 4, each box represents a single year from 2010 to 2022, illustrating the distribution of the yearly mean absolute error (MAE) for the different meteorological stations. White boxes and green boxes correspond to PET and $\widehat{ET}_0$, respectively. The mean of the PET MAE fluctuates between 8 and 12 mm among the years, while for $\widehat{ET}_0$, it ranges between 2 and 3 mm, suggesting that the linear adjustment significantly reduced the MAE. This reduction in mean MAE was statistically validated through a paired t-test, confirming a significant decrease in the mean yearly MAE from 10.06 mm to 2.48 mm. The year-to-year variability of $\widehat{ET}_0$ has also decreased, as shown by more compact box plots, narrower interquartile ranges, and shorter whiskers. Additionally, within each year, the MAE values of $\widehat{ET}_0$tend to be tightly clustered and close to the mean. This indicates that the local adjustment effectively reduces the variability of the error across different meteorological stations, likely due to their spatial distribution.

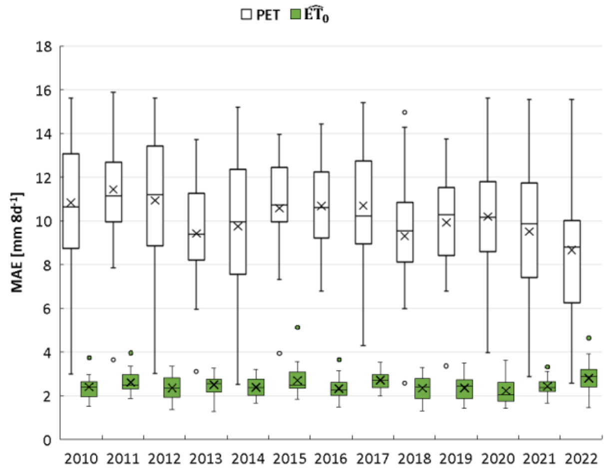

Figure 4. Box plot showing the annual MAE, measured in mm/8d MOD16A2GF and ground ET$_0$ estimates for the period 2010-2022. The box illustrates the distribution of MAE values across various meteorological stations within that year.

Figure 5 and Figure 6 provide a clearer view of the magnitude and seasonal pattern of bias throughout the year. Figure 5 illustrates the trend of MAE, while Figure 6 displays MRE, both averaged across all stations and locations.

Native PET values are consistently higher than ET$_0$, with a maximum overestimation of 13.12 mm/8d during the June–August period, as shown in Figure 5. These findings were also noted by Westerhoff, 2015. This significant overestimation in summer could result in excessive irrigation for crop no alignment is done, reinforcing this approach. Differently, $\widehat{ET}_0$ exhibits only a slight average positive difference of 2.5 mm/8d when compared to ground-based ET$_0$. Native PET values show a higher bias during winter and a lower one in summer (May–August), $\widehat{ET}_0$ follows a similar seasonal trend but with reduced differences, ranging from 30% down to 0% (Figure 6). Although the largest absolute discrepancies between PET and ground-based ET$_0$ occur in summer, the highest relative errors are observed in winter. This is because, during periods of low evapotranspiration, even small absolute errors can lead to disproportionately high relative errors when expressed as a percentage of the observed value

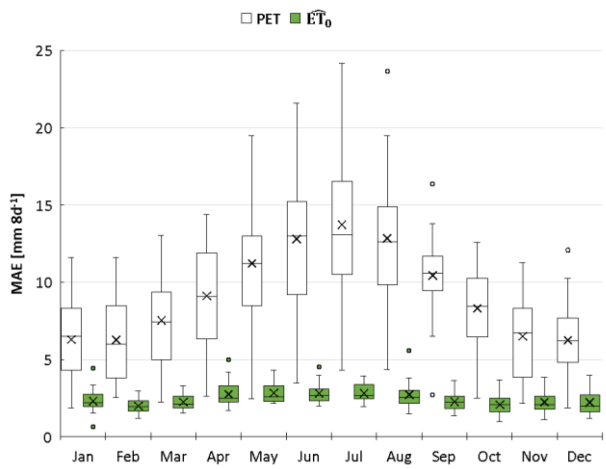

Figure 5. . Box plot showing the monthly MAE distribution (mm/8d) for the period 2010-2022 including all meteorological stations before and after bias removal.

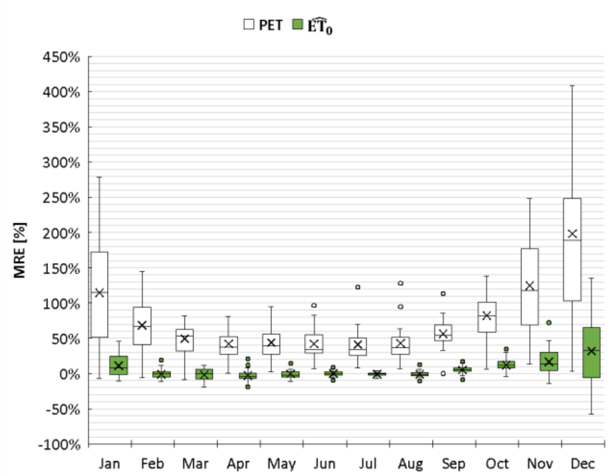

Figure 6. Box plot showing the distribution of monthly MRE, for the period 2010-2022, including all meteorological stations before and after bias removal.

Figure 7a shows that the central area of the Piemonte region exhibits higher gain values (0.88–0.98, shown in dark green), suggesting that the model effectively captures the spatial variability of evapotranspiration in these zones. In contrast, lower gain values (0.48–0.68, represented in red and orange) are found in the northern, western, and southern parts of the region. These zones correspond to mountainous regions where complex topography and sparse vegetation may limit the model's accuracy. Big differences between PET values and ET_0 measurements were found in areas that had high altitudes (Dias et al. 2021). This can suggest that there's an influence of altitude on PET values. However, it is important to note that a high gain does not necessarily imply a lower absolute error, as this metric primarily reflects the model's ability to reproduce relative changes rather than absolute accuracy.

Figure 8a reveals negative error values in the central area (red and orange, ranging from -8.4 to -4.4 mm), indicating that the model systematically overestimates potential evapotranspiration in this region. These central zones are characterized by plains and hills and are predominantly cultivated areas. This behavior suggests that, despite the model's ability to follow the variability (as shown by high gain), it introduces a consistent positive bias. This may be related to the known limitations of remote sensing models in agricultural areas, where heterogeneity and management practices can reduce predictive performance (Kim et al. 2012).

Figures 7b and 8b display the standard deviation of the gain and offset values across the meteorological stations over the years. Unlike the clear spatial patterns observed in the gain and offset maps, the standard deviation does not reveal any consistent spatial trends. This suggests that the year-to-year variability in the gain and offset values is not dependent on spatial factors.

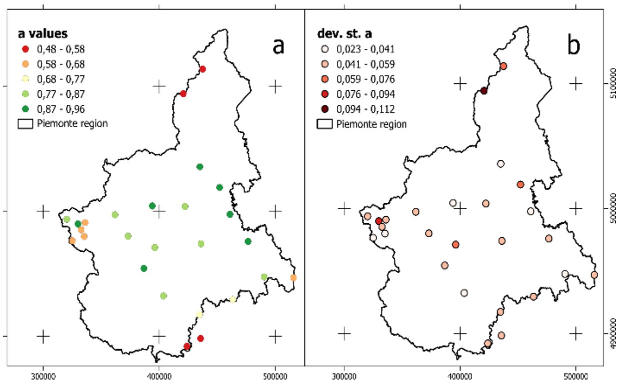

Figure 7. Spatial distribution of gain values (panel a) and the corresponding standard deviation (panel b) across the Piemonte region.

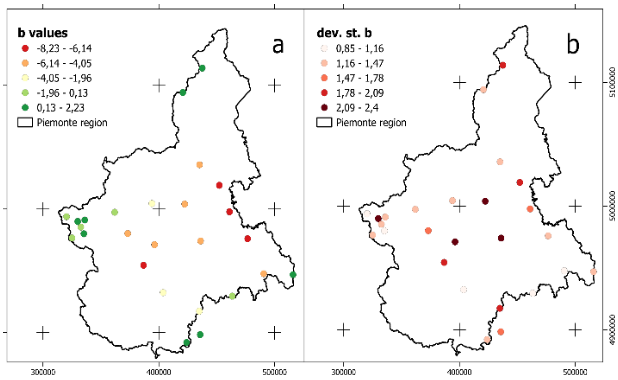

Figure 8. Spatial distribution of the offset values (panel a) and the corresponding standard deviation (panel b) across the Piemonte region.

4. Conclusions

The performance of the MOD16A2GF product in estimating evapotranspiration showed a strong correlation with ground-based ET_0 values across most meteorological stations in the Piemonte region. However, some discrepancies were observed during specific periods, particularly in winter, confirming that MODIS-based PET products, while effective in capturing seasonal trends, can be affected by specific climatic and land-cover conditions. The application of a simple bias-correction method based on local linear regressions significantly improved the agreement with ground-based ET_0, reducing the Mean Absolute Error from 10.06 mm/8 d to 2.48 mm/8 d. This substantial reduction, consistent across the region, highlights the robustness of the correction method and its potential applicability in other data-scarce regions. The adjusted dataset ($\widehat{ET}_0$) could therefore support operational water resource management, especially in areas lacking sufficient meteorological infrastructure. Nonetheless, this study has some limitations. In particular, it does not account for potential measurement errors in the ground-based ET_0 data, which may influence the accuracy of the regression models used for adjustment. Future research should explore the influence of environmental factors, such as altitude, vegetation cover, and land use, on the accuracy of PET estimates from MODIS products. Including these variables in the calibration process, possibly through the use of Biome Property Look-Up Tables (BPLUTs), may further enhance the reliability of satellite-based evapotranspiration estimates for agricultural and hydrological applications.

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