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Impact of uncertainty in solar radiation and wind speed on FAO-56 reference evapotranspiration estimates

Viera RATTAYOVÁ*, Milan ONDERKA, Zuzana NÉMETOVÁ, Jozef PECHO, Kamila HLAVČOVÁ

Accurate meteorological observations are essential for reliable estimation of reference evapotranspiration (ET_0) using the FAO-56 Penman-Monteith model. In practical applications, several input variables, particularly solar radiation, are often not directly measured but estimated, introducing uncertainty into ET_0 calculations. This study investigates how uncertainties in wind speed (u_2) and shortwave solar radiation (Rs) propagate into ET_0 estimates when applying the standard FAO-56 formulation. Controlled linear perturbations were used to simulate systematic measurement errors and extreme deviations, and the effect of replacing daily observations with long-term monthly mean values was also evaluated. Model sensitivity was assessed using linear sensitivity analysis, Monte Carlo simulations, and variance-based Sobol indices, enabling quantification of both the direct and interaction effects of input variables on ET_0 variance. Linear perturbation experiments showed a nearly proportional response of ET_0 to variations in solar radiation, reflecting its role in determining net radiation. In contrast, the response to wind speed was weaker and slightly nonlinear.

Variance-based decomposition identified maximum air temperature as the dominant contributor to ET_0 variability, due to its influence on multiple components of the Penman-Monteith equation. Vapor pressure also showed a notable contribution, while wind speed influenced ET_0 primarily through interaction effects.

The results indicate that moderate uncertainties in wind speed and solar radiation inputs may have a limited impact on ET_0 estimates under the analyzed conditions. Notably, air temperature, although is not expressed explicitly in the PM equation, emerged as the dominant contributor to ET_0 variability through its influence on multiple equation components. These findings suggest that, for applications relying on estimated or remotely sensed data, careful attention to temperature accuracy is more critical than minimizing uncertainty in solar radiation, while wind speed improvements provide modest but non-negligible reductions in ET_0 uncertainty.

KEY WORDS: FAO56 Penman-Monteith evapotranspiration, sensitivity analysis, Sobol method, reference evapotranspiration

Introduction

Evapotranspiration (*ET*) represents a key component of the terrestrial water cycle, mediating the transfer of water from land surfaces and vegetation to the atmosphere. Reference evapotranspiration (ET_0), as defined by the FAO-56 Penman-Monteith methodology, is a widely adopted proxy for estimating crop water demand and modeling hydrological processes in agriculture, ecology, water resource management (Danáčová et al., 2024; Allen et al., 1998). Reference evapotranspiration (ET_0) is a fundamental hydrometeorological variable extensively used in water resource management, irrigation scheduling, and climate impact assessments. The FAO-56 Penman-Monteith (PM) equation is widely recognized as one of the most accurate and physically based models for estimating ET_0 (Soussi et al., 2024) by integrating meteorological inputs such as air temperature, humidity, wind speed, and solar radiation (Allen et al., 1998). However, the reliability of ET_0 estimates is strongly dependent on the precision and temporal resolution of the input meteorological measurements.

Previous studies have extensively investigated the sensitivity of ET_0 to various input parameters. Notably, the importance of solar radiation and wind speed has been repeatedly highlighted as dominant drivers of ET_0 variability (Paredes et al., 2019; Sabino and de Souza, 2023). Under humid conditions, ET_0 is more sensitive to solar radiation, whereas under dry, clear-sky conditions with low atmospheric humidity, the aerodynamic effect of wind speed becomes dominant on ET_0 and its sensitivity increases (Sabino and de Souza, 2023; Tabari and Hosseinzadeh Talaee, 2014; Zhang et al., 2021). Among the suite of meteorological factors driving *ET*, wind speed plays a particularly pivotal role by enhancing the removal of water vapor from surface and leaf boundaries, thus intensifying both evaporation and plant transpiration rates (Guo et al., 2017; Sabino and de Souza, 2023). For instance, Paredes et al. (2018) demonstrated that uncertainties in solar radiation

measurements exert a more profound influence on ET_0 variability compared to other inputs, while wind speed was shown to affect ET_0 mainly through its interactions with other meteorological variables. Even moderate variations in wind speed can induce significant changes in ET_0, especially in arid and semi-arid climates where advective conditions prevail (Paredes et al., 2018). Zhao et al. (2015) identified wind speed as the second most influential parameter affecting the variance of ET_0 in the Heihe River Basin, China, while relative humidity was found to be the most important contributor. Wind reduces aerodynamic resistance above soil and canopy surfaces, intensifying vapor pressure deficit-driven water vapor fluxes and sustaining high *ET* even under suboptimal thermal or radiative conditions. Conversely, low wind regimes may limit *ET* by reducing the atmospheric demand for water vapor, underscoring wind's dual role as both a driver and a regulator of surface moisture loss. Despite its quantitative importance, the accurate characterization of wind inputs remains challenging due to spatial heterogeneity, temporal variability, and instrumentation limitations. Measurement uncertainties in wind speed can thus propagate through *ET* models, resulting in substantial output biases that may impact water management strategies and climate impact assessments. Recent advances in sensitivity analysis, particularly the application of variance-based methods such as Sobol indices (Sobol, 1993; Sobol, 2001; Arenas-Bautista et al., 2024), have enabled researchers to rigorously partition the relative contribution of wind to *ET* variability, taking account of both its direct role and its interactions with other climatic factors (DeJonge et al., 2012; Sabino and de Souza, 2023). Laluet et al. (2023) applied Sobol analysis to assess sensitivity of a FAO-56 dual crop coefficient to various field conditions over 37 agricultural seasons.

Guo et al. (2017) used variance-based sensitivity methods, such as Sobol indices, to partition the contribution of individual climatic factors to the total ET_0 variance, confirming the dominant role of solar radiation and highlighting significant interaction effects involving wind speed. Ha et al. (2024) conducted a study at 3 stations in Gia Lai province, located in the Central Highlands of Vietnam. The results indicated that solar radiation (SH) is generally the most influential variable for *ET*, with first-order sobol analyses index values ranging from 0.42 to 0.48 and relative humidity also plays a significant role. Despite these advances, there remain gaps concerning the systematic quantification of measurement uncertainty impacts on ET_0, especially when inputs are subjected to extreme perturbations or when aggregated long-term monthly mean data are used instead of high-resolution daily observations. The potential bias introduced by temporal aggregation has been acknowledged but is poorly discussed (DeJonge et al., 2012) Moreover, few studies have rigorously combined Sobol sensitivity analysis with uncertainty quantification methods (e.g., bootstrapping) to evaluate both the direct and interactive effects of input variability on ET_0. Although many studies demonstrate that solar radiation and wind speed are the primary drivers of ET_0 variability, research conducted in semi-arid and arid regions has shown that air temperature can become the most influential factor under semi-arid climatic conditions (Saci et al., 2025; Sharifi and Dinpashoh, 2014).

The aim of this study was to evaluate how uncertainties in wind speed and shortwave solar radiation influence reference evapotranspiration (ET_0) estimated using the FAO-56 Penman-Monteith model. To assess model sensitivity to these inputs, three complementary approaches were applied: (i) linear sensitivity analysis, (ii) Monte Carlo simulation, and (iii) variance-based global sensitivity analysis using Sobol indices. The Sobol framework was combined with bootstrapping in order to quantify both the individual (first-order) and interaction (higher-order) contributions of the selected variables, as well as the associated uncertainty bounds of the sensitivity estimates. This integrated methodological approach provides a comprehensive evaluation of how input variability propagates into ET_0 estimates and clarifies the relative importance of aerodynamic and radiative controls on model variance. The results offer important insights for studies focused on ET_0 modeling and hydrometeorological applications. They indicate that wind speed and solar radiation-variables that are often unavailable at many meteorological stations, can be substituted by remotely sensed products, which may have lower precision, without causing substantial distortion of ET_0 estimates under the analyzed conditions.

The FAO-56 Penman-Monteith equation does not use shortwave solar radiation (*Rs*) directly, but rather net radiation (*Rn*), derived from *Rs* together with surface and atmospheric characteristics. Since net radiometers are not available at most meteorological stations, *Rn* must be calculated from *Rs* measurements following the standard FAO-56 procedure. Errors in *Rs* therefore propagate into ET_0 through *Rn*.

It is also important to distinguish the parameters explicitly present in the PM equation from those treated as uncertain inputs in Monte Carlo and Sobol analyses. Although air temperature is not expressed explicitly in the equation, it is embedded in multiple components, the slope of the saturation vapor pressure curve (Δ), saturation vapor pressure (e_s), and the aerodynamic term, which explains why sensitivity analyses consistently identify temperature as the dominant driver of ET_0 variability, a result that may appear counterintuitive given the equation's structure.

Material and methods

The analysis was carried out using measured meteorological data from 34 climatological stations obtained from the Slovak Hydrometeorological Institute (SHMÚ) database for the period 1980–2020. The selected stations are located at altitudes ranging from 105 to 2635 m a.s.l. (Fig. 1), allowing for the assessment of altitude-dependent variability in climatic conditions across diverse landscapes in Slovakia. The spatial distribution of the stations ensures representation of a wide range of morphological and climatic environments within the country.

For the calculation of reference evapotranspiration (ET_0), measured daily data of minimum air temperature (*Tmin*), maximum air temperature (*Tmax*), wind speed at 10 m height (u_{10}), actual vapor pressure (e_a), and actual sunshine duration were used. Wind speed measured at 10 m was converted to the standard 2 m height according to FAO-56 recommendations. Reference evapotranspiration (ET_0) was calculated using the FAO-56 Penman–Monteith method according to the following equation (Allen et al., 1998):

$$ET_0 = \frac{0.408*\Delta*(R_N-G)+\Upsilon\frac{900}{T+273}*u_2+(e_s-e_a)}{\Delta+\Upsilon*(1+0.34*U_2)} \quad (1)$$

where ET_0 is the reference evapotranspiration [mm day^{-1}]; R_n is the net radiation at the crop surface [MJ m^{-2} day^{-1}]; G is the soil heat flux density [MJ m^{-2} day^{-1}]; T is the mean daily air temperature at 2 m height [°C]; u_2 is the wind speed at 2 m height [m s^{-1}]; e_s is the saturation vapor pressure [kPa];e_a is the actual vapor pressure [kPa]; D is the slope vapor pressure curve [kPa °C^{-1}]; Υ is the psychrometric constant [kPa °C^{-1}].

The study employed three complementary analytical approaches (Table 1) to assess the influence of key meteorological variables on FAO-56 Penman–Monteith reference evapotranspiration (ET_0). These three methods differentiate between the potential influence of individual variables, their practical importance under real conditions, and their contribution to output uncertainty, thereby providing a comprehensive assessment of ET_0 sensitivity and reliability. The impact of solar radiation

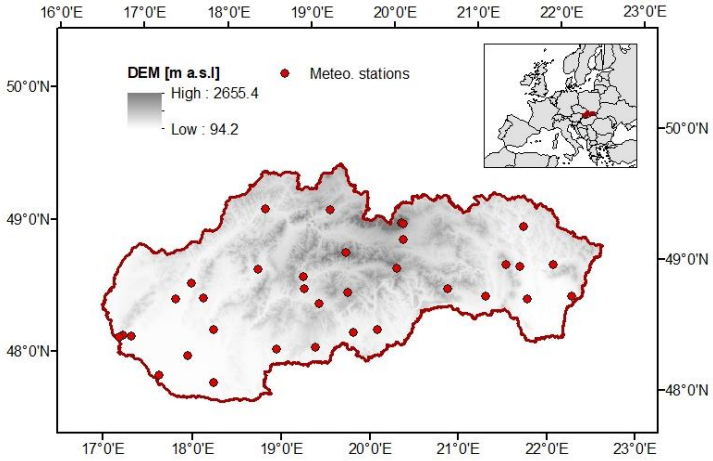


Fig. 1. Spatial distribution of the selected meteorological stations used in the analysis.

Table 1. The summary of complementary analytical methods used to quantify the effect of the key meteorological variables on FAO-56 Penman-Monteith reference evapotranspiration (ET_0)

Analytical Approach	Purpose	Methodology	Outputs
Linear Sensitivity Analysis	Quantify model response to controlled changes in individual inputs	Systematic perturbation of parameters (solar radiation, wind speed) while holding all other variables constant	Isolation of the theoretical influence of each variable on ET_0 bias, independent of natural variability
Monte Carlo Uncertainty Propagation	Propagate uncertainty of input variables	Sampling from realistic statistical distributions (derived from station observations) for solar radiation and wind speed; bootstrap validation	Quantification of each variable's contribution to ET_0 variability in practical applications and robustness testing
Sobol variance-based sensitivity analyse	Quantify the relative contribution of individual inputs and their interactions	lobal variance decomposition using Sobol indices; estimation of first-order and total-order sensitivity indices	Identification of dominant drivers of ET_0 variability; quantification of both independent and interaction effects of meteorological variables under real climatic conditions.

and wind speed on ET_0 calculated using the Penman–Monteith equation represents a common challenge in reference evapotranspiration modelling, primarily due to the frequent lack of spatial coverage and the limited availability or insufficient length of measurement time series. The research therefore provides valuable insights for hydrological and agricultural modelling by determining the potential impact on ET_0 estimates when using biased data from alternative sources.

Linear sensitivity analysis

To evaluate how uncertainties in wind speed and solar radiation propagate into ET_0-PM estimates, we applied systematic perturbations: wind speed at 2 m height and shortwave solar radiation were varied in 5% increments from –95% to +100% relative to measured values. Other model inputs remained fixed at their original station measurements. This procedure was designed to evaluate how systematic deviations in these inputs influence ET_0-PM estimates through the FAO-56 Penman–Monteith formulation, compared to the baseline values obtained from measured meteorological data. Results were summarized as station-wise mean biases between perturbed and reference ET_0, with 95% confidence intervals estimated via bootstrapping. In the bootstrapping procedure, we generated 10,000 resampled datasets and computed the mean bias for each, constructing confidence intervals using the percentile method.

Monte Carlo simulation

In the second part of the study, Monte Carlo simulations were employed to explore the propagation of input variability into ET_0 estimates. Wind speed and solar radiation values were generated through 1000 random samplings. The distributional characteristics of each variable at each station were then tested for normality using the D'Agostino test (α=0.05). For variables consistent with a normal distribution, the mean and standard deviation of the fitted distribution were estimated. ET_0 was recalculated for each sample of input variables using the simulated wind speed and solar radiation, while all other inputs were kept as measured values from the stations. For each simulation, the following statistics were derived:

- Mean ET_0,
- 5th and 95th percentile confidence limits of the mean (via bootstrapping with 10.000 resamples),
- Standard deviation of the mean from bootstrapping.

Final results were reported as the average of these values across all 1.000 simulations (i.e., mean of ET_0 means, average 5th and 95th percentiles, and average standard deviation).

Sobol sensitivity analysis

Finally, a Sobol sensitivity analysis was applied to quantify the contribution of each input variable to the overall variance of ET_0-PM outputs. Sobol analysis is a variance-based global sensitivity method that quantifies the contribution of each input variable to the total variance of model output. This approach is well suited for nonlinear models with interactions among inputs. In this study, we computed two Sobol indices: the first-order index (S_1) and the total-order index (ST). The resulting indices represent the relative contribution of each input variable to the variance of ET_0-PM outputs. The first-order index measures the direct effect of an input on ET_0 variance, excluding interactions, and quantifies the direct contribution of individual inputs to output variance. The total-order index captures both the direct effect and all interaction effects. A low first-order index combined with a high total-order index indicates that the variable's impact arises primarily through interactions with other inputs. Second-order sensitivity indices quantify the fraction of the total variance in the model output that is attributable to the interaction between two uncertain input parameters.

Results and discussion

Propagation of solar radiation and wind speed uncertainty into ET_0 bias

The analysis quantified how uncertainties in selected FAO-56 PM inputs, specifically solar radiation (*Rs*) and wind speed (u_2), propagate into ET_0 bias, while holding all other parameters constant. This controlled design isolates each variable's contribution, allowing the model's response to be evaluated without interference from other meteorological drivers. Incremental changes in *Rs* produced a linear response in ET_0 bias (Fig. 2), characterized by a slope of 0.944. While small deviations in *Rs* had minimal impact on ET_0 bias, a +100% increase in *Rs* induced an ET_0 bias of approximately +0.94 mm day^{-1}. Although previous SOBOL-based sensitivity studies have identified temperature and aerodynamic variables as the largest sources of FAO-56 PM ET_0 variability, our controlled perturbation of *Rs* revealed an almost one-to-one correspondence between changes in *Rs* and ET_0 bias. This reflects the role of *Rs* in determining net radiation within the FAO-56 formulation when other inputs are held constant. The relationship between wind speed variations and ET_0 bias exhibited a quadratic pattern (Fig. 3), indicating that the effect was not uniform across the entire range of values. Incremental changes in wind speed generally elevated ET_0 bias; however, the marginal impact diminished at both extremes of the wind speed spectrum. This nonlinear response reflects the aerodynamic component of the FAO-56 Penman–Monteith equation, in which wind speed influences evapotranspiration through its interaction with vapor pressure deficit and other terms, resulting in diminishing marginal effects at higher values.

Monte Carlo simulated uncertainty

Monte Carlo simulation was applied to quantify

the uncertainty and variability in ET_0 arising from wind speed and solar radiation inputs by repeatedly sampling random values from their assumed probability distributions (Table 2). The impact of uncertainty in solar radiation on ET_0 estimates was relatively small under the analyzed conditions, the standard deviation of the simulated daily mean ET_0 values ranged from 0.007 to 0.020 mm.day^{-1} (Table 2), and the long-term daily mean ET_0 varied only slightly, from 1.87 to 1.93 mm day^{-1}. Standard deviations were consistent across stations at all altitudes, indicating no substantial interaction between solar radiation and other model variables. The small variability in mean ET_0 values across simulations with perturbed solar radiation inputs suggests a limited contribution of solar radiation uncertainty to overall ET_0 variability in this analysis.

The standard deviation of long-term mean ET_0 values across wind speed simulations was higher at mountainous stations located at higher altitudes, where values reached up to 0.06 mm day^{-1}. When stations situated above 1000 m a.s.l. are excluded, the mean standard deviation across stations and simulations decreases to 0.014 mm day^{-1}. Changes in wind speed therefore have a stronger effect on ET_0 at high-altitude (mountain) stations; however, the influence of wind speed on ET_0 was generally smaller at lower-altitude stations, which are often representative of agricultural regions (Fig. 4). Bootstrapping of ET_0 means using simulations of both wind speed and solar radiation produced only small standard deviations across stations, indicating that uncertainties in these variables resulted in only small deviations in ET_0 estimates under the analyzed conditions.

Sobol sensitivity analysis of input contributions to ET_0 variability

Sobol analyses quantify the relative contributions of multiple input variables to ET_0 variability under conditions where inputs change simultaneously. In this study, we evaluated the proportional impact of FAO-56 Penman–Monteith model inputs on ET_0 variance, with particular focus on solar radiation and wind speed in relation to, and in interaction with, other variables.

The first-order and total-order Sobol indices indicate that both the direct and interactive contributions of solar radiation to ET_0 variance are very small under the analyzed conditions (Fig. 5), with all examined indices near zero. In contrast, wind speed contributes primarily through interactions with other variables rather than through its direct effect (first-order index: 0.04; total-order index: 0.12).

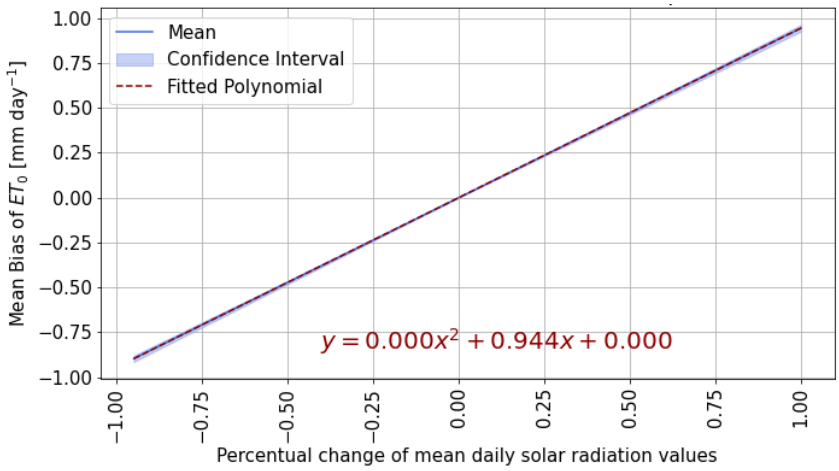


Fig. 2. Response of ET_0 bias to perturbations in solar radiation (Rs).

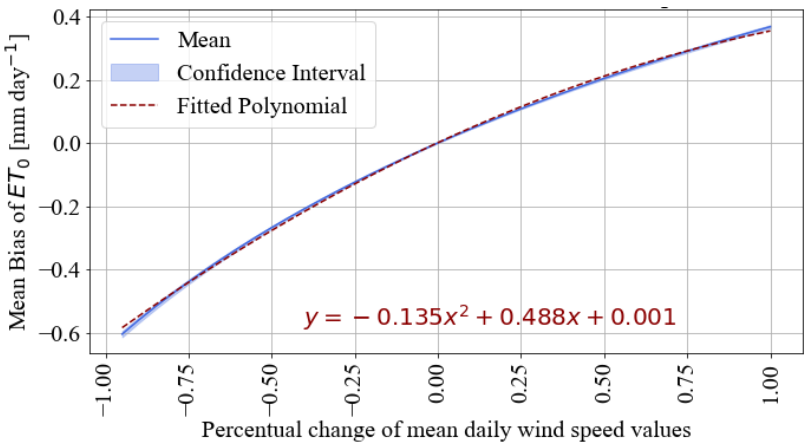


Fig. 3. Sensitivity of ET_0 bias to percentage changes in mean daily wind speed.

Table 2. Mean, confidence levels and standard deviation of long term mean daily ET_0 values from Monte Carlo simulations of wind speed and solar radiation

Station ID	Solar Radiation [MJ m^{-2} day^{-1}]				Wind speed [m s^{-1}]			
	mean	lower CL	higher CL	std	mean	lower CL	higher CL	std
11810	2.33	2.30	2.36	0.015	2.54	2.51	2.57	0.020
11813	2.58	2.55	2.61	0.016	2.76	2.73	2.8	0.020
11816	2.44	2.41	2.47	0.015	2.62	2.59	2.66	0.020
11818	1.96	1.94	1.99	0.014	2.26	2.23	2.29	0.020
11819	2.36	2.33	2.39	0.015	2.54	2.51	2.58	0.020
11820	2.09	2.06	2.12	0.014	2.38	2.35	2.41	0.020
11826	2.26	2.23	2.29	0.015	2.44	2.41	2.47	0.020
11841	1.73	1.71	1.75	0.013	1.98	1.95	2	0.010
11846	2.02	1.99	2.04	0.014	2.28	2.25	2.31	0.020
11855	2.42	2.38	2.45	0.017	2.62	2.58	2.65	0.020
11858	2.34	2.32	2.37	0.015	2.55	2.51	2.58	0.020
11867	1.99	1.97	2.02	0.014	2.22	2.19	2.25	0.010
11880	1.87	1.84	1.90	0.013	2.17	2.14	2.2	0.010
11892	1.46	1.44	1.49	0.012	1.76	1.74	1.79	0.010
11898	1.89	1.87	1.92	0.014	2.11	2.08	2.14	0.010
11903	1.82	1.79	1.85	0.013	2.07	2.05	2.1	0.010
11904	1.79	1.76	1.81	0.013	2.06	2.03	2.09	0.010
11905	1.90	1.87	1.92	0.013	2.19	2.16	2.22	0.010
11910	1.53	1.51	1.55	0.011	1.83	1.81	1.86	0.010
11916	1.04	1.02	1.05	0.008	1.25	1.14	1.34	0.060
11927	2.01	1.98	2.04	0.014	2.25	2.22	2.28	0.010
11930	1.12	1.10	1.13	0.007	1.27	1.24	1.3	0.020
11931	1.38	1.37	1.40	0.009	1.56	1.5	1.6	0.030
11934	1.88	1.85	1.90	0.012	2.06	2.03	2.08	0.010
11938	1.67	1.65	1.70	0.011	1.91	1.88	1.93	0.010
11942	2.00	1.97	2.03	0.014	2.23	2.2	2.26	0.010
11946	1.70	1.68	1.73	0.012	1.95	1.92	1.98	0.010
11963	1.78	1.76	1.81	0.013	2.03	2.01	2.06	0.010
11966	1.65	1.63	1.68	0.012	2	1.98	2.03	0.010
11968	2.15	2.13	2.18	0.015	2.33	2.3	2.36	0.020
11976	1.73	1.70	1.75	0.012	2.05	2.02	2.08	0.010
11978	1.98	1.95	2.01	0.014	2.22	2.19	2.25	0.020
11984	1.93	1.91	1.96	0.014	2.22	2.19	2.25	0.010
11993	1.78	1.76	1.80	0.013	2.07	2.05	2.1	0.010

Most ET_0 variability is explained by maximum air temperature (T_{max}), actual vapor pressure (e_a), and minimum air temperature (T_{min}). For each of these variables, interaction effects exceed individual effects. T_{max} shows the largest contribution to ET_0 variance, accounting for 0.52 of ET_0 variance in the first-order analysis and 0.59 when interactions are included.

Second-order Sobol analysis revealed the interaction effects of wind speed and solar radiation on ET_0 variability. Solar radiation showed very small interaction effects, with all second-order interaction indices involving T_{max}, T_{min}, and e_a near zero. Wind speed interacted modestly with T_{max} (4%), e_a (3%), and T_{min} (1%), indicating that its contribution to ET_0 variability arises primarily through these interactions. Overall, wind speed and solar radiation together account for only a small fraction of the total ET_0 variance in the FAO-56 Penman–Monteith model.

The present study advanced the understanding of FAO-56 Penman–Monteith (PM) evapotranspiration modeling by rigorously quantifying the sensitivity and uncertainty of ET_0 estimates to perturbations in solar radiation (Rs) and wind speed (u_2). Employing three complementary methodologies, i.e., linear sensitivity analysis, Monte Carlo-based uncertainty propagation, and Sobol variance-based sensitivity analysis, the results demonstrated that, notwithstanding its theoretical role in the PM formulation, uncertainty in Rs contributes only marginally to the overall uncertainty in ET_0 estimates under the analyzed conditions. In contrast, wind speed exerts a more substantive influence, primarily through higher order interactions with temperature and humidity variables.

The near one-to-one linear response of ET_0 bias to Rs perturbations confirms the radiative term's its role in determining net radiation under constant aerodynamic

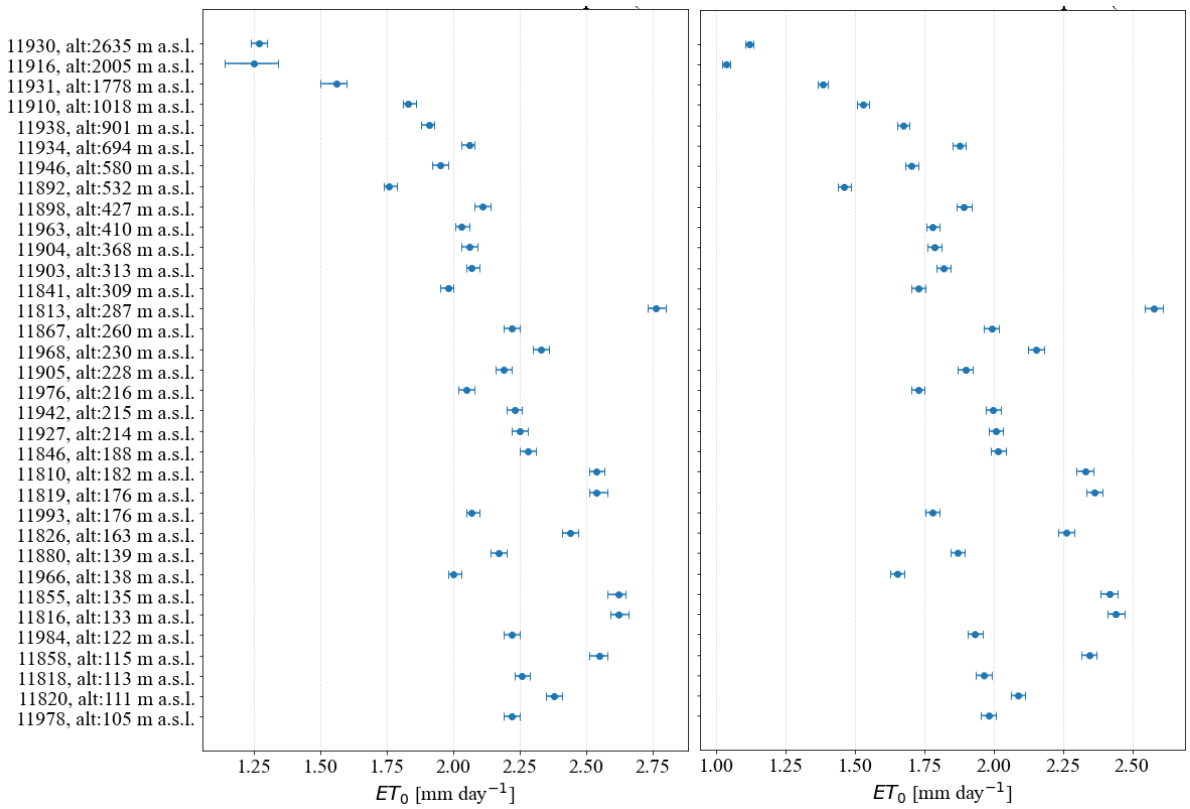


Fig. 4. Monte Carlo–derived mean ET_0 [mm day^{-1}] with 95% bootstrap confidence intervals for wind speed sensitivity (left panel) and solar radiation sensitivity (right panel) across stations grouped by altitude.

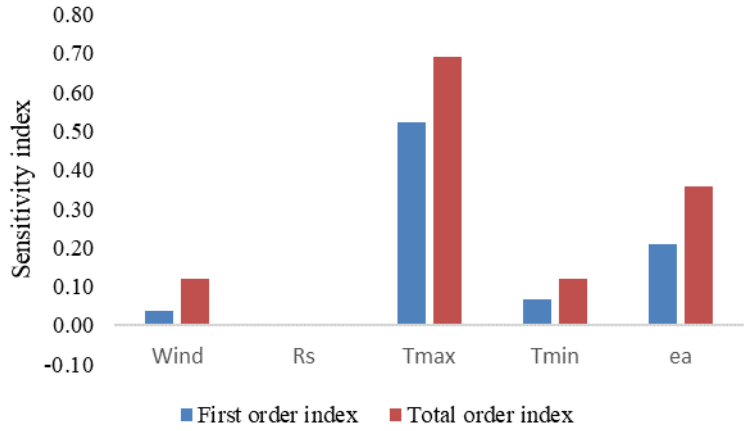


Fig. 5. First- and Total-order Sobol sensitivity indices for FAO-56 Penman–Monteith input variables (wind speed, solar radiation, Tmax, Tmin, e_a).

conditions, yet the small standard deviations (<0.02 mm day^{-1}) observed in Monte Carlo simulations indicate that typical measurement errors or even large systematic biases in *Rs* contribute only slightly to overall ET_0 uncertainty (Section 3.4). This finding aligns with Paredes et al. (2018), who reported less than 5% contribution of *Rs* measurement errors to multi-year ET_0 variance. Conversely, Sobol first-order indices for *Rs* were close to zero (Fig. 5), indicating a very small contribution of solar radiation to ET_0 variance when temperature and humidity vary simultaneously (Guo et al., 2017).

Wind speed, by contrast, showed modest direct effects (first-order index=0.04, Fig. 5) but substantial interaction effects (total-order index=0.12). This pattern corroborates earlier SOBOL-based studies that identified

wind as a secondary driver whose influence amplifies through coupling with vapor pressure deficit and aerodynamic resistance (DeJonge et al., 2012; Sabino and de Souza, 2023). Our second-order Sobol analysis pinned these interactions primarily on maximum air temperature (4%), actual vapor pressure (3%), and minimum air temperature (1%), indicating that wind enhances ET_0 most strongly when combined with high thermal and moisture gradients. (Ha et al., 2024) reported a different sensitivity pattern for *ET* variance, with solar radiation and relative humidity as the dominant drivers. However, Saci et al. (2025), based on their study conducted in Algeria, reported that maximum air temperature exerted the strongest influence on ET_0 variance. This finding is consistent with our results, which also indicate a dominant role of maximum temperature under the analyzed conditions. This suggests that the relative importance of meteorological inputs depends strongly on regional climate, particularly in hot, humid environments such as Vietnam compared with temperate Central European conditions. Therefore, sensitivity results should be interpreted in a region-specific context, and conclusions should not be transferred across climatic regions without careful evaluation. The dominant impact of solar radiation on the variance of the FAO-56 Penman–Monteith ET_0 model in humid regions was also demonstrated by Sabino and de Souza (2023) who reported that the relative contribution of solar radiation increases with rising atmospheric humidity. Our results are consistent with the findings of Allen et al. (1998), who noted that the influence of wind speed on ET_0 is generally limited, except in regions where arid conditions prevail and aerodynamic effects become more significant.

Conclusion

By integrating bootstrapping with Monte Carlo, this study provides robust uncertainty bounds alongside sensitivity rankings. Such an approach may enable practitioners to prioritize investments in meteorological monitoring: improving the accuracy of solar radiation estimates may lead to only limited reductions in ET_0 uncertainty, whereas improvements in wind speed estimates, particularly through interactions with other variables, could reduce ET_0 uncertainty by up to 12% in this analysis. We recommend that future ET_0 modeling efforts emphasize fine-scale wind observations and include automated quality control for temperature and humidity sensors to ensure reliable aerodynamic gradient estimation.

Although our analysis covered a broad altitude gradient (105–2 635 m a.s.l.), regional climate regimes beyond Central Europe may exhibit different sensitivity patterns, especially under monsoonal or maritime influences. Extending this framework to tropical and semi-arid climates, as well as incorporating additional drivers such as net longwave radiation and soil moisture feedbacks, would further refine ET_0 uncertainty assessments. Finally, coupling this sensitivity framework with ensemble crop-yield simulations could quantify the downstream agronomic impacts of meteorological input errors, thereby translating methodological insights into actionable management strategies.

In summary, the dominant contribution of temperature and vapor pressure to ET_0 variance emphasizes the need for precise thermodynamic measurements, while wind speed plays an important role primarily through interaction effects. Uncertainty in solar radiation contributes only slightly to ET_0 estimation uncertainty under the analyzed conditions.

Based on the integrated analysis presented, the following practical recommendations are offered to practitioners estimating ET_0 with the FAO-56 Penman-Monteith model:

- Ensure the highest possible accuracy of air temperature measurements, as temperature errors propagate through multiple components of the PM equation and are the primary source of ET_0 uncertainty.
- Prioritize the quality and spatial representativeness of wind speed observations, particularly at high-altitude and exposed stations, where interaction effects with temperature and vapor pressure are strongest.
- Moderate uncertainties in solar radiation, including those arising from the use of estimated or remotely sensed *Rs* data in place of direct measurements, are unlikely to introduce substantial bias in ET_0 estimates under Central European climatic conditions, provided that the calculation of net radiation from *Rs* follows the standard FAO-56 procedure.

These findings are region-specific; practitioners working in tropical, monsoonal, or arid climates should independently evaluate the sensitivity structure before applying these recommendations.

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Ing. Viera Rattayová, PhD. (*corresponding author: v.rattayova@regioclim.eu)
Slovak Hydrometeorological Institute
Jeséniova 17
831 01Bratislava
Slovak Republic

Mgr. Milan Onderka, PhD.
Prof. Ing. Kamila Hlavčová, PhD.
Faculty of Civil Engineering, Slovak University of Technology
Radlinského 11
811 05 Bratislava
Slovak Republic

Ing. Zuzana Németová, PhD.
Institute of Hydrolgy SAS
Dúbravská cesta 9
841 04 Bratislava
Slovak Republic

Ing. Viera Rattayová, PhD.
Mgr. Milan Onderka, PhD.
Mgr. Jozef Pecho
Regional Climatological Institute
900 68 Plavecký Štvrtok 794
Slovak Republic