Sensitivity Analysis and Investigation of the Behaviour of the UTOPIA Land-Surface Process Model: A Case Study for Vineyards in Northern Italy

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Sensitivity analysis and investigation of the behaviour of the UTOPIA land-surface process model: A case study for vineyards in northern Italy

(MANUSCRIPT)

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Abstract

We used sensitivity analysis techniques to investigate the behaviour of the land-surface model UTOPIA while simulating the micrometeorology of a typical northern Italy vineyard (*Vitis vinifera* L.) under average climatic conditions. Sensitivity analysis experiments were performed by sampling the vegetation parameter hyperspace using the Morris method and quantifying the parameter relevance across a wide range of soil conditions. This method was used since it proved its suitability for models with high computational time or with a large number of parameters, in a variety of studies performed on different types of biophysical models. The impact of input variability was estimated on reference model variables selected among energy (e.g. net radiation, sensible and latent heat fluxes) and hydrological (e.g. soil moisture, surface runoff, drainage) budget components. Maximum vegetation cover and maximum leaf area index were ranked as the most relevant parameters, with sensitivity indices exceeding the remaining parameters by about one order of magnitude. Soil variability had a high impact on the relevance of most of the vegetation parameters: coefficients of variation calculated on the sensitivity indices estimated for the different soils often exceeded 100%. The only exceptions were represented by maximum vegetation cover and maximum leaf area index, which showed a low variability in sensitivity indices while changing soil type, and confirmed their key role in affecting model results.

Keywords

Energy balance, Hydrological balance, Land-surface model, Morris method, Vegetation cover, *Vitis vinifera* L.

1. Introduction

Any sensitivity analysis is aimed at quantifying the role of uncertain factors (i.e., parameters or driving variables) in explaining the variability of variables simulated by mathematical models (Park and Droegemeier, 2000; Cariboni et al., 2007). Sensitivity analysis is traditionally done to identify the parameters with the highest relevance to model results (e.g., Asseng et al., 2002; Saltelli et al., 2005). These are the parameters to be determined with the greatest accuracy (e.g., via direct measurements) or those on which to apply optimization algorithms.

In recent years, sensitivity analysis has been increasingly used to analyze model behaviour and to support model development (Park and Droegemeier, 1999), also through the reduction or simplification processes aimed at avoiding redundancies in model structure and/or too complex parametrizations (Tarantola and Saltelli, 2003; Jakeman et al., 2006). This is particularly important when interactions among different factors affect model estimations (Ratto et al., 2001), since other techniques such as conventional multivariate statistics (principal component analysis to investigate interactions) proved to be only partially adequate (Spear et al., 1994). In this context, sensitivity-analysis-based indicators and criteria were also developed (e.g., for model balance, Confalonieri, 2010) to provide synthetic metrics for evaluating model performances. Different studies (e.g., Refsgaard et al., 2005) suggest adopting an iterative procedure in which model results are analyzed and modified throughout the model development (Ravetz, 1997; Jakeman et al., 2006). These findings lead us to consider sensitivity analysis as a prerequisite for model development and use (Ratto et al., 2001).

The University of TOrino land-surface Process Interaction model in the Atmosphere (UTOPIA – Cassardo, 2012) is a land-surface model (LSM) aimed at evaluating the interactions among physical, hydrological and biological processes taking place within the atmospheric surface layer. LSMs are suitable tools for analyzing and describing radiative fluxes and for estimating hydrological balance components. They can be coupled to general or mesoscale atmospheric circulation or climate models in order to improve their lower boundary conditions (Balsamo et al., 2004), or used as stand-alone tools for supporting both climatic (Galli et al., 2010) and agricultural (Francone et al., 2010) studies. UTOPIA was developed and has been evaluated for different vegetation types under a variety of soil and weather conditions. The model was recently calibrated and tested for simulating transfer at the vegetation/soil-atmosphere interface using observations collected in a northern Italy vineyard (Francone et al., 2010). The results achieved in that study underlined the suitability of the model in reproducing soil processes, while suggesting further studies to improve the turbulent flux parametrization, with a particular focus on the vegetation parameters.

Most sensitivity studies carried out with LSMs assume parameter independence and explore the individual impact of parameters through one-at-a-time factor variations, without the use of sampling strategies allowing for the effective exploration of the parameter hyperspace (e.g., Wilson et al., 1987; Gao et al., 1996; Gulden et al., 2008). The use of advanced sensitivity-analysis techniques, such as factorial experimental design analysis, improves the effectiveness of the analyses and investigates the interactions among parameters (e.g., Liang and Guo, 2003). However, the small timestep needed by LSMs and, sometimes, the presence of a large number of parameters lead to a high sensitivity-analysis computational time. Moreover, sensitivity-analysis experiments are needed each time the application context changes, since their results depend on the biophysical conditions explored. This often limits the feasibility of this kind of approach within LSMs (Bastidas, 1999).

The present paper focuses on the application of the Morris sensitivity-analysis method (Morris, 1991) to the UTOPIA model for the simulation of the micrometeorology of a typical northern Italy vineyard (*Vitis vinifera* L.). The aim here is to quantify the parameter relevance and the sub-processes needing possible improvements. Since the model response can be greatly affected by the physical properties of soil, the analyses were performed using different soil types.

2. Materials and methods

2.1. The UTOPIA model

UTOPIA is the upgraded version of the Land-Surface Process Model (LSPM), a one-dimensional model developed at the Department of General Physics of the University of Torino (Cassardo et al., 1995). The soil is represented with a multi-layer configuration, with each layer defined by specific physical properties depending on water content and temperature. The latter are calculated on the basis of the heat diffusion law (Fourier) and the water mass conservation equations, via soil-type dependent input parameters (thermal and hydraulic conductivities, soil porosity, permanent wilting point, dry soil heat capacity; see Table 1). The vegetation is represented as a single uniform layer (big leaf approximation), whose features are a function of maximum vegetation cover and leaf area index, vegetation height, albedo, minimum stomatal resistance, leaf size, emissivity, and root depth (see Table 2). The momentum, sensible heat, and latent heat fluxes are evaluated using the resistance formulations (Garratt, 1994) between the atmosphere at a reference height and the soil/canopy surface. Vegetation cover (i.e., the percentage of vegetation over unit surface of soil) is a multiplicative factor that weights the relative importance of vegetation over bare soil in radiative and energy balance terms. Leaf area index is used in the flux parametrization for up-scaling from the leaf (characterized by minimum stomatal resistance and leaf size) to the canopy level. The height of the vegetation is then necessary for the evaluation of the zero-plane displacement and the aerodynamic roughness length for vegetated soil. The albedo and emissivity of vegetation are used to parametrize shortwave and longwave radiation fluxes, respectively. Root depth is involved in the calculation of soil water content, which in turn is needed to parametrize the canopy resistance (Dickinson et al., 1986), with the latter used to simulate the evapotranspiration process.

A subset of relevant simulated variables was thus selected for the sensitivity analysis, in order to study the impact of vegetation parameters on the heat and water vapour fluxes, and on the terms in the hydrological budget (Table 3).

UTOPIA needs a set of soil and vegetation parameters, and a high resolution meteorological dataset (e.g., 30 minutes), since its internal timestep is one minute. In addition the carrying out of preliminary trials is necessary to identify the length of the spin-up period, that is the simulation lapse of time needed to minimize the impact of the uncertainty in the initialization of soil water content.

The complete description of algorithms is provided in the UTOPIA user's manual (Cassardo, 2012).

2.2. The Morris sensitivity-analysis method

The high computational requirements due to the need of running the model with a small internal timestep suggested carrying out the sensitivity analysis with a method parsimonious in terms of model runs. Morris (1991) proposed a method particularly well suited when the number of uncertain factors is high and/or the model is expensive in terms of computational time. In spite of its low number of model execution requirement, the Morris method proved its effectiveness in ranking parameters according to their relevance in different studies where it was compared with other methods (e.g., Campolongo et al. 2007; Confalonieri et al., 2010; Yang, 2011). In particular, Yang (2011) demonstrated that, although the method is unable to quantify the amount of variance a parameter is responsible for, it provides a good approximation of the relative importance of each parameter and also information on parameter interaction.

The Morris method is considered global, since the final measure is obtained by averaging local (elementary) effects (Kucherenko et al., 2009). It is based on a particular design of the sensitivity-analysis experiment, derived from independent sampling strategies for the exploration of the parameter hyperspace, and on the assumption that simulated variables are at least once differentiable with respect to inputs. The latter allows us to determine which parameters can be considered to have effects on model results that are, (i) negligible, (ii) linear and additive, or (iii) nonlinear or involved in interactions with other parameters.

Assuming k is the total number of model parameters, $X = (x_1, \ldots, x_k)$ is the parameter vector. Each parameter x_i, after being scaled in the interval [0, 1], may assume values in the set $\{0, 1/(p-1), 2/(p-1), \ldots, 1\}$, where p is the number of levels. The parameter space Ω is then defined as a k-dimensional p-level unit hypercube. Assuming Δ as $1/[2(p-1)]$ and $y(X)$ as the model output, an elementary effect of the i-th factor is therefore calculated as:

$$R_i(X, \Delta) = \frac{y(x_1, \ldots, x_{i-1}, x_i + \Delta, x_{i+1}, \ldots, x_k) - y(X)}{\Delta}, \quad (1)$$

where the finite distribution of R_i is obtained by randomly sampling X in Ω, and is composed of a total of $p^{k-1}[p-\Delta(p-1)]$ elements for each x_i. The mean (μ_i) and standard deviation (σ_i) of each distribution of R_i are the sensitivity measures, where μ_i represents the overall influence (or total effect) of the parameter x_i, whereas σ_i identifies – for high values – non-linearities in the model response or interactions with other parameters. Morris suggested a random sampling design to estimate μ and σ over a smaller number of elementary effects. The method selects in the Ω hyperspace r different trajectories composed by (k+1) points. At each point, Δ is applied to a single parameter. This design is a noticeable improvement with respect to varying one factor at a time, both because during the sampling procedure parameters, when varied, do not assume any of the previous values, and because r is usually > 1 (Saltelli, 2010). In this way, the total number of model evaluations is lowered to $r(k+1)$, in turn decidedly lowering the computational time. After this sampling phase, parameters are transformed from the unit hypercube to their physical values.

In this study, the evolution of the Morris method proposed by Campolongo et al. (2007) was used. This approach allows (i) selection of the r trajectories in such a way as to maximize their dispersion in the input space Ω, and (ii) obtaining values of μ_i* (instead of μ_i), which is the estimate of the mean of the distribution of the absolute values of the elementary effects R_i:

$$\mu_i{*} = \frac{\sum_{i=1}^{r} |R_i|}{r} \quad (2)$$

The use of μ_i* (μ* hereafter) solves the problems due to the effects of opposite signs that occur when the model is non-monotonic.

2.3. Study site and sensitivity-analysis experiments

The observations used for the simulation scenario are from an experiment carried out in a vineyard located in Cocconato, Piemonte region, northern Italy, latitude 45° 05' N, longitude 8° 03' E, altitude 311 m a.s.l. during 2008 and 2009. The site belongs to the Monferrato sub-region, an area particularly suitable for grapevine, and the climate of the experimental area is continental, mitigated by the relative closeness to the Mediterranean Sea. For the last decade (i.e., 1998-2008), the average daily summer temperature was 22.3 ± 0.7 °C, with precipitation (670 ± 66 mm per year) concentrated mainly in spring and autumn. The 2008-09 period is representative of the mean climatology of the area, as highlighted by the comparison of summer daily minimum and maximum temperatures (18.2 ± 2.9 °C and 29.1 ± 2.9 °C, respectively) with corresponding normal values in the period of 1979-2008 (16.4 ± 2.8 °C and 28 ± 3.4 °C, respectively). Summer precipitation exhibits a value of 176 ± 3 mm for the study period and a climatic average of 162 ± 54 mm. Further details about the experiment can be found in Francone et al. (2010).

The UTOPIA simulations commenced on April 11, 2008 and ended on September 12, 2009 (i.e., the 2009 grape harvest time), although the model sensitivity to vegetation parameters was analyzed only for the second year (average period between April 15, 2009 and September 12, 2009; see Table 3). The starting date for the period of analysis was chosen both for biological (i.e., start of the vine vegetative cycle) and computational (i.e., the spin-up period) reasons. Since soil water content was influenced by the 11 different soil types (see Table 1) used in the sensitivity analysis, the adopted spin-up was 12 months, thus ensuring a proper initialization for all the soil conditions explored. The choice of seasonal average was again motivated by two factors: firstly, the need to meet a requirement of the Morris method, in which a single simulated variable value should correspond to each sampled combination of parameters. The second reason derives from biological aspects of the studied system, since there is a correspondence between the period in which model results were averaged and the vegetative cycle.

The sensitivity analyses were carried out on the parameters involved with vegetation. Table 2 lists the UTOPIA vegetation-related parameters, and the sources of information used to retrieve their distributions. In most of the cases, distribution parameters were derived by calculating means and standard deviations of the values found in the cited literature, after normality verification. When a single literature source was only available, a normal distribution with a standard deviation of 5% of the source value (in turn assumed as the mean) was used, according to a standard practice for sensitivity analysis used in biophysical models (e.g., Richter et al., 2010). The domain of each parameter was limited by truncations at the 10^{th} and 90^{th} percentiles. Model sensitivity was quantified for different soil types (Table 1), in order to explore the effect induced by the soil type on the UTOPIA sensitivity to vegetation parameters. This solution was preferred to the simultaneous analysis of vegetation and soil parameters relevance, since (i) the aim of this study is to investigate vegetation-related processes, and (ii) the analysis of parameters related with distinct sub-systems (i.e., vegetation and soil in this case) could lead to situations where the relevance of the parameters belonging to a sub-system hides that of the others, lowering the discriminating capability of the whole analysis.

The Morris method was applied with 10 trajectories and eight levels, for a total of 90 model executions for each sensitivity analysis and a grand total of 990 executions for the 11 soil types tested.

The simulated variables on which the sensitivity analysis was performed are listed in Table 3.

3. Results and discussion

Morris sensitivity indices μ^* and σ for the simulated mean fields at the surface and soil variables are shown in Figures 1 and 2, respectively. Error bars indicate the indices' variability due to the 11 soil types on which the analyses were performed (Table 1). The parameters with the highest sensitivity are those located in the top-right quadrant of μ* versus σ plot (high total effect and high non-linearities).

In both figures the sensitivity indices of maximum leaf area index (LAI_{max}) and vegetation cover (σ_{fmax}) exceed by about one order of magnitude the values of the other parameters, which are located in a narrow area close to the origin (highlighted by the zoom on the top-left of each graph). In most cases, even the zoom does not allow to discriminate between the effects of the remaining parameters, implying that their impact was negligible under the explored conditions. LAI_{max} and σ_{fmax} were therefore the vegetation parameters that played the major role in influencing the UTOPIA results. In six out of nine cases (i.e., the total number of variables investigated), LAI_{max} achieved the highest values for μ*, whereas in eight out of nine cases it obtained the highest values for σ, i.e., it was the parameter most involved in interactions with others and with non-linear model responses. For the same two parameters, the relative variability of both μ* and σ due to the different soil types (errors bars in Fig. 1 and 2) was lower compared to that of the remaining parameters. The average coefficients of variation, evaluated as the ratio between the standard deviation and the mean of the sensitivity index, were 0.21 and 0.33, respectively, for μ* values of LAI_{max} and σ_{fmax}, with corresponding σ = 0.23 and 0.28, respectively. The other parameters (minimum stomatal resistance, root depth, second leaf dimension, vegetation emissivity and height) were characterized by a relevant sensitivity index variability due to soil features for all the studied variables, with an average (on all the variables) coefficient of variation often exceeding 100%.

A more in-depth analysis of the variables related to the energy balance showed that σ_{fmax} was the parameter with the highest influence on net radiation (Fig. 1a) and sensible heat flux (Fig. 1b) (μ^* = 45 ± 3 and 33 ± 3, respectively), whereas it was less relevant for the latent heat flux (Fig. 1c) (μ^* = 7 ± 3). For most of the energy balance variables, the magnitude of σ for σ_{fmax} was lower than that of LAI_{max}: on average, σ = 8 for σ_{fmax} and σ = 16 for LAI_{max}. These results reflect the role played in UTOPIA by vegetation cover, linearly involved in determining bare soil and vegetated surface components of the fluxes (Francone et al., 2010). Within the same algorithms, the role of the leaf area index is indirectly accounted for in the canopy resistance factors. The influence of LAI_{max} overcame that of σ_{fmax} in both $\mu*$ and σ for latent heat and atmosphere-soil-canopy heat fluxes (Fig. 1b-1d), whereas for transpiration, its total effect was almost half that of σ_{fmax} one, but its value for σ was slightly higher (Fig. 1e). Among the radiative fluxes, net radiation (Fig. 1a) is estimated by means of a linear relationship with the vegetation cover and the surface albedoes (soil, vegetation and snow), without the use of canopy resistance (Cassardo, 2012). As can be observed, the relevance of the vegetation albedo (α_f) was, in this case, comparable with that of LAI_{max}.

A focus on the analysis of soil variables (Fig. 2) revealed that the impact of the soil variability on parameter relevance (error bars in the figure) was higher compared to that discussed for the variables describing the energy balance. LAI_{max} represented the most relevant vegetation parameter for both the sensitivity metrics, especially for drainage (Fig. 2a), with $\mu* = 57 \pm 29$ and $\sigma = 50 \pm 23$. Completely different results were achieved by the same parameter for soil moisture and temperature (Fig. 2c-2d), with sensitivity indices some orders of magnitude lower. This can be partly explained by noting that these variables were averaged within the soil profile by weighting the different soil-layer thicknesses. Since thicker layers are the deepest ones (i.e., those less influenced by short-term variations), they affect the overall results by lowering the relevance of the surface parameters. Nevertheless, a stronger impact of soil features on soil moisture and temperature was emphasized by a high variability of $\mu*$ and σ for both LAI_{max} and σ_{fmax}, especially when weighted for their absolute values (e.g., for σ_{fmax}, $\mu* = 0.02 \pm 0.01$ in Fig. 2c). Compared to the others, the influence of these two parameters on surface runoff (Fig. 2b) was moderately greater, although root depth achieved a relevant value for the total effect ($\mu* = 5.2 \pm 2.0$). This behaviour can be explained by the influence of the averaged soil moisture in the root layers on surface runoff (proportional to the root soil moisture).

These results definitely attest the relevance of LAI_{max} and σ_{fmax} in affecting the UTOPIA variables explored. The importance of the same two parameters was noted also in a sensitivity analysis carried out on a similar model (e.g., BATS1e) applied at five different sites by Bastidas et al.

(2006), with a total number of model runs exceeding by about one order of magnitude those in the present study.

4. Conclusions

The sensitivity analysis of the UTOPIA model allowed (i) deriving the key information on the influence of vegetation-related parameters on simulated fluxes and hydrological variables under different soil conditions, and (ii) testing the Morris method, for the first time applied to a land-surface model

Results indicated maximum leaf area index and vegetation cover as the vegetation parameters with the greatest influence on the energy and hydrological processes. The model response for the two parameters was highly non-linear and the sensitivity index values suggested a degree of interaction between them. These main findings are in agreement with other investigations using a similar model (Bastidas et al., 2006), thus confirming the Morris method suitability in discriminating among relevant parameters. Moreover, our analysis required a noticeably lower number of model evaluations and, in general, was less time consuming with respect to the previous analysis methods. As a consequence, it effectively improved the knowledge on the model behaviour while reproducing the vineyard agro-ecosystem (Francone et al., 2010).

More specifically, few of the remaining vegetation parameters (i.e., vegetation albedo and root depth) showed a comparable relevance only with respect to net radiation and accumulated surface runoff. The differences among the explored soil conditions greatly affected the model sensitivity to parameters, with the only exceptions represented by maximum leaf area index and vegetation cover. This further proved the relevance of these two parameters on the modelled processes, regardless of the soil type considered.

In light of the results obtained in this study, a possible further development of UTOPIA would be the implementation of a more sophisticated approach for modelling the canopy structure, possibly also distinguishing between tree and crop species, when they are both present in the field, as in many Italian vineyards and olive groves. Moreover, the procedure used in this study demonstrated its suitability for LSM assessment, thus favouring the adoption of standard sensitivity-analysis techniques within the process of LSM development.

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Tables

Table 1. Soil types for which the model sensitivity to vegetation parameters was quantified (Clapp and Hornberger, 1978).

Soil type	Exponent for the calculation of unsaturated ψ and K_η (b)	Saturated hydraulic conductivity ($K_{\eta s}$, m s^{-1})	Porosity (η_s, m^3 m^{-3})	Permanent wilting point (η_{wi}, m^3 m^{-3})	Saturated moisture potential (ψ_s, m)	Dry soil thermal capacity per unit of volume (ρ_c; J K^{-1} m^{-3})
Sand	4.05	0.01760	0.395	0.0677	−12.1	1.465
Loamy sand	4.38	0.01563	0.410	0.0750	−9.0	1.407
Sandy loam	4.90	0.00341	0.435	0.1142	−21.8	1.344
Silt loam	5.30	0.00072	0.485	0.1794	−78.6	1.273
Loam	5.39	0.00070	0.451	0.1547	−47.8	1.214
Sandy clay loam	7.12	0.00063	0.420	0.1749	−29.9	1.177
Silty clay loam	7.75	0.00017	0.477	0.2181	−35.6	1.319
Clay loam	8.52	0.00025	0.476	0.2498	−63.0	1.227
Sandy clay	10.40	0.00022	0.426	0.2193	−15.3	1.177
Silty clay	10.40	0.00010	0.492	0.2832	−49.0	1.151
Clay	11.40	0.00013	0.482	0.2864	−40.5	1.088

Table 2. Parameters and statistical settings used for sensitivity analysis experiments.

Parameter	Unit	Mean value	Standard deviation	Source[a]
Maximum vegetation cover (σ_{fmax})	-	0.40	0.18	1, 2, 3, 4
2nd leaf dimension (d_0)	m	0.18	0.01	5[b]
Vegetation albedo (α_f)	-	0.20	0.02	3, 6, 7
Vegetation emissivity (ε_f)	-	0.042	0.002	8 [b]
Minimum stomatal resistance (r_{min})	s m^{-1}	146.0	7.3	9 [b]
Maximum leaf area index (LAI_{max})	m^2 m^{-2}	3.2	1.9	1, 4, 7, 10
Vegetation height (h_f)	m	2	0.2	1, 2, 4
Root depth (d_R)	m	1	0.05	5[b]

[a] 1: Lopez-Lozano et al. (2009); 2: Spano et al. (2000); 3: Trambouze et al. (2001); 4: Zarco-Tejada et al. (2005); 5: Brancadoro (personal communication, 2011); 6: Pieri (2010); 7: Ortega-Farias et al. (2010); 8: UTOPIA default value; 9: Zhang et al. (2008); 10: Yunusa et al. (2004).

[b] A single value was available; for the sensitivity analysis, the standard deviation was set to 5% of the mean value (Tarantola, personal communication, 2011).

Table 3. UTOPIA variables used in the sensitivity analysis. For the cumulative variables, the value at the end of the simulation was used, while for the others the average value over the period April 15 2009 – September 12 2009 was calculated.

Variable	Units	Variable use
Net radiation	W m^{-2}	Averaged
Sensible heat flux	W m^{-2}	Averaged
Latent heat flux	W m^{-2}	Averaged
Atmosphere-soil-canopy heat flux	W m^{-2}	Averaged
Transpiration flux	W m^{-2}	Averaged
Soil moisture [a]	% porosity	Averaged
Cumulated surface runoff	m	Cumulative
Cumulated drainage	m	Cumulative
Soil temperature [a]	°C	Averaged

[a] average of the soil profile (five layers of 0.05, 0.10, 0.15, 0.20, 0.40 m thickness from surface to 0.90 m)

Figures

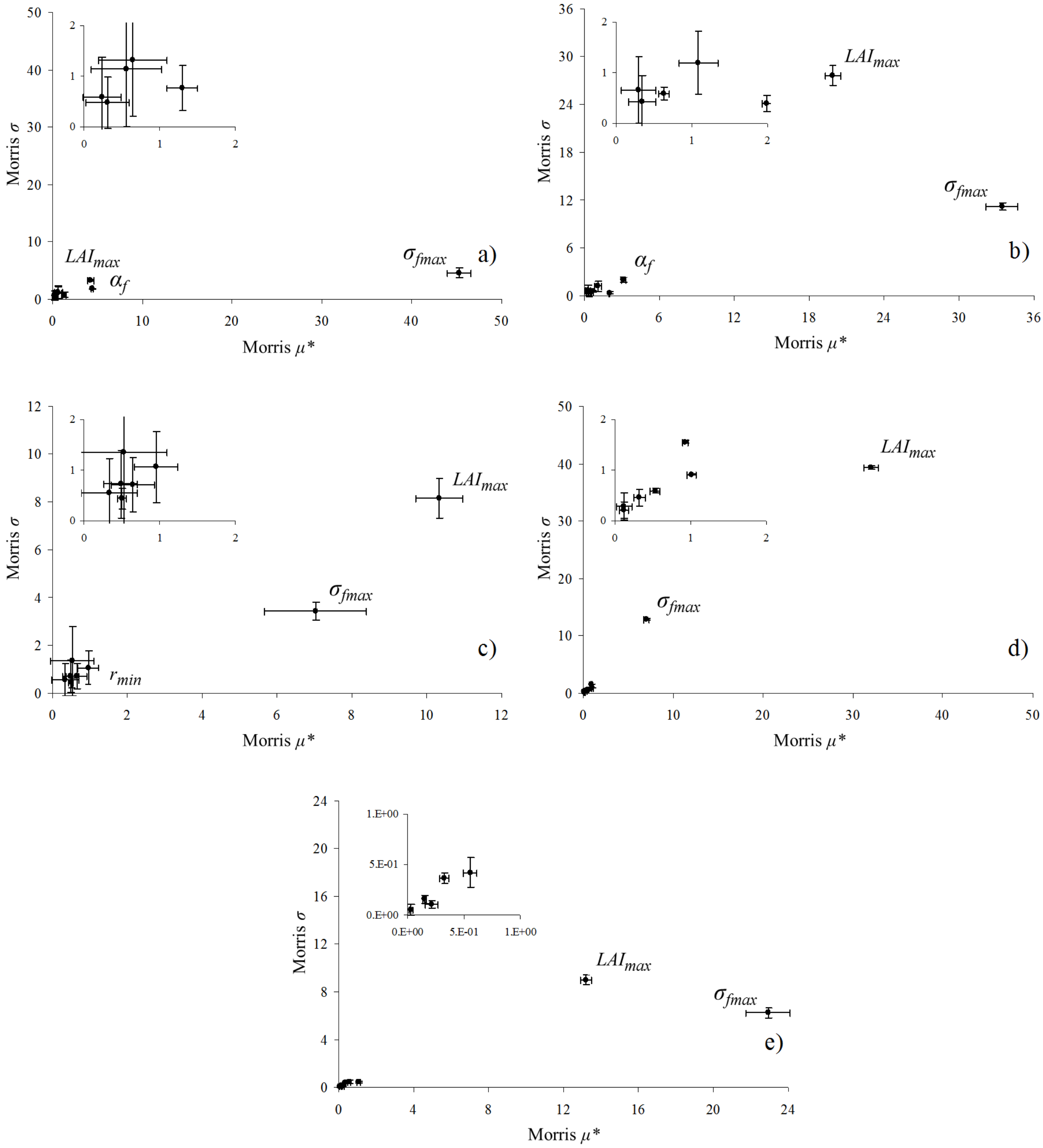

Figure 1. Sensitivity analysis results (Morris method) concerning the variables related with surface energy. Error bars (± 0.5 standard deviation) represent the effect of different soil types (Table 1) on Morris μ^* and σ. a) net radiation (W m^{-2}); b) sensible heat flux (W m^{-2}); c) latent heat flux (W m^{-2}); d) atmosphere-soil-canopy heat flux (W m^{-2}); e) transpiration flux (W m^{-2}). Labels are inserted to highlight the most relevant parameters.

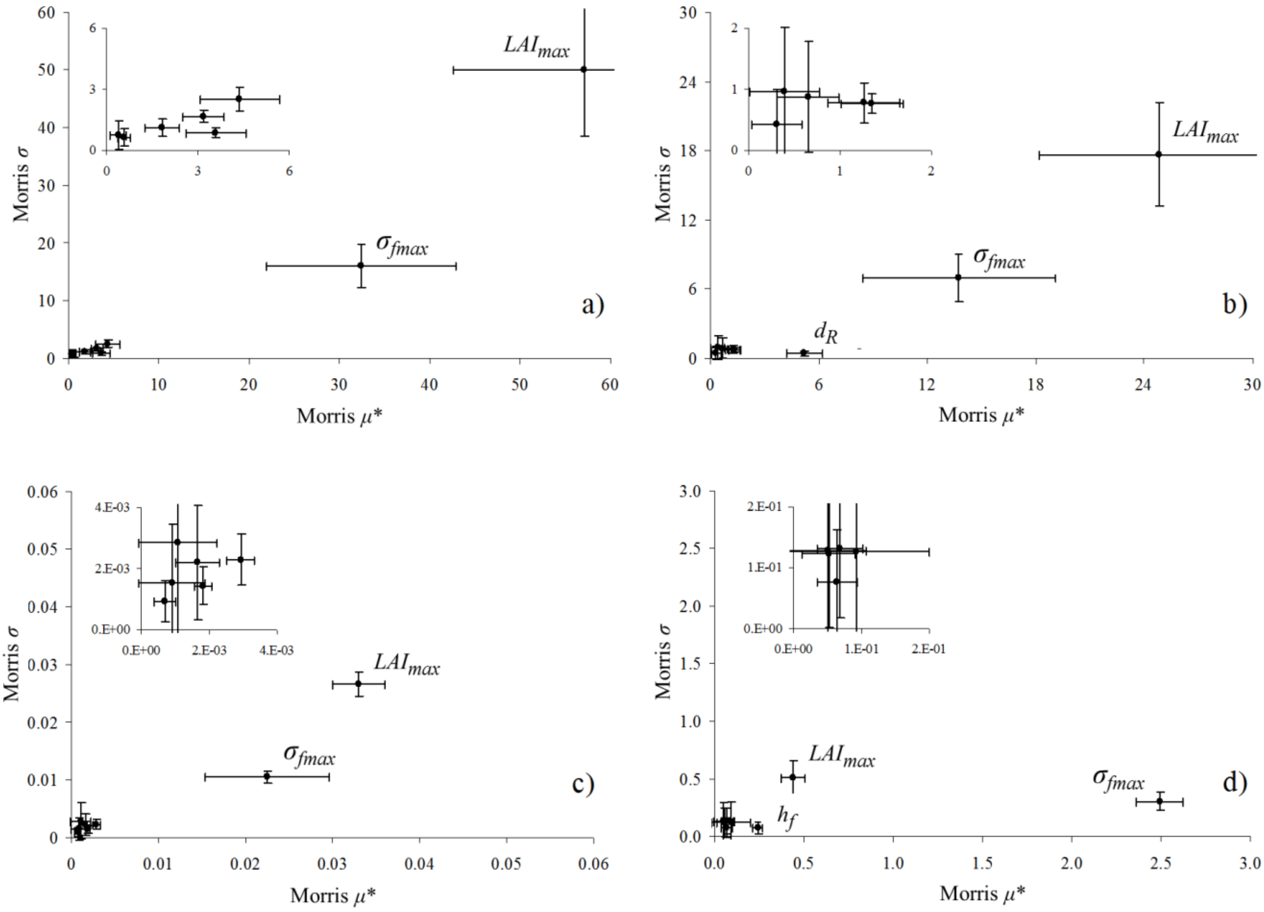

Figure 2. Sensitivity analysis results (Morris method) concerning the soil variables. Error bars (± 0.5 standard deviation) represent the effects of different soil types (Table 1) on Morris μ* and σ. a) cumulated drainage (m); b) cumulated surface runoff (m); c) soil moisture (% porosity; mean of the profile); d) soil temperature (°C). Labels are inserted to highlight the most relevant parameters.