A model-driven Decision Support System for vineyard water status management: a time-dependent parameters sensitivity analysis

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Abstract

The global sensitivity analysis (SA) of a dynamic soil water balance model embedded in a Decision Support System for vineyard water management is achieved *via* Sobol variance-based method. The sensitivity analysis is applied sequentially at each simulation step, which enables to follow the variation of parameters influence over time. Results allow to identify four soil-related parameters having the highest influence at the vine plot scale, and for various climate scenarios. This provides fundamental information for the operational use of the model, i.e. when few input data are available to the end-user.

Keywords: water budget, grapevine, model, SVAT, Sobol.

Introduction

Increases in drought and heat waves occurrences in Mediterranean vineyards have been recorded in the last twenty years (Ojeda 2007) and are expected to increase in the future. In this context, implementing efficient irrigation management strategies, including decision support systems (DSS), to monitor vine water deficit may become increasingly important for ongoing wine production and profitability (Battaglini et al, 2009).
One of the reference indicators of vine water status is the predawn leaf water potential (PLWP) (Pellegrino et al, 2004). However its direct measurement on the field remains occasional since it is both costly and tedious. An appealing alternative consists in simulating the PLWP by using a simple soil-vegetation-atmosphere-transfer (SVAT) (Lebon et al, 2003; Pellegrino et al, 2006). But the major issue when using models is that the accuracy of the results strongly depends on the accuracy of its input parameters. Besides, even simple SVAT models require many parameters whose values are potentially difficult and costly to measure in the field. This is even truer for parameters specific to each configuration studied, like soil properties. It is thus essential to identify the parameters having a large influence on the model output variability, in order either to concentrate experimental efforts on their measure when possible, or to calibrate them otherwise.
Sensitivity analysis (SA) techniques are used to this end, since they enable to assess the most relevant parameters of agro-meteorological models. Celette et al. (2010) for instance have realized a 'one-at-a-time' SA of a model simulating water partitioning in an intercropped vineyard, which consists in varying one model input at a time while keeping all other fixed and thus does not detect the presence of parameters interactions. Recently, more advanced global SA methods have been increasingly applied to evaluate the output variability when all inputs vary simultaneously in their whole uncertainty

range (Saltelli et al, 2000). The specificity of SVAT models is that they provide a time-dependent output that varies with weather data, so that parameters influence may also depend on climate variability. SA methods have already been applied in such a context. For instance, for a discrete-time model at a daily time step, Lamboni et al. (2009) computed sequentially the SA at each simulation date. This enabled to follow the variations of parameters influence over time.

The goal of this study was to evaluate a simple soil water balance model parameterized for vine for the prediction of PLWP dynamics, in the objective of its practical use in a DSS for vineyard water management by winegrowers and vineyard advisors of the Mediterranean Languedoc-Roussillon region, Southern France. This objective was achieved by identifying *via* a SA the parameters whose uncertainty at the vine plot scale significantly influence the PLWP uncertainty for various climates scenarios.

Materials and methods

SVAT model description

A model describing soil water balance dynamics parameterized for vine (Lebon et al, 2003) was amended to account for runoff (USDA, 2004, Celette et al, 2010). This model computes the fraction of transpirable soil water (FTSW) at a daily time step taking into account: radiation absorption (Riou et al, 1989), vine canopy growth and transpiration (Lebon et al, 2003), bare soil evaporation (Brisson & Perrier, 1991) runoff and drainage. FTSW ranges from 0 to 1 and is defined as the ratio between the daily and the total amount of transpirable soil water (TTSW), where TTSW is the amount of water between field capacity and wilting point for a given rooting depth. The weather variables necessary for driving the model are daily precipitations, solar radiation, mean air temperature and potential evapotranspiration (ETP). The model runs starting January 1st, and the PLWP is estimated from bud-break to senescence from an exponential relation with FTSW (Pellegrino et al, 2006).

SA method

We used the global sensitivity analysis method by Sobol (1990), based on a decomposition of the variance V of the model output, similar to that used in the classical analysis of variance of factorial experimental designs. The decomposition aims at quantifying the variance contribution of input parameters to the total model variance. For a model with p independent parameters, it reads:

$$V = \sum_{i=1}^{p} V_i + \sum_{1 \le i < j \le p} V_{ij} + \cdots + V_{12\ldots p} \quad (1)$$

where $V_{i=1\ldots p}$ are the individual contributions of the p parameters and the other terms are the contribution of the combination of two or more parameters. The Sobol sensitivity indices are defined as the ratio between the terms on the right-hand side of equation (1) and V, mainly

$$S_i = \frac{V_i}{V} \quad \text{and} \quad \mathrm{ST_i} = \frac{V_i + \sum_{j \ne i} V_{ij} + \cdots}{V} \quad (2)$$

which are called the first-order and total sensitivity indices respectively. They allow to distinguish between the average contribution of individual parameter and the total contribution including interactions with other parameters. The sensitivity indices are estimated via a Monte Carlo sampling of the parameters probability distributions at a cost of N(2p+2) model evaluations (Saltelli, 2002). N must be chosen large enough to provide stable results, which is the main drawback of the method if the model computational time is high.

SA description

The SVAT model requires the definition of 21 input parameters. Among them, some have fixed nominal values like vine-dependent parameters, while others are plot-dependent like soil characteristics and thus have different nominal values depending on vine plot. In order to scan the range of vine plots and climate variability of the Languedoc-Roussillon region, several independent SA were performed by crossing 24 sets of vine plot parameters with three years of weather data, representative of dry, medium-dry and humid years. The weather data were classified on the basis of a climatic index defined as the total rainfall minus ETP during the vegetative cycle. The uncertainty ranges and probability distributions of all parameters were set according to literature or field expertise. An exhaustive preliminary screening SA (not presented) via the Morris method (Campolongo et al, 2007) has allowed to identify 6 parameters as having a negligible influence on the model output. These parameters have been fixed to nominal values in the SA presented here. They include the soil albedo and the cumulative thermal time defining the transition between phenological stages. Out of the 15 remaining parameters, 7 are plot-dependent and it would have been ideal to perform the SA on all possible combinations. However, excessive computational time led to restrict the number of SA. Preliminary Morris tests and field expertise allowed to identify 4 of the plot parameters as having the highest impact on the output. SA analysis were thus performed for 2 or 3 representative values of those 4 parameters, as defined in Table 1. The other parameters have a single representative value in all SA, or follow a uniform distribution (see Table 1). All SA were achieved with N=5000.

Table 1. Parameters of the SVAT model, with the probability distribution chosen for the SA, i.e. either a uniform distribution in the range (b_{inf}, b_{sup}) or a normal distribution of mean μ and standard deviation ☐ truncated in the range (b_{inf}, b_{sup}).

Parameters	Description	Probability distribution	Range (b_{inf}, b_{sup})	μ_1	μ_2	μ_3	σ
TTSW [mm]	total amount of transpirable soil water	normal	25-350	100	175	250	50
H_{max} [m]	foliage maximum height	normal	0.25-1.5	0.8	1.1	-	0.2
L_{max} [m]	foliage maximum width	normal	0.2-51	0.35	0.55	-	0.5
$FTSW_{initial}$ [-]	FTSW value at January 1st	normal	0-1	0.5	1	-	0.3
$FTSW_{threshold}$ [-]	threshold under which vine transpiration declines linearly with FTSW from its maximum value to zero	normal	0.3-0.9	0.4	-	-	0.2
CN [-]	runoff parameter	uniform	60-99	-	-	-	-
Po_{min} [-]	minimum proportion of foliage gap	normal	0.1-0.5	0.2	-	-	0.2
D [m]	inter-row distance	normal	1.5-3.5	2.5	-	-	0.1
orientation [rad]	row orientation	normal	-	π/2	-	-	π/4

b_1 [mm]	parameter of the bare soil evaporation model (Brisson & Perrier, 1991)	normal	5-21	14	-	-	5
b_2 [-]	parameter of the bare soil evaporation model (Brisson & Perrier, 1991)	normal	0.05-0.18	0.12	-	-	0.03
U [m]	parameter of the bare soil evaporation model (Brisson & Perrier, 1991)	uniform	2-6	-	-	-	-
THT_{Hmax} [°C.d]	parameter of the vegetation growth model (Lebon et al, 2003)	uniform	350-750	-	-	-	-
THT_{Lmax} [°C.d]	parameter of the vegetation growth model (Lebon et al, 2003)	uniform	350-750	-	-	-	-
THT_{Pomin} [°C.d]	parameter of the vegetation growth model (Lebon et al, 2003)	uniform	350-750	-	-	-	-

Results

For all tested combinations of climate scenarios and plot parameters, the results were qualitatively identical. In every case, marked variability was associated to variations of TTSW. This is the reason why the following results are presented for a single year and for fixed mean values of H_{max}, L_{max}, and $FTSW_{initial}$.

Figure 1 compares the results obtained for mean values of TTSW equal to 250 (a-b), 175 (c-d) and 100 mm (e-f). All simulations were realized with the medium-dry weather data scenario, and for mean values of H_{max}, L_{max} and $FTSW_{initial}$ set to 0.8m, 0.35m and 0.5 respectively. Figures 1.(a,c,e) present the daily evolution of the sensitivity indices. Figures 1.(b,d,f) show the related uncertainty range of PLWP represented by its median, interquartile range (range between the 1^{st} and 3^{rd} quartiles) and interdecile range (range between the 1^{st} and 9^{th} deciles). Figure 1.g shows the corresponding precipitations histogram. The growing season was divided into three phases: a phase of constant plant water constraint, a soil-drying phase and a soil-wetting phase.

In every case, the PLWP variance changes over time as shown in figures 1.(b,d,f). It is strongly related to precipitations as highlighted by the comparison with the precipitations histogram, since the uncertainty range diminishes after a rain event. For low TTSW, the PLWP variations are the widest. This is due to the exponential relation between PLWP and FTSW; the smaller the TTSW, the more sensitive the PLWP to soil-water content variations.

Figures 1.(a,c,e) show that when the PLWP variations are high, i.e. during the drying and wetting phases, they are mainly explained by the individual contributions of 4 soil-related parameters: TTSW, $FTSW_{threshold}$, CN and $FTSW_{initial}$. The individual influence of other parameters and of parameters interaction remains limited in the drying phase and tends toward zero in the wetting one.

For days of the drying phase when PLWP variations are high, the predominant parameter is TTSW, especially when its value decreases, i.e. when the rooting depth decreases for a fixed texture. This is partly due to the fact that the standard deviation of the TTSW distribution, chosen from field expertise, has an absolute value of 50 mm in all case (and so a relatively higher deviation for low TTSW).

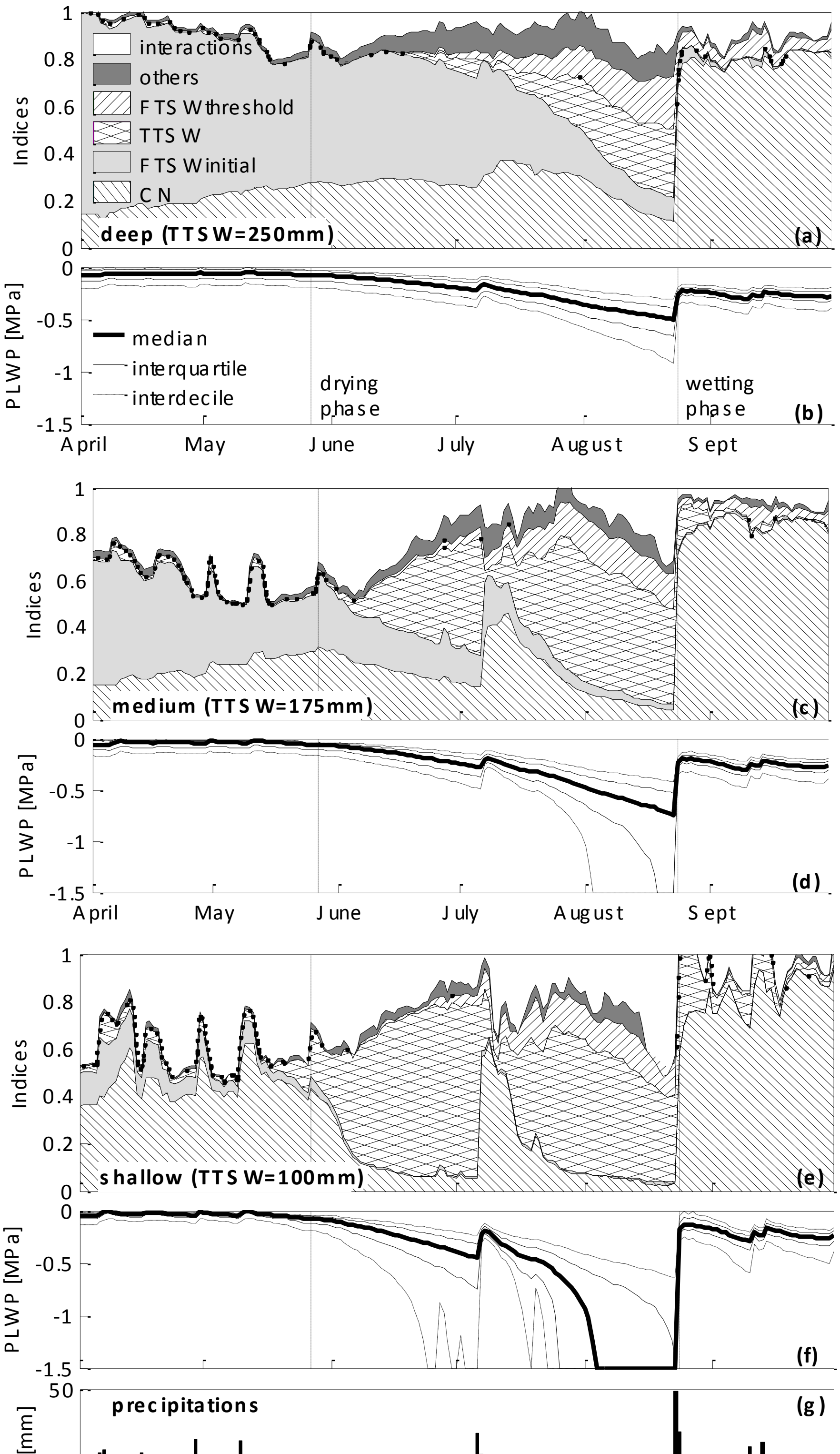

Figure 1. Daily SA results for a mean value of TTSW equal to 250 (a-b), 175 (c-d) and 100 mm (e-f). Figures (a, c, e) show the daily pie chart of sensitivity indices (first order and interactions). Figures (b, d, f) show the related uncertainty range of PLWP represented by its median, interquartile range (range between the 1st and 3rd quartiles) and interdecile range (range between the 1st and 9th deciles). Figure (g) shows the corresponding rain histogram. Vertical dotted lines mark the beginning of the soil-drying and soil-wetting phases.

The relative contribution of $FTSW_{threshold}$ is limited to the drying season and seems to be independent of TTSW.
The influence of runoff parameter CN in the drying phase is not negligible, even though rain events are scarce. Since the runoff model, and thus CN, comes into play only when daily precipitations are non-zero, the parameter influence in non-rainy days is the consequence of previous precipitations. In the soil-wetting phase, almost all the PLWP variations are explained by CN. This phase corresponds to leaf senescence, where soil water extraction decreases, which means that the soil-water variations are mainly due to precipitations and bare soil evaporation. Besides, the rain events are important at this time of the year in the Languedoc-Roussillon region, and the influence of CN in the runoff model increases with the amount of precipitations.
The value of $FTSW_{initial}$ at January 1st is influent essentially in the first phase of the season, which is of reduced interest since the PLWP variations are small at that time. Still, it has a non-negligible influence in the drying phase when the rooting depth increases (Figure 1.a). It still explains around 20% of the output variability in August, whereas for shallower rooting depths, the initial influence is damped at some point by rain events.

Discussion

The issue here is to make best use of these results for a practical use of the SVAT model in a DSS. Results show that of the 21 parameters present at the beginning, only 4 soil-related ones condition at least 60% of the total PLWP variability. In practice, this means that the user is allowed some error in defining the other parameters. However a particular effort has to be done for the definition of these 4 parameters, either by looking for relations between these parameters and parameters more easily accessible to the end-user, or by calibrating them if necessary.
The most influent parameter is by far the TTSW, which confirms previous studies (Gaudin & Gary, 2012, for instance). Besides, this parameter is subject to a large uncertainty when evaluated in the field, which is critical for low TTSW values as seen above. When the model is used in the DSS, the TTSW is estimated from the average soil texture and average rooting depth given by the end-user. The difficulty in estimating it lies in the fact that, more than the actual average rooting depth, it is based on an effective depth that supposes the presence of water-absorbent roots only, and homogeneously distributed in the soil, which is clearly untrue for vine roots. Hence, the best option seems to calibrate the TTSW against field data for each vine plot.
Concerning $FTSW_{threshold}$, the choice was made to keep it fixed to its nominal value of 0.4. It would be interesting in the future to look for a physical relation between this parameter and other measurable parameters.
The parameter CN is very difficult to measure and, in the practical use of the model, is estimated roughly from soil texture classes and previous rain events (USDA, 2004). However, its estimation is less critical than that of TTSW since its effect concentrates essentially in the soil-refilling phase. This phase is less critical than the previous drying phase, since it influences mainly the soil-water refilling of the year to come, more than the grape quality and yield of the current year. It is to be noted that for a humid year, the influence of CN is more consequent in the first phase of the vegetative cycle (results not shown).

$FTSW_{initial}$ is the value at January 1st, while the PLWP is computed from bud-break at the beginning of April. Under these circumstances, one would have hoped to see its influence damped by rain events before the vegetative cycle. As seen in the results above, this is the case most of the time in the regional climatic context, except for large TTSW values. $FTSW_{initial}$, as an estimate of soil-water filling, is more easily evaluated on the field than the TTSW. However, when field data are not available, an option would be to calibrate it along with the TTSW.

Conclusions and perspectives

The SA presented above has enabled to identify the most influent parameters of the SVAT model used to simulate PLWP in a DSS for vine water management. Based on these results, the choice was made to calibrate the most influent parameter only. This calibration is currently done by hand and the following step is now to automate it in the DSS. An option would be to include some other hard-to-measure influent parameters in the calibration process, especially the runoff parameter CN. Besides, another important step is now to evaluate the sensitivity to parameters uncertainty of the DSS recommendations, like irrigation schedule and quantity.

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References

Battaglini, A., Barbeau, G., Bindi, M. and Badeck, F.-W. 2009. European winegrowers' perceptions of climate change impact and options for adaptation. Reg Environ Change **9** 61-73.

Brisson, N. and Perrier, E. 1991. A semi-empirical model of bare soil evaporation for crop simulation models. Water Resources Research **27** 719-727.

Campolongo, F., Cariboni, J. and Saltelli, A. 2007. An effective screening design for sensitivity analysis of large models. Environmental Modelling & Software **22** 1509-1518.

Celette, F., Ripoche, A. and Gary, C. 2010. Walis - a simple model to simulate water partitioning in a crop association: The example of an intercropped vineyard. Agricultural Water Management **97** 1749-1759.

Gaudin, R. and Gary, C. 2012. Model-based evaluation of irrigation needs in Mediterranean vineyards. Irrigation Science **30** 449-459.

Lamboni, M., Makowski, D., Lehuger, S., Gabrielle, B. and Monod, H. 2009. Multivariate global sensitivity analysis for dynamic crop models. Field Crops Research **113** 312-320.

Lebon, E., Dumas, V., Pieri, P. and Schultz, H. R. 2003. Modelling the seasonal dynamics of the soil water balance of vineyards. Functional Plant Biology **30** 699-710.

Ojeda, H. 2007. Irrigation qualitative de précision de la vigne *(*Qualitative precision irrigation in the vineyard). Le Progrès Agricole et Viticole **7** 133-141.
Pellegrino, A., Lebon, E., Voltz, M. and Wery, J. 2004. Relationships between plant and soil water status in vine (*Vitis vinifera L.*). Plant & Soil **266** 129-142.
Pellegrino, A., Gozé, E., Lebon, E. and Wery, J. 2006. A model-based diagnosis tool to evaluate the water stress experienced by grapevine in field sites. European Journal of Agronomy **25** 49-59.
Riou, C., Pieri, P. and Valancogne, C. 1989. Un modèle simple d'interception du rayonnement solaire par la vigne - vérification expérimentale. Agronomie **9** 441-450.
Saltelli, A., Chan, K. and Scott, E.M. 2000. Sensitivity analysis. John Wiley and Sons.
Saltelli, A. 2002. Making best use of model evaluations to compute sensitivity indices. Computer Physics Communications **145** 280-297.
Sobol, I. M. 1990. On sensitivity estimation for nonlinear mathematical models. Matematicheskoe Modelirovanie **2** 112-118.
USDA. 2004. Chapter 10 - Estimation of direct runoff from storm rainfall. National Soil Conservation Service: National Engineering Handbook, Washington D.C., USA.