UNCERTAINTY IN THE SPECIFICATION OF SURFACE CHARACTERISTICS, PART II: HIERARCHY OF INTERACTION-EXPLICIT STATISTICAL ANALYSIS

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Abstract. The uncertainty in the specification of surface characteristics in soil-vegetation-atmosphere-transfer (SVAT) schemes within planetary boundary-layer (PBL) or mesoscale models is addressed. The hypothesis to be tested is whether the errors in the specification of the individual parameters are accumulative or whether they tend to balance each other in the overall sense for the system. A hierarchy of statistical applications is developed: classical one-at-a-time (OAT) approach, level 1; linear analysis of variance (ANOVA), level 1.5; fractional factorial (FF), or level 2; two-factor interaction (TFI) technique, or level 2.5; and a non-linear response surface methodology (RSM), or level 3. Using the First ISLSCP Field Experiment (FIFE) observations for June 6, 1987 as the initial condition for a SVAT scheme dynamically coupled to a PBL model, the interactions between uncertainty errors are analyzed. A secondary objective addresses the temporal changes in the uncertainty pattern using data for morning, afternoon, and evening conditions.

It is found that the outcome from the level 1 OAT-like studies can be considered as the limiting uncertainty values for the majority of mesoscale cases. From the higher-level analyses, it is concluded that for most of the moderate surface scenarios, the effective uncertainty from the individual parameters is balanced and thus lowered. However, for the extreme cases, such as near wilting or saturation soil moisture, the uncertainties add up synergistically and these effects can be even greater than those from the outcomes of the OAT-like studies. Thus, parameter uncertainty cannot be simply related to its deviation alone, but is also dependent on other parameter settings. Also, from the temporal changes in the interaction pattern studies, it is found that, for the morning case soil texture is the important parameter, for afternoon vegetation parameters are crucial, while for the evening case soil moisture is capable of propagating maximum uncertainty in the SVAT processes.

Finally, a generic hypothesis is presented that an appropriate question for analysis has to be rephrased from the previous ‘which parameters are significant?’ to ‘what scenarios make a particular parameter significant?’

Keywords: Planetary boundary layer, SVAT, Factorial analysis, Atmospheric interactions, Uncertainty analysis, Sensitivity analysis.

1. Introduction

Soil-vegetation-atmosphere transfer (SVAT) processes are pivotal in atmospheric analysis. These transfers influence features of such diverse magnitude as evapotranspiration, surface and air temperature, circulation and advection of scalars, and precipitation patterns (Sellers et al., 1997). At a local scale, SVAT regulates

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surface heating and cooling, influencing the moisture availability in and above the soil. This feature is documented extensively both from observations (cf. André et al., 1986; Sellers et al., 1988; Goutorbé et al., 1994; Raman et al., 1998) and numerical simulations (cf. Noilhan and Planton, 1989; Bosilovich and Sun, 1995; Alapaty et al., 1997a; among others). Gradients in the temperature and moisture availability due to the underlying surface generate differential surface heat fluxes that influence the regional circulation pattern (Segal et al., 1988). The circulation pattern influenced by the surface features can have a preferential mechanism for moisture accumulation and precipitation for certain geographical setups such as semi-arid grasslands (Anthes, 1984; Hong et al., 1995). For example, the changes in the precipitation pattern in the United States over the years are significantly correlated to the changes in the regional landscape (Pielke et al., 1991). Such changes influence the ecological balance and dynamically alter the vegetation pattern and preferences for regeneration of forests and grasslands (VEMAP members, 1995; Sellers et al., 1997). This coupling of the transfer processes at different temporal and spatial scales makes the SVAT mechanism both an important and an uncertain component of an analysis.

The uncertainty associated with the coupled parameters has been a critical issue in atmospheric analysis (cf. Lorenz, 1969, 1982; Jones et al., 1991; Gerloff et al., 1991; Hamill and Walks, 1995; Randall and Weilicki, 1997). SVAT schemes require a large number of inputs depending on the complexity of the scheme. For example, a detailed scheme such as SiB2 (Sellers et al., 1996) requires information for about 30 parameters, while less complex schemes in mesoscale models may require no more than 10 parameters (cf. Alapaty et al., 1997a; Noilhan and Planton, 1989). However, significant uncertainty exists for the input surface characteristics in a terrestrial ecosystem despite rapid developments in monitoring and assimilation techniques. How the uncertainty in the initial surface parameters manifests itself in mesoscale models or in boundary-layer processes is the focus of our recent study (Niyogi, 1996; Niyogi and Raman, 1997a, b; Niyogi et al., 1995, 1996, 1997a, b, 1998; Alapaty et al., 1997b).

Part I of this study (Alapaty et al., 1997b; henceforth Part I), attempted to quantify the impact of uncertainty on the boundary-layer structure, of inputs such as soil moisture, minimum stomatal resistance, soil texture, leaf area index, and fractional vegetal cover. The methodology assigns a different (than ‘observed’) value for one of the five parameters (see Table I) and assess the deviation of the boundary-layer parameters from the reference (all parameters ‘known’ or ‘observed’) case. In other words, in Part I, we performed the ‘pristine’ or the one-at-time (OAT) mode of analysis (cf. Niyogi, 1996; Randall and Weilicki, 1997; Niyogi et al., 1997a) where every parameter is perturbed individually. In reality, all the parameters can have *simultaneous* uncertainty. How this simultaneous uncertainty in individual parameters couples up to a *net* or an *effective* system uncertainty is the focus of our present study.

TABLE I
'Observed' input for June 6th, 1987 during FIFE along with the uncertainty specified in the analysis.

Parameter	Abbr.	Observed	Higher range	Lower range
Min. stomatal resistance (s m^{-1})	R_{smin}	60.0	450	40
Leaf area index	LAI	1.90	3	1
Vegetation cover	Veg	0.99	0.66	0.33
Soil texture	Soil	Silty clay loam	Clay	Loamy sand
Layer 1 vol. soil moisture (m^{-3} m^{-3})	W_{g1}	0.23	0.322	0.24
Layer 2 vol. soil moisture (m^{-3} m^{-3})	W_{g2}	0.25	0.322	0.24
Surface roughness length (m)	z_o	0.045	0.045	0.045
Layer 1 soil temperature (K)	T_{g1}	298.15	298.15	298.15
Layer 2 soil temperature (K)	T_{g2}	293.35	293.35	293.35

In the OAT approach adopted in Part I (as in various other atmospheric studies), the change in the output is related directly to the change in the initial setting. For example, if fractional vegetal cover is altered from 0.1 to 0.9, and the corresponding surface latent heat flux (LHF) increases from 50 W m^{-2} to 200 W m^{-2}, the difference in the LHF is translated simply as an increment due to altered fractional vegetal cover. In reality, the cause and effect coupling is more complex. A change in the vegetal cover can alter the moisture retentive ability of the soil through interception, modify the surface roughness of the domain, and affect the temperature of the surface as well. Thus, the uncertainty in LHF prediction is not related simply to the uncertainty in only vegetal cover *per se*, but it is also *interactively* linked to the uncertainty manifested in other parameters coupled within the system. Hence, without resolving the interactions, the results are prone to bias (cf. Stein and Alpert, 1993; Alpert et al., 1995; Niyogi, 1996; Niyogi et al., 1995, 1996, 1997a, b; Niyogi and Raman, 1998). By explicitly resolving interactions clearer insight into the uncertainty propagation in SVAT analysis is expected.

The next section describes the graphical-statistical methodology adopted to test the impact of simultaneous uncertainty and interactions in a fully-coupled (two-way coupling) SVAT-PBL model.

2. Methodology

The hierarchy of techniques used in this study is shown in Table II. Accordingly, Part I (OAT-like) corresponds to level 1 where no interactions are explicitly pursued

TABLE II

Hierarchy of analysis adopted in this study.

Hierarchy	Method applied	Comments
Level 1	On-At-Time (OAT)	No explicit interactions, parameter independence assumed
Level 1.5	Analysis of Variance (ANOVA)	Implicit interactions for system variability
Level 2	Fractional Factorial (FF)	Explicit interactions resolved for the system
Level 2.5	Two-Factor Interaction (TFI)	Explicit analysis of the interactions resolved in Level 2 analysis; implicit non-linear interactions extracted
Level 3	Response Surface Methodology (RSM)	Explicit non-linear interactions analyzed

and are not repeated here. Level 1.5 is the standard 'Analysis of Variance' (ANOVA) approach (see example, Box et al., 1978). In this, main effects and implicit linear interactions can be extracted. Again this is a widely used technique and is not described here. Level 2 is the Fractional Factorial (FF) approach (Haaland, 1989; Niyogi et al., 1997a), which resolves the effect into a main effect, as in the earlier levels, and explicit interactions for all the parameters. The Two-Factor Interaction (TFI) analysis is the next level of analysis (level 2.5), which helps prescribe limits, and deduces implicit non-linear feedback mechanisms from the interactions resolved in the FF approach. The final level (level 3) in the hierarchy is the Response Surface Methodology (RSM). In RSM, in addition to the main effect, and linear interactions resolved in the lower levels, second-order, non-linear interactions are also explicitly analyzed.

In the present study, interaction in the uncertainty from five different SVAT parameters is analyzed (with extreme limits): soil texture ('loamy sand': soil type 2 or 'clay': soil type 11, see Noilhan and Planton, 1989), fractional vegetation cover (0.33, 0.66), LAI (1.0 and 3.0), initial soil moisture (0.24 m^3 m^{-3} and 0.322 m^3 m^{-3}), and minimum stomatal resistance (40 s m^{-1} and 450 s m^{-1}) (and hence stomatal resistance, see Niyogi and Raman, 1997). A detailed explanation regarding the choice of the parameters and their settings (limits) is provided in Part I (also shown in Table I). The design adopted in this study is a two-level fractional factorial (FF) design for five parameters consisting of 16 combinations. The three-level RSM design is an extension of the FF design with 30 combinations (or runs) (see Haaland, 1989 or Niyogi, 1996 for details). In both the FF and RSM analyses, high and low parameter settings correspond to the parameter values shown in Table I, while the median value in the RSM design corresponds to an average of high and low input values. Other dynamic features such as the planetary boundary-layer

(PBL) model (using transilient turbulence non-local closure, and surface similarity theory as in Alapaty et al., 1997a), a prognostically coupled vegetation and soil moisture scheme (Noilhan and Planton, 1989) for surface fluxes (using Jarvis-type evapotranspirative analysis and effective representation of vegetation and soil, with two layers in the sub-surface), and initial conditions (FIFE June 6th 1987 soundings, Sellers et al., 1988), are identical as described in Part I. Predicted surface sensible heat flux (SHF), surface latent heat flux (LHF), and the PBL height are the three characteristics analyzed in this study, as they represent the net outcome or the causal feedback from the system. All the simulation outcomes are subjected to transformation and outlier tests using normal, half-normal plots, active-contrast analysis, main-effect analysis, and scatter plots, (see, Niyogi, 1996; Niyogi et al., 1997a for details). Then, the simulation outcomes are used in the analysis presented in the following sections.

In Part I, uncertainty analysis is performed (using level 1 or the OAT approach) for 1300 local time (LT). The following section describes a hierarchical analysis (levels 1.5 to 3) for the same period. A secondary objective addresses the temporal changes in the uncertainty and parameter interactions within the dynamic SVAT-PBL system. This is described in Section 4, and finally in Section 5, we present the conclusions.

3. The Hierarchical Analysis

3.1. Level 1 or the OAT analysis

Figure 1 summarizes one of the pertinent results of the level 1 OAT study described in Part I. It shows that the interaction-deficient approach is close to linear in terms of the cause and effect relationship. Decreasing SHF corresponds to increasing LHF (and vice versa), which is linked solely to the change in the input parameter alteration. Thus, for uncertainty propagation in the model prediction, the order of importance obtained is soil texture, soil moisture, minimum stomatal resistance, vegetal cover, and LAI. Such results are often obtained in different sensitivity type studies related to SVAT analysis. Apart from the concerns already described in Stein and Alpert (1993), Alpert et al. (1995), Niyogi (1996), and Niyogi et al. (1995, 1996, 1997a, b) about the bias of such a level 1 analysis, a few other points deserve elaboration: (i) the impact of multiple or system uncertainty is not extractable, that is, the role of all the parameters having uncertainty all the time (which is a realistic scenario) is still not known; and (ii) only an intuitive interpretation and an insight into the causal mechanism is possible. Hence, higher levels of analyses are necessary as described in the following sections.

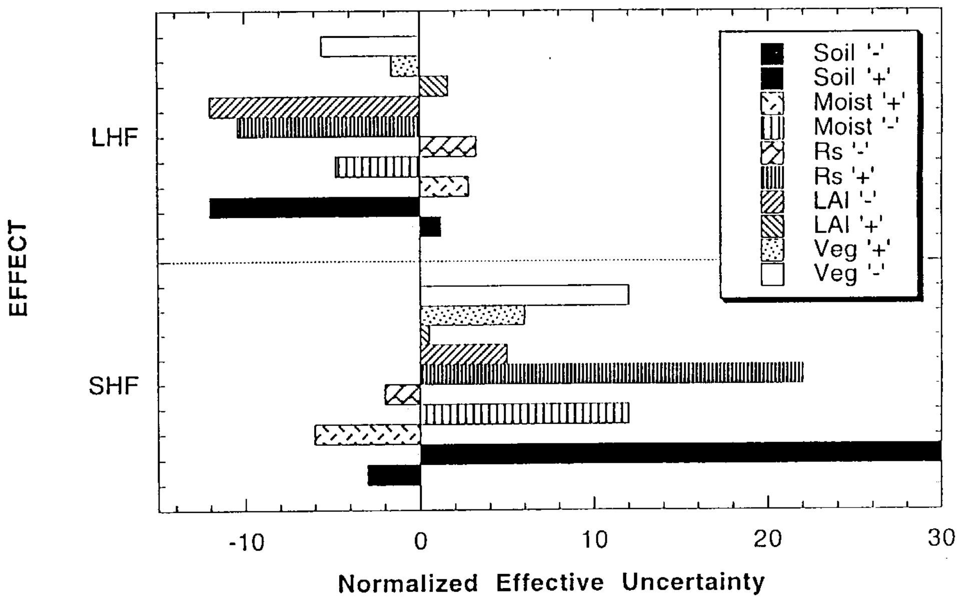

Figure 1. Representation of the OAT (level 1) outcome from Part I. The uncertainty is normalized as the ratio of the deviation of the heat flux value from observations for that input to the reference simulation deviation (all inputs as actual 'observations'). The reference deviation is 25 W m^{-2} for LHF and 10 W m^{-2} for SHF. The linearity in the OAT perception is highlighted.

3.2. Level 1.5 or the ANOVA analysis

Figure 2 shows the level 1.5 or the ANOVA analysis outcome with implicit interactions. In these plots, the bigger the line joining the lower (L) and higher (H) setting (corresponding to Table I), the larger the importance associated with the uncertainty in that parameter. For instance, for SHF (Figure 2a), the minimum stomatal resistance (*Rsmin*) specification is crucial, closely followed by errors in soil texture and soil moisture prescription. Lower (than actual) specification of *Rsmin* would lead to lower-than-actual SHF. Vegetal cover and LAI specification have similar responses, while lower (loamy sand) soil texture and lower soil moisture specification lead to higher-than-actual SHF prediction. Note, that both soil texture and soil moisture have similar lengths or impacts assigned as parameters. Hence, net uncertainty in prescribing soil moisture *and* soil texture together is *synergistically interactive and will be different than individual uncertainty* (quantified in level 1 analysis) alone. That is, prescribing higher soil moisture for a loamy soil as a combination will have effectively lesser uncertainty than anticipated in level 1 analysis. Thus, a 'worst-case' scenario in terms of uncertainty propagation in SHF is a combination of low *Rsmin* for low vegetation cover over clayey soil under high moisture availability (and, high minimum stomatal resistance for high vegetation cover over loamy soil for lower moisture availability). Hence, the net uncertainty will be more than quantified in a level 1 analysis (Part I) for the ‘worst-case’ combination, while for other situations it can be less than the level 1 values.

For LHF, the results are similar except that LAI is more significant than fractional vegetal cover in the simulations. This is consistent with previous published analyses of field observations (see, Niyogi et al., 1997a for an analysis using HAPEX-MOBILHY data). Thus LHF predictions are more prone to uncertainty in LAI than in vegetal cover. Once again, *Rsmin* specification is crucial, followed by LAI and soil moisture, then soil texture and finally vegetal cover. The ‘worst case’ scenario for LHF prediction is specification of higher minimum stomatal resistance, higher LAI, lower soil moisture and a loamier-than-actual soil texture for higher-than-actual vegetal cover (and the converse, that is, lower minimum stomatal resistance, vegetal cover, and LAI with higher-than-actual soil moisture for clayey soil texture).

For the PBL height, a combination of various effects is active in the coupled simulations. This reflects a combined impact of surface temperature, moisture, and energy fluxes all together. For the afternoon case, soil texture specification is vital for PBL height. Similarly, uncertainty in soil moisture, vegetal cover, and minimum stomatal resistance specification propagates in the model prognostications. LAI uncertainty is not significant for PBL-height predictions, which is consistent with the LHF and SHF results. The following are the least-confidence scenarios for PBL height estimates: loamy, wet soil with lower-than-actual vegetal cover, minimum stomatal resistance, and LAI; or its converse (that is, clayey dry soil with higher-than-actual vegetal cover, minimum stomatal resistance and LAI).

Note that the level 1.5 analysis yields more information than level 1 regarding the uncertainty propagation and the scenario that can have the highest uncertainty. We are now able to develop a hypothesis that the *net uncertainty in the system will be significantly different than that quantified in individual parameters*. The results from the level 1.5 ANOVA analysis suggest an interactive role for various parameter uncertainties in the system. The next level (level 2) using the FF approach attempts to resolve these interactions explicitly.

3.3. Level 2 or the FF analysis

For this analysis, a graphical method using Pareto plots is adopted (Haaland, 1989; Niyogi, 1996; Niyogi et al., 1997a). Pareto plots represent effects in a descending order of significance (cf., Figure 3). The ‘Size of Effect’ is the net impact of the parameter on the entire system (see, Haaland, 1989; or Box et al., 1978 for details). The effects are resolved as main effect and interaction terms. Thus, for example, the Pareto plot for LHF shows ‘*Rsmin*’ is the crucial term; the negative sign for the effect indicates an inverse relation, whilst a lower parameter value will yield a higher effect. Terms such as Veg:Moist, for instance, are the interaction terms, and this one in particular is an interaction between vegetal cover and soil moisture. The analysis is done using a pseudo-standard error (PSE) analysis with 5% level

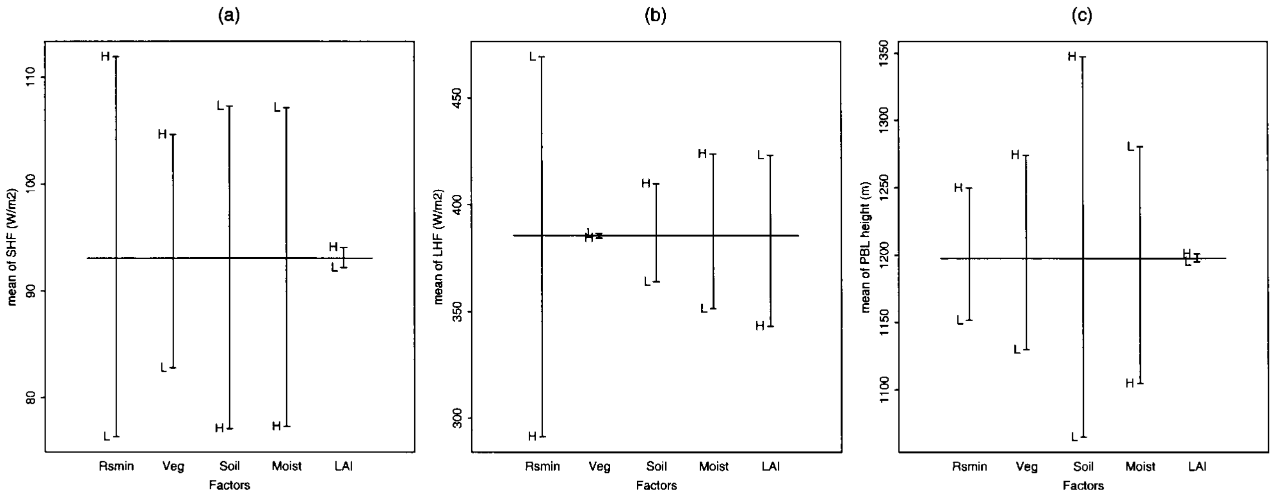

Figure 2. Level 1.5/ANOVA outcome for 1300 LT. ‘L’ and ‘H’ refer to the lower and higher values used in the experiment (see text). (a) refers to the sensible heat flux (W m^{-2}) analysis; (b) corresponds to the latent heat flux (W m^{-2}), while (c) refers to the PBL-height (m) analysis.

of significance (see, Haaland, 1989 for details). The vertical line can be taken as an indicator as to the crucial parameters in a system. However, instances where the vertical line is beyond all the parameters does not necessarily mean that any of the effects are insignificant (P. Haaland, pers. comm., 1996). The efficient use of Pareto plots in analyzing atmospheric data is already discussed by Niyogi et al. (1997a) and is not repeated here.

Thus, for SHF, the level 2 analysis reveals a number of active main effect and interaction terms. The order of main effects is the same as obtained in the level 1.5 analysis: minimum stomatal resistance, soil texture, soil moisture, vegetal cover, and LAI. Additionally, there are significant interactions present in the system, including vegetal cover and soil moisture, vegetal cover-soil texture, minimum stomatal resistance-LAI, soil texture–soil moisture, and others as shown in the Pareto plots (Figure 3). An assessment can be made of the role of uncertainty propagation comparing both the parameter main effects and related interactions. Consider minimum stomatal resistance, a crucial main-effect term for SHF. Specifying a higher-than-actual minimum stomatal resistance value would lead to higher SHF as an effect suggested by the positive sign of the effect quantified. Higher resistance implies lower transpiration and higher sensible heating, hence the perceived direct effects are physically consistent. The interaction term between minimum stomatal resistance and LAI is significant in the ranking in the Pareto plot. Both LAI and the minimum stomatal resistance have a direct relation with SHF, and so does their interaction term *Rsmin*-LAI. This is a synergistic relationship and suggests the uncertainty obtained from level 1 is lower-than-actual if there exists an uncertainty in specifying *both Rsmin* and LAI simultaneously. On the other hand, the vegetal cover-soil moisture interaction is opposing. Vegetal cover is directly, while soil moisture is inversely, related with SHF. Their interaction term (Veg: Moist) is intense and positively related with SHF. This suggests, as a combination, the impact of uncertainty in specifying vegetal cover is more, while it is lesser for soil moisture, than ascribed in level 1. Similarly, an intense direct interaction is obtained for soil moisture and soil texture while each of these parameters by themselves are inversely related. Hence, it is inappropriate to prescribe the uncertainty obtained in level 1 and scenarios can exist where the uncertainty is significantly different from the level 1 uncertainty. These and other parameter uncertainty interactions can be extracted. Typically for SHF we find lowered *net* (interaction and main effect together) uncertainty in stomatal resistance, soil texture, and soil moisture related changes, and increased uncertainty in vegetal cover and LAI.

Similarly for LHF, there are several significant interactions influencing the effects. First, all the parameters tend to interact with vegetal cover such that LHF is overpredicted. Hence, this uncertainty may exist under a majority of scenarios. On the other hand, all the parameters interact with soil texture so as to provide a lower LHF value. Thus, individually, both soil texture and vegetal cover are prone to higher uncertainty than obtained in the level 1 analysis. Also LAI tends to behave in a manner similar to vegetal cover in its interactions for LHF predictions; altern-

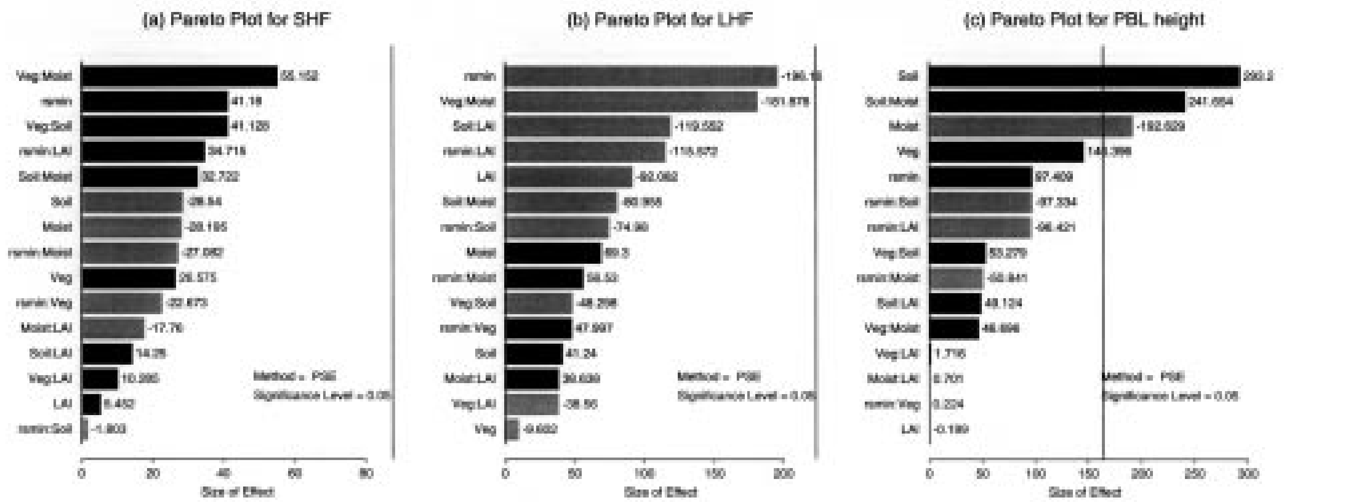

Figure 3. Level 2/Fractional Factorial analysis outcome for 1300 LT. The Pareto plots explicitly bring out the interactions between the parameters.

atively, LAI shows higher LHF bias. However, other terms may have a much higher or lower bias, thus balancing the overall uncertainty. Overall, we note interactions tend to balance (for LHF estimation) uncertainties in soil texture and soil moisture, while the uncertainties in LAI and vegetal cover are enhanced.

The PBL-height analysis shows some additional features not seen in the energy fluxes. Of the top five parameters affecting the outcome, three in LHF and four in SHF are interaction terms. For the PBL height, however, only one interaction term (soil texture–soil moisture) is the ‘winner’ and the rest are main effects that dominate the outcome. This suggests that less complex schemes may provide acceptable estimates of boundary-layer variables such as the inversion height, even though the surface energy budget may be incorrect. Hence, for model performance evaluation, particularly for a regional scale domain where limited information is available on observed fluxes, a good scalar predictability may not be a sufficient criterion, and the uncertainty in flux estimation may still be unresolved in the evaluation. Also, as in the present analysis, the uncertainty associated with soil moisture is pivotal if the soil type has any uncertainty, and the two can have a synergistic interaction for the overall system.

Thus, in the level 2 analysis, significant interactions are explicitly resolved for the system. These interactions provide additional insight into the uncertainty propagation mechanism. How the uncertainty controls the system outcome is revealed through the level 2.5 TFI analysis described in the next section.

3.4. Level 2.5 or TFI analysis

The TFI analysis is a graphical analysis of the interactions explicitly resolved in the level 2 analysis. The aim is to examine the response of the effects to different interactions in terms of parameter settings. Through level 1.5 and level 2 analyses, we determine settings that can have worst uncertainty propagation. Learning from the previous analysis, we begin with a hypothesis that parameter values have a significant impact in the manner in which they propagate uncertainty. Some interactions can multiply, while others can balance the net uncertainty.

As mentioned, we perform a graphical TFI analysis. Thus, for example, consider Figure 4a, which shows the interactions with vegetal cover for soil moisture and then with soil texture. The dotted line corresponds to the higher parameter setting for soil moisture (0.322 m^3 m^{-3}) and represents the change in the effect (SHF) corresponding to a mean outcome from ‘low’ (0.33) to ‘high’ (0.66) vegetal cover change. The solid line is the change in effect for ‘low’ soil moisture (0.24 m^3 m^{-3}) availability from the same low to high vegetal cover. The interpretation of the results is based on aspects such as the slope of individual lines, whether the two lines intersect each other, and the difference in the effect for the two-parameter settings. For instance, the uncertainty with vegetal cover prescription is higher for higher soil moisture as the slope is greater than that for the lower soil moisture. Also the uncertainty in specifying initial soil moisture is lowest for intermediate vegetal cover values and interactively increases for both low and high parameter settings. Overall, lower vegetal cover and higher soil moisture conditions display high uncertainty when SHF is the effect. Similarly, for soil texture and vegetal cover interaction, lower soil type (loamy sand) has lower uncertainty for vegetal cover prescription while the higher (clay) soil type has large uncertainty in the vegetal cover prescription. Also, for soil moisture, soil texture uncertainty is least for intermediate vegetal cover, hence larger for both lower and higher vegetal cover availability. Overall, loamy soil appears to have significant synergistic interaction with soil moisture uncertainty in the parameterization that compounds for the lower vegetal cover cases.

The parameter interactions and uncertainty propagation for SHF through minimum stomatal resistance prescription is shown in Figure 4b. Overall, higher *Rsmin* cases have higher uncertainty. Only for vegetal cover do higher *Rsmin* cases have a lower uncertainty. Also, apparently the soil specification does not directly interact with stomatal resistance for SHF outcome, and both low soil moisture and low LAI scenarios (Figure 4c) have large uncertainties. Other settings that can be deduced from the TFI plots pertaining to uncertainty in each parameter are: typically high LAI, low vegetal cover, clayey soil texture, and high soil moisture cases are prone to higher uncertainty. However, low LAI, high soil moisture, and a high vegetal cover combination can compensate uncertainty in minimum stomatal resistance and soil texture specification. Also, low vegetal cover, high LAI, and low soil moisture settings are prone to high net uncertainty. Overall, with SHF as an effect, it is reaffirmed that intermediate parameter settings tend to compensate the individual parameter uncertainty.

A similar graphical analysis is performed for LHF as an effect (not shown), where an intense interaction is seen for vegetal cover and soil moisture. Extreme settings (‘high’ and ‘low’ soil moisture or vegetal cover) have large uncertainty propagation while the intermediate settings once again show a compensating tendency that minimizes the system uncertainty. For uncertainty in soil texture, extreme LAI settings are synergistic while low soil moisture, low vegetal cover, and low minimum stomatal resistance specification combine to create the worst scenario. Intermediate parameter settings can conversely and substantially reduce the system’s effective uncertainty. For uncertainty in *Rsmin* specification, the high LAI, low soil moisture scenario for clayey soil and extreme vegetal covers is highly synergistic. Conversely, parameter settings such as low LAI, high soil moisture, and intermediate vegetal cover balance uncertainty particularly over a loamy sandy soil. The soil moisture uncertainty appears to persist through the system. For extreme vegetal cover and high *Rsmin* specification over a loamy soil, the uncertainty is highest, while clayey soils with low *Rsmin* and intermediate vegetal cover specification have the least uncertainty relatively. In contrast, LAI uncertainty is largest for clayey soils, although moderately low *Rsmin* and vegetal cover tend to balance it effectively.

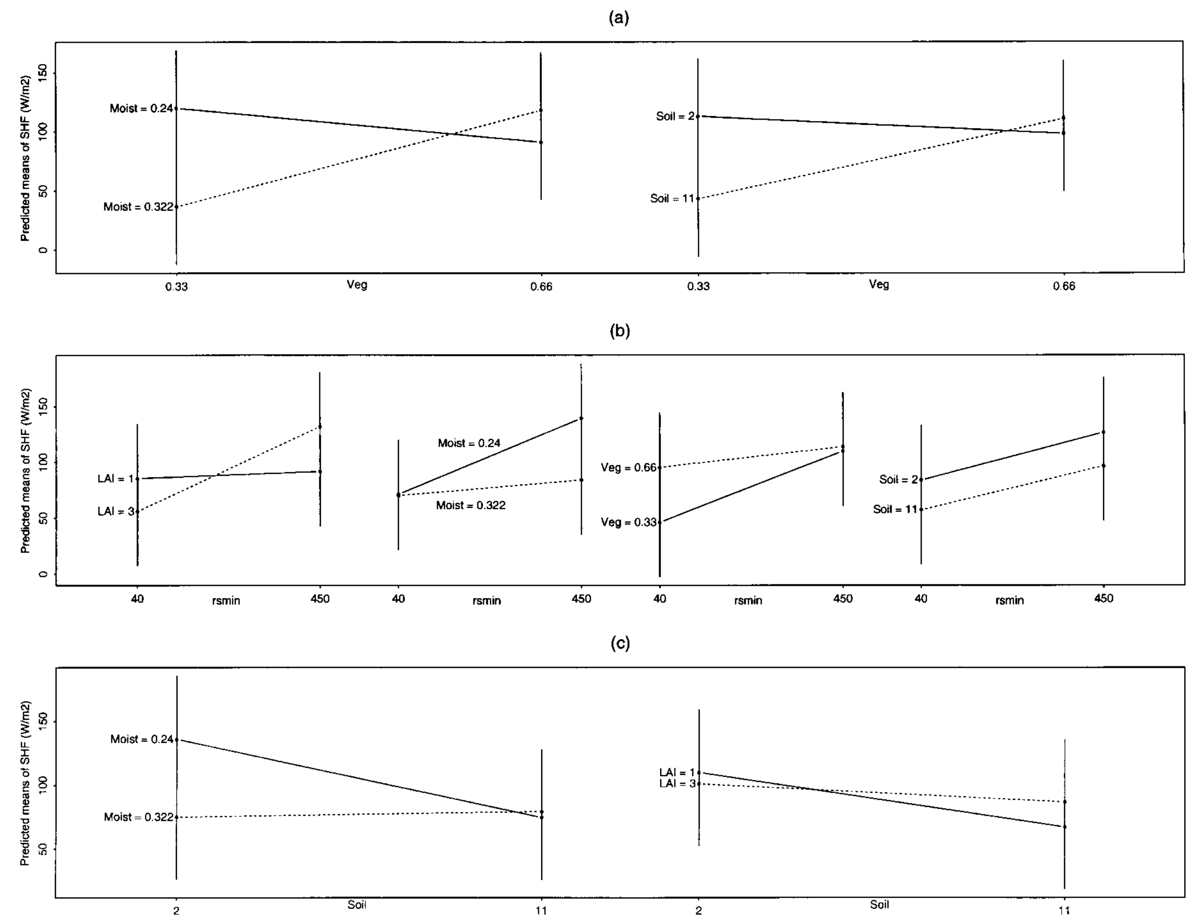

Figure 4. Level 2.5/Two-Factor Interaction (TFI) plots for sensible heat flux (W m^{-2}). (a) denotes interactions a propos vegetal cover, (b) the minimum stomatal resistance (s m^{-1}), and (c) shows the soil texture related interactions. The dotted line corresponds to the higher parameter setting.

For the PBL heights (also not shown), the interactions, though significant, are not the dominant mechanism for uncertainty propagation. This is also revealed in the level 2 analysis. For example, for PBL height as the effect, the uncertainty in vegetal cover persists and is not compensated for by other parameter uncertainties. However, for *Rsmin* uncertainty, loamy soil with low LAI and soil moisture has large uncertainty propagation capability while the clayey soil, with high LAI and high soil moisture scenario compensates and minimizes the overall uncertainty. For soil texture specification, high soil moisture, low *Rsmin* and extreme LAI cases can be uncertainty propagating while low soil moisture, intermediate LAI and high to very high *Rsmin* cases can act in a compensatory manner to minimize the system uncertainty. Soil moisture is largely interactive with the system parameters for PBL height. Very high *Rsmin* and low vegetal cover over a loamy soil lead to high system uncertainty, while very low *Rsmin*, moderately clayey soil and very high vegetal cover can balance the errors. Similarly, for LAI uncertainty, extreme values for parameters such as soil texture (clay or loam) and *Rsmin* (very low or very high) propagate large uncertainty while intermediate values minimize uncertainty significantly.

Thus, from the level 2.5 analysis, various parameter interactions, as a function of a system scenario, can be analyzed. It is found that, the confidence in the overall system output due to uncertainty in prescribing the initial state of the variable alters dynamically with the value other variables take in the simulations. *Thus a static uncertainty description is invalid and the significance of each variable is explicitly dependent on the values other variables attain.* The TFI analysis extracts some non-linearity in terms of the interactions with extreme settings showing highest uncertainty. To study all the non-linear interactions explicitly, a level 3 or RSM analysis is undertaken as described in following section.

3.5. LEVEL 3 OR RSM ANALYSIS

Thirty simulation results were analyzed using a graphical representation referred to as 'response surface plots' (Haaland, 1989; Niyogi, 1996). The plots show a significantly non-linear variation of the effect as a function of interactions between two parameters. Figures 5a–c show the typical response surfaces for the three effects (SHF, LHF, and PBL height), where gradients in the image plots indicate the sensitivity for uncertainty propagation. For instance, consider the response surface for LAI and soil moisture with SHF as an effect. There are two important features – the first is a significant curvature to the surface indicating dominant non-linear interactions. The second feature is that the net uncertainty is balanced for intermediate settings while the extreme settings tend to be in lesser equilibrium. Several such surfaces are analyzed for the RSM analysis. Based on such observations, the ability for uncertainty propagation for different parameter settings is prescribed.

For SHF, vegetal cover and soil moisture have more uncertainty than minimum stomatal resistance. At low stomatal resistances intermediate soil moisture val-

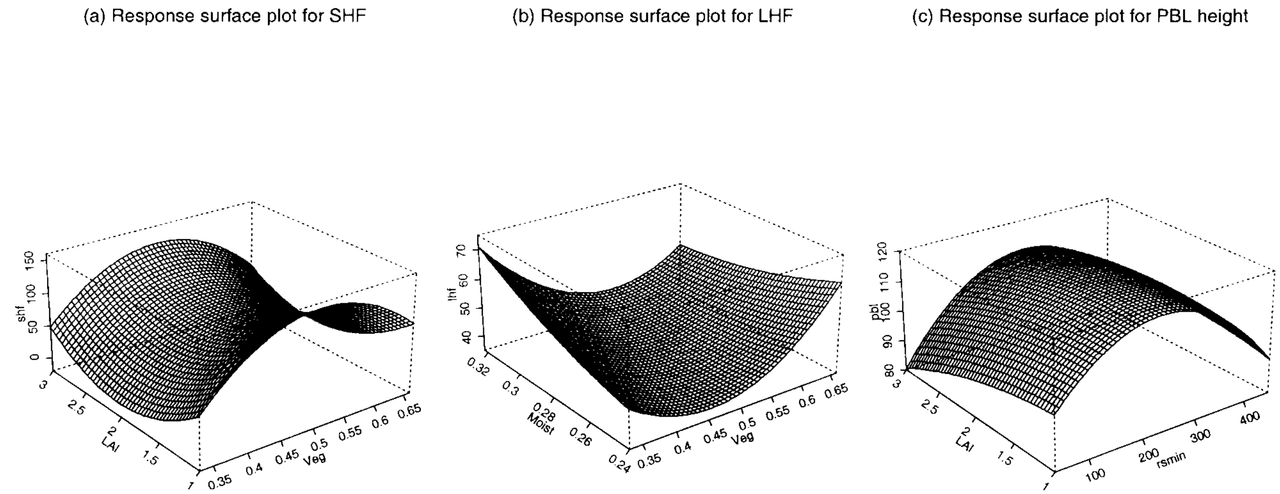

Figure 5. Level 3/Response Surface Methodology (RSM) based plots for 1300 LT. (a) refers to the interactions between LAI and vegetal cover for sensible heat flux (W m^{-2}), (b) indicates soil moisture (m^3 m^{-3}) and vegetal cover interactions for latent heat flux (W m^{-2}), while (c) shows the LAI and minimum stomatal resistance (s m^{-1}) interactions for mean PBL height (m). Note that the latent heat flux and mean PBL height are scaled by 0.1 in the plots. The RSM analysis depicts explicit non-linear synergies between interacting variables.

ues are passive while the combination of extreme soil moisture regimes and high stomatal resistance is dynamically interactive. Similar response is seen for the LAI-minimum stomatal resistance interaction. Also interesting is the soil texture and vegetal cover interaction; extreme vegetal covers have a high ability to propagate, while soil texture is lesser dynamic. Low minimum stomatal resistance and soil texture have relatively less interactive uncertainties in their specification. Thus, uncertainties in these parameters will neither diminish nor increase, but will persist for the simulation. Similarly, the uncertainty associated with wet loamy sandy soil or dry clayey soil texture specification is higher. The LAI-vegetal cover uncertainty is additive and, with increasing vegetal cover, the soil texture uncertainty decreases. Similarly for wet soil, the uncertainty in *Rsmin* specification is reduced, and for clayey soil the LAI uncertainty is higher. Interestingly, the LAI-soil moisture outcome for the response surface provides strong support for the hypothesis that, for intermediate values, the parameterization uncertainty is compensatory, while for extreme values it is multiplicative. This poses some interesting implications regarding the robustness and universality of the results for climate or even mesoscale circulation analysis for extreme situations, and those other than the 'well validated' model case scenarios. It may be stated, for a typical daytime surface layer, that the following scenario will have least uncertainty for the SHF outcome from the model: intermediate LAI and vegetal cover fraction with a low to moderately high stomatal resistance over a sandy, wet soil. Alternatively, highest interactive uncertainty will exist for a combination such as: high minimum stomatal resistance over clayey surfaces for extreme LAI or vegetal cover fraction.

The results for LHF analyses further suggest that intermediate ranges demonstrate lesser uncertainty. Dry loamy sand and wet clay have low uncertainty, while the opposite scenario propagates uncertainty. Similarly, the uncertainty for LAI increases with the clayey soil texture, while the soil texture uncertainty is lowest for intermediate LAIs. For the soil moisture–minimum stomatal resistance interaction, for intermediate moisture ranges, the *Rsmin* uncertainty is balanced, while for high *Rsmin*, the soil moisture uncertainty increases. At higher stomatal resistances the intermediate vegetal cover has least uncertainty for all soil types. For increasing *Rsmin*, the uncertainty in specification of other surface parameters such as LAI decreases while that for soil texture, soil moisture, and vegetal cover increases. Stomatal resistance is thus a dominating parameter here with an active interaction between soil variables (texture and moisture). Also, for increasing soil moisture availability, the uncertainty in the soil texture specification decreases while the LAI uncertainty increases. This is more pronounced for clayey soils. Thus, the lowest uncertainty scenario for a typical daytime LHF prediction is: sandy, wet soil with an intermediate LAI and vegetal cover, and high *Rsmin*. Conversely the highest uncertainty is associated with clayey moist soil, with extreme vegetal cover for high LAI and *Rsmin*.

For PBL height, once again, the results appear to show a fairly compensatory behaviour over a wide range of values and still show that the response alters sharply for extreme values (Figure 5c). This is probably best seen in the 'saucer-like' outcome for soil texture and minimum stomatal resistance, soil moisture and minimum stomatal resistance, and soil moisture and vegetal cover. Intermediate specifications of minimum stomatal resistance, soil moisture, and soil texture tend to demonstrate maximum compensation, while their extreme values could lead to highly uncertain scenario predictions. Similarly, LAI uncertainty does not interact with other parameters and propagates through the system. Overall, the soil moisture uncertainty is greater for both clayey soils and higher vegetal covers. Thus, the reliable settings for PBL height outcome correspond to intermediate vegetal cover, intermediate minimum stomatal resistance over a loamy sandy soil under moderately dry conditions. Conversely, the outcome for clayey soil with high vegetal cover, high LAI, high minimum stomatal resistance, and extreme soil moistures (closing to either wilting or near-saturation) has the highest uncertainty.

Thus, the level 3 or RSM analysis helps in understanding the non-linear interactions affecting the uncertainty propagation in the SVAT parameterizations. Optimum parameter settings and corresponding scenarios that can affect model uncertainty can also be identified. Two hypotheses can be affirmed: (i) for moderate or intermediate input parameter specifications, the net system outcome is fairly compensatory or sluggish, while the system uncertainty increases rapidly for the scenario predictions for extreme input values; (ii) no single parameter dictates the outcome; rather it is the synergistic pairing with different variables that sets the trend for the system response. This has several major implications: (i) previous results pertaining to SVAT analysis and model sensitivities have to be re-examined as to validity towards a more universal outcome from the singularities often examined. This should greatly assist the possibility of finding a deviation from the expected result that should be central to such a test (cf. Popper, 1959, Oreskes et al., 1994; or Randall and Weilicki, 1997; for an interesting critique), and (ii) using the knowledge about whether a parameter is active or inactive for uncertainty propagation, confidence limits can be ascribed as a function of geographical features such as soil texture and seasonal vegetation for a domain, for applications such as short-range weather forecasting. Conversely, the results suggest that reasonably accurate scenario generation (often also termed 'prediction') under moderate, fair-weather conditions may not provide a robust test of the model parameterizations in the stand-alone mode. Finally, based on the different analysis presented here, the role of non-linear and interaction-explicit equations is highlighted for applications such as assimilation. Simple linear equations (cf. Mahfouf, 1991) may work well for moderate conditions but extreme input conditions, in particular, require non-linear equations to minimize the errors in initialization.

One of the other questions pertinent to the dynamic models and initialization or assimilative studies concerns the prognostic variability of the uncertainty for a dynamic SVAT system. The results presented above are for a typical mid-day scenario. The SVAT parameters have significantly different values for other hours such as early morning or evening hours. The effect of a parameter on the outcome depends not only on the value the parameter takes, but also on the values of other system parameters. Hence, it is relevant to analyze the perceived dynamics of the temporal variation in uncertainty propagation. Also the feedback of the terrestrial biosphere is different for the developing (early morning) or collapsing (evening) boundary layer (cf. Niyogi, 1996). Hence, the final aspect we report in this study is the application of hierarchical techniques to study the temporal variability in the interactions and hence the uncertainty propagation.

4. Temporal Changes in the Interaction Pattern

For the dynamically coupled SVAT-PBL system, diurnal variability is a key aspect principally induced due to temporal changes in the solar radiation. Three periods can be identified where the boundary layer and the SVAT processes show different characteristics: (i) morning, when the boundary layer is developing and the radiation processes are initiated; (ii) afternoon, when the convective boundary layer and SVAT terms are quasi-stationary; and (iii) evening, with the collapsing boundary layer around sunset. For the analysis presented in the earlier sections (and also in Part I), the afternoon convective case is analyzed in detail. In this section we analyze the remaining two, morning and evening cases, using level 1.5 (ANOVA) to level 2.5 (TFI) analysis techniques. Level 1 is not considered because of the limitations associated with it, as discussed earlier (Stein and Alpert, 1993; Alpert et al., 1995; Niyogi, 1996; Niyogi et al., 1995, 1996, 1997a). Level 3 is not performed due to the computational cost involved. Also, as shown earlier, the majority of the level 3 results can be extracted efficiently from the level 2 and level 2.5 analysis. Hence, a fairly comprehensive uncertainty analysis is expected for the two other cases as discussed below.

4.1. Developing Boundary

The simulation results for 0900 LT are considered representative for this case. It is expected that the surface heating with increasing solar radiation will be the dominant mechanism and that physiological processes will be dormant as compared to the convective case. Figure 6 shows the level 1.5 (ANOVA) and the Pareto plots from the level 2 analysis. The TFI analysis plots are not shown for brevity (see, Niyogi, 1996 for details). From these analyses, soil texture is the key system parameter for all the three effects considered. Note that, for the convective case, only PBL height resolved soil texture as a crucial term while for fluxes, minimum stomatal resistance is the 'winner'. Also soil moisture and LAI are important main effects for this case.

For SHF, soil texture is the critical parameter. Interestingly, all the interactions tend to reduce the system uncertainty through soil texture. The worst scenario we expect from the variance analysis is a lower-than-actual vegetal cover and higher

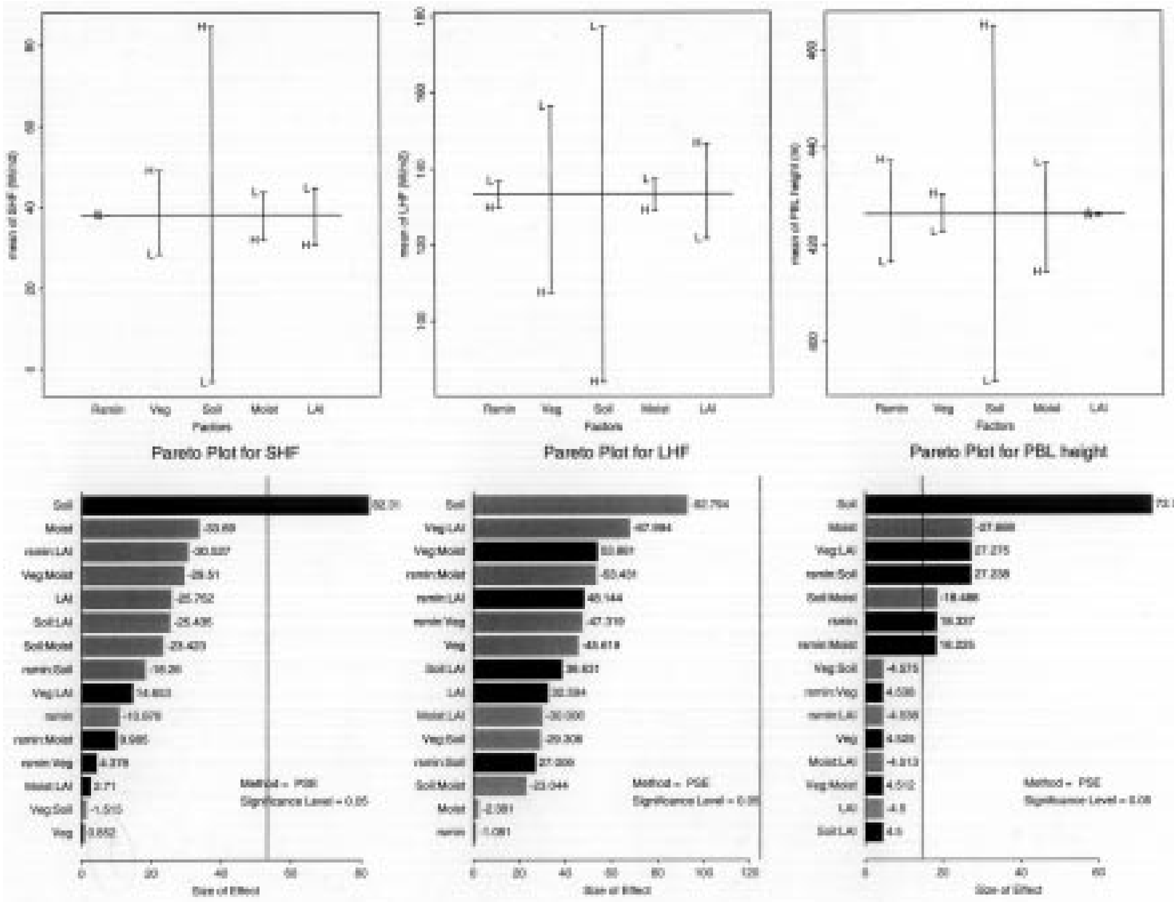

Figure 6. Level 1.5 (ANOVA) and level 2 (FF) based plots for the developing boundary layer (0900 LT). Soil texture is seen to be the most important parameter for this morning case.

soil moisture and LAI for a loamier-than-actual soil specification; or, high vegetal cover for wetter and clayey soil with higher-than-actual LAI. A level 2.5 analysis is also performed but the results are not presented here. Overall, moderate initial values have lower uncertainty for the majority of scenarios.

For LHF, the order of importance of the variables is fairly similar to that for SHF. Note, that once again, LAI-LHF is directly related, while vegetal cover-LHF is inversely related. For SHF, the opposite case has been observed (for both morning, as well as previously discussed afternoon case). Another interesting feature is the increase in vegetal cover uncertainty due to interactions with other parameters. Other parameter uncertainties are fairly well compensated in terms of their net outcome. The critical setting with highest uncertainty, as per level 1.5 analysis, corresponds to: higher-than-actual minimum stomatal resistance, vegetal cover and soil moisture for clayey soil with lower-than-actual LAI; or lower-than-actual minimum stomatal resistance, vegetal cover and soil moisture for loamy soil with higher-than-actual LAI. Other such limiting scenarios can be easily deduced from the level 2.5 analysis (not shown, see Niyogi 1996).

The PBL height is strongly affected by the soil type and soil moisture (and to a certain extent, the minimum stomatal resistance) specification and other SVAT related interactions. The worst scenario for uncertainty arises for: lower-than-actual minimum stomatal resistance and vegetal cover and higher soil moisture for loamier-than-actual soil texture; or higher-than-actual minimum stomatal resistance and vegetal cover with drier clayey soil. For this effect, the minimum stomatal resistance and vegetal cover uncertainty can tend to increase through interactions with other parameter uncertainties. However, this can be balanced with low uncertainty in specified soil texture and soil moisture.

Thus, in the morning developing boundary-layer case soil texture determines the surface heating, and hence the SVAT interactions. The interactions, on the other hand, appear to regulate the changes induced by the soil texture and radiation.

4.2. Collapsing Boundary Layer

Simulation results corresponding to 1800 LT are analyzed for the collapsing boundary-layer case. Here, radiative dominance and hence the physiological interaction is expected to be lower than the morning or convective afternoon cases. Corresponding to this case, Figure 7 shows the level 1.5 plots, and the Pareto plots from the level 2 analysis. (Once again, the TFI plots from the level 3 analysis are not plotted but can be found in Niyogi, 1996.) From the analysis, the evident feature is the dominance of soil moisture as the principal parameter. Note that, the morning case has soil texture as the ‘winner’ while the convective afternoon case has physiological dominance. In addition to the soil moisture dominance, various physiological interactions are also active, as hypothesized.

From the analysis, the highest uncertainty scenario for SHF as an effect corresponds to: higher-than-actual vegetal cover and LAI for moist loamier-than-actual

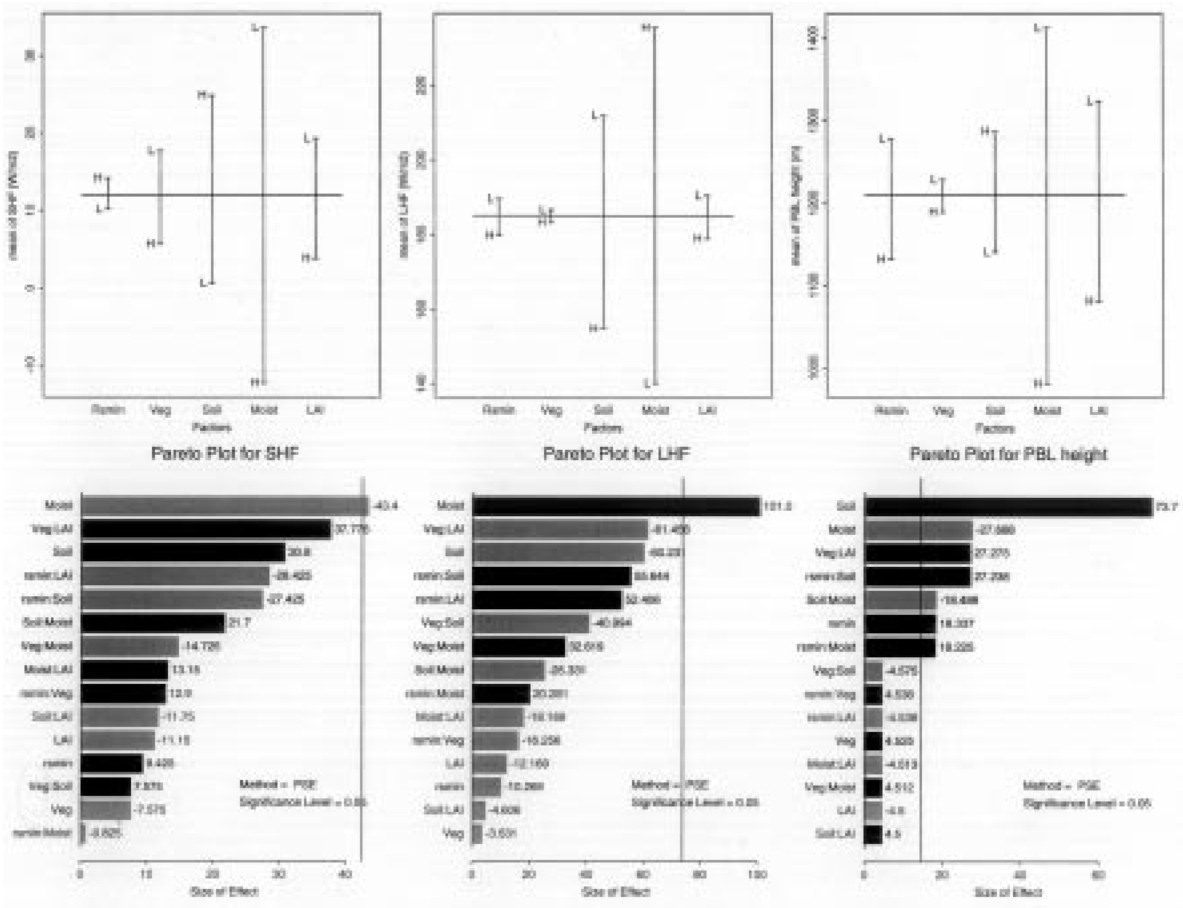

Figure 7. Same as Figure 6 except for the collapsing boundary layer (1800 LT). Soil moisture specification becomes the crucial parameter for the evening case.

soil with lower minimum stomatal resistance; or lower-than-actual vegetal cover and LAI with higher minimum stomatal resistance for drier clayey soil. An effective balance in the uncertainty propagation is anticipated. Note that, for this case (for all the parameters), both LAI and vegetal cover synergistically interact with other parameters to lower the fluxes (and the PBL height). Once again the level 2.5 analysis (not shown) suggests that extreme parameter values propagate highest uncertainties in the effect.

For LHF, the worst scenario corresponds to a drier and clayier-than-actual surface with higher other parameter values; or wet and loamier-than-actual conditions with lower-than-actual other surface parameters. From the interactions, LAI uncertainty appears to be compensatory.

The PBL height variation, apart from being dominated by soil moisture, has significant LAI, soil texture, and minimum stomatal resistance interaction (Figure 7). The worst case corresponds to wet, loamy soil with higher surface parameters; or dry, clayey soil with lower-than-actual parameter values. Also, all the interactions tend to compensate the uncertainty bias in the effect. Several interactive scenarios are evident for this case. The hypothesis regarding moderate parameter values yielding lower uncertainty overall appears to be valid.

In summary, we noticed a temporal change in the uncertainty pattern for the surface parameters that could have a significant impact on the reliability of the model predictions and on the assimilative or initialization techniques (cf. Mahfouf, 1991). Starting from the morning towards evening case, the SVAT control seems to change from soil texture to the plant physiology and finally to soil moisture. All the interactions aid this transition in the system constantly. This conclusion can be a guide for various analyses (such as surface assimilation, downscaling from GCM results, and sub-grid scale averaging) using SVAT schemes.

5. Conclusions

SVAT processes are essential for realistic analysis. However, their specification is highly uncertain. Part I of this study analyzes the impact of five surface parameters: minimum stomatal resistance, initial soil moisture, LAI, fractional vegetal cover, and soil texture on the boundary-layer predictions using one-at-time (OAT) analysis. A fully coupled SVAT-PBL model, with FIFE observations for 6 June 1987 as initial conditions, is employed for this purpose. In the present study, we address the following question: how does the system respond when all the parameters have uncertainty simultaneously (rather than individually as in Part I)? That is, does the uncertainty add up or does it balance out?

For this it is shown that the OAT approach is inadequate as it assumes inherent independence for the parameters. Accordingly, a hierarchy of interaction-related analyses is proposed, with the OAT as level 1, analysis of variance (ANOVA) as level 1.5, fractional factorial (FF) as level 2, two-factor interaction analysis (TFI) as level 2.5, and the non-linear response surface methodology (RSM) as level 3. These levels are assigned based on interactions resolved in the analysis (implicitly or explicitly, linear or non-linear). Using this hierarchy, a number of scenarios are analyzed. The level 1 analysis (Part I) gives interaction-free ranking to the various parameters. From the level 1.5 study, the tendency of the system to alter the individual uncertainties using implicit interactions is analyzed. Using level 2 and level 2.5 methodologies, changes in the uncertainty pattern with varying scenarios of surface features are presented. It is shown that parameter uncertainty depends not only on its deviation from a true value, but also on the values assigned to other parameters. Alternatively, *parameter response can vary greatly for the same uncertainty under different conditions.* It is shown that for the majority of scenarios corresponding to moderate (non-extreme) parameter initial values, the overall system response is compensatory. The level 3 analysis confirmed this hypothesis: the *highest uncertainty is associated with extreme initial values.* The results thus suggest that the uncertainties will be larger for isolated scenarios and, in fact, for a large domain with area-averaging and effective parameters, the net uncertainty of the prediction is lowered (cf. Noilhan and Lacarrerre, 1995).

Typically, for loamy sandy and drier soils the parameterization reliability is high, while the uncertainty is higher in most of the surface features for clayey soils. The gravity effect and water retention ability of the clayey soil for a two-layered soil model may be one of the reasons for this uncertainty. It is seen that, overall, LAI and vegetal cover tend to produce opposite effects to each other in terms of the response. For a known simulation domain, fixing the surface landscape features, a hierarchy of experiments, as in this study, can be effectively used for ascertaining the confidence in a model forecast under different surface regimes. Similarly, for assimilation approaches, the role of non-linear or interaction-explicit equations is stressed.

To understand the diurnal variation in the uncertainty propagation, interactions for developing, convective, and collapsing boundary layers are analyzed. It is shown that, from the point of initializing a biospheric model, with poor information regarding initial soil moisture input but with good soil texture information, the morning initialization is best. With reliable soil moisture information, commencing the simulations from evening conditions can decrease the uncertainty in other parameters. For near-correct physiological inputs, the outcome reliability is highest for the afternoon conditions. Overall, we conclude that OAT-like approaches, while more convenient, can be misleading and interaction-based higher level experiments can be effectively designed so as to have minimum model runs for maximum outcome. Such high level analyses are essential and distinctly useful in defining the possible causal nature of a specific phenomenon.

Finally, one can argue that the results are model specific (similar to various other studies that performed OAT-like analyses alone). The interactions resolved here are not singular and hence have larger deductive universality than from previous studies. However, such a feature is the classical ‘problem of inductance’ (Popper,

1959) and should be considered inherent to atmospheric systems (as with the closure problem for turbulence modeling). Overall, this study provides answers to some important practical questions. Its main contribution is that it now allows us to pose a more pertinent question. Rather than asking: ‘which parameters are sensitive or important?’, as in previous studies, a more proper question is ‘under what conditions do each of these parameters become sensitive or important?’. The former may assume a redundancy in the parameterization implying that some parameters may be even unnecessary; the latter, however, does not take liberty with such an assumption and hence more generally applicable.

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