SimSphere Model Sensitivity Analysis Towards Establishing its Use for Deriving Key Parameters Characterising Land Surface Interactions

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Abstract

Being able to accurately estimate parameters characterising land surface interactions is currently a key scientific priority due to their central role in the Earth's global energy and water cycle. To this end, some approaches have been based on utilising the synergies between land surface models and Earth Observation (EO) data to retrieve relevant parameters. One such model is SimSphere, the use of which is currently expanding, either as a stand-alone application or synergistically with EO data. The present study aims at exploring the effect of changing the atmospheric sounding profile on the sensitivity of key variables predicted by this model assuming different probability distribution functions (PDFs) for its inputs/outputs. To satisfy this objective and to ensure consistency and comparability to analogous studies conducted previously on the model, a sophisticated, cutting edge sensitivity analysis (SA) method adopting Bayesian theory is implemented herein on SimSphere. Our results did not show dramatic changes in the nature or ranking of influential model inputs in comparison to previous studies. Model outputs examined using SA were sensitive to a small number of the inputs; a significant amount of first order interactions between the inputs was also found, suggesting strong model coherence. Results obtained suggest that the assumption of different PDFs for the model inputs/outputs did not have an important bearing on mapping the most responsive model inputs and interactions, but only the absolute SA measures. This study extends our understanding of SimSphere's structure and further establishes its coherence and correspondence to that of a natural system's

behaviour. Consequently, the present work represents a significant step forward in the efforts globally on SimSphere verification, especially those focusing on the development of global operational products from the synergy of SimSphere with EO data.

1 Introduction

Understanding the natural processes of the Earth as well as how the different components (i.e. lithosphere hydrosphere, the biosphere and atmosphere) of the Earth's systems interplay, especially in the context of global climate change, has been recognised by the global scientific community as a very urgent and important research direction requiring further investigation (Battrick et al. 2006). This requirement is also of crucial importance for addressing directives such as the EU Water Framework Directive. To this end, being able to accurately estimate spatio-temporal estimates of parameters such as the latent (LE) and sensible (H) heat fluxes as well as of soil moisture is of great importance. This is due to their important role in many physical processes characterising land surface interactions of the Earth system as well as their practical use in a wide range of multi-disciplinary studies and applications (Kustas and Anderson, 2009; Seneviratne et al. 2010).

As a result, deriving information on the spatio-temporal distribution of these parameters has attracted the attention of scientists from many disciplines. Over the past few decades, a wide variety of approaches for their retrieval have been proposed operating at different observation scales, including datasets from ground instrumentation, simulation models and Earth Observation (EO). Recent studies have also focused on exploring the synergies between EO data and land surface process models (see reviews by Olioso, 1992 and Petropoulos, 2013). Essentially, these techniques endeavour to provide improved predictions by combining the horizontal coverage and spectrally rich content of EO data with the vertical coverage and excellent temporal resolution of simulation process models.

One such group of approaches, so-called the "triangle" method (Carlson, 2007), is used to predict regional estimates of LE, H fluxes and soil moisture content (SMC). SimSphere is a Soil Vegetation Atmosphere Transfer (SVAT) model, originally developed by Carlson and Boland (1978) and considerably modified to its current state by Gillies et al. (1997) and Petropoulos et al. (2013a). SVAT models are essentially mathematical representations of 1-dimensional 'views' of the physical mechanisms controlling energy and mass transfers in the soil/vegetation/atmosphere continuum, providing deterministic estimates of the time course of various variables characterising land surface interactions at time-steps appropriate to the dynamics of atmospheric processes (Olioso et al., 1999). An overview of SimSphere use was recently provided by Petropoulos et al. (2009a). The different facets of the SVAT model's overall structure, namely the physical, the vertical and the horizontal, are illustrated in Figure 1 (left). An extensive mathematical description of the model can be found in Carlson and Boland (1978), Carlson et al. (1981) and Gillies and Carlson (1995). The SimSphere model is maintained and is distributed freely globally (both the executable version and model code) from Aberystwyth University, United Kingdom (http://www.aber.ac.uk/simsphere).

As regards the "triangle" method in particular, it has its foundations in the physical properties encapsulated in a satellite-derived scatterplot of surface temperature (Ts) and vegetation index (VI), linked with the SimSphere model. Petropoulos et al. (2009b) have underlined the potential of this group of approaches for operational implementation in deriving estimates of LE/H fluxes and/or SMC. A recent description of the "triangle" workings can be found in Petropoulos and Carlson (2011). At present variants of this method are explored - or even some already implemented in practice - for deriving, in some cases operationally and on a global scale, estimates of LE and H fluxes and/or SMC (Chauhan et al., 2003; Piles et al., 2011; ESA STSE, 2012). In addition, SimSphere use is continually expanding worldwide both as an educational and as a research tool - used either as a stand-alone application or synergistically with EO data - to conduct studies aiming to improve understanding of land surface processes and their interactions. Considering the research and practical work with respect to SimSphere use, it is evidently of primary importance to execute a variety of validatory tests to evaluate its adequacy and coherence in terms of its ability to accurately and realistically represent Earth's surface processes.

Performing a sensitivity analysis (SA) provides an important and necessary validatory component of any computer simulation model or modelling approach before it is used in performing any kind of analysis. SA allows determining the effect of changing the value of one or more input variables of a model and observing the consequence that this has on given outputs simulated by the model. Its implementation on a model allows understanding the model's behaviour, coherence and correspondence to what it has been built to simulate (Saltelli et al., 1999; 2000; Nossent et al., 2011). As such, SA provides a valuable method to identify significant model inputs as well as their interactions and rank them (Chen et al., 2012), offering guidance to the design of experimental programs as well as to more efficient model coding or calibration.

Indeed, by means of a SA unrelated parts of the model may be dropped or a simpler model can be built or extracted. The latter can reduce, in some cases significantly, the required computing power while maintaining the models' correspondence to natural system's behaviour to real world (Holvoet et al., 2005).

A range of SA approaches have been proposed, a comprehensive overview of which can be found for example in Saltelli et al. (2000). One group includes the so-called Global SA (GSA) methods. These techniques aim to apportion the output variability to the variability of the input parameters when they vary over their whole uncertainty domain, generally described using probability densities assigned to the model's inputs. The sensitivity of the input parameters is examined based on of the use of samples derived directly from the model, which are distributed across the parameter domain of interest. These methods, despite their high computational demands, have become popular in environmental modelling due to their ability to incorporate parameter interactions and their relatively straightforward interpretation (Nossent et al., 2011). They also account for the influence of the input parameters over their whole range of variation, which in turn enables obtaining SA results independent of any "modelers' prejudice", or site-specific bias (Song et al., 2012).

Petropoulos et al. (2009a) in a recent review of SimSphere exploitation underlined the importance of carrying out SA experiments on the model, as part of its overall verification. In response, Petropoulos et al. (2009c; 2010; 2013a,b,c) performed advanced GSA on SimSphere based on a Gaussian process emulator. As previous SA studies on SimSphere had been scarce, their results provided for first time an insight into the model architecture, allowing the mapping of the sensitivity between the model inputs and key model outputs. Although these studies varied all the model input parameters across their full range of variation, a particular atmospheric sounding setting had been used in these GSA experiments by the authors. In addition, the effect of different probability distribution functions (PDFs) for the model inputs/outputs to the obtained had not been adequately explored.

In this context, the aim of the present study was to perform a GSA on SimSphere using an atmospheric sounding derived from a different region and evaluate the effect of atmospheric sounding on the SA results obtained on SimSphere assuming different PDFs for the model inputs/outputs. This will allow us to extend our understanding of this model structure and further establishing its coherence.

2 The Bayesian Sensitivity Analysis method

To satisfy the objectives of this study and to ensure consistency and comparability of our work to previous studies on SimSphere, SA is conducted here by employing a sophisticated, cutting edge GSA method adopting on Bayesian Analysis of Computer Code Outputs (BACCO; Kennedy and O'Hagan, 2001). It is implemented using the GEM-SA software, the development of which was funded by the National Environmental Research Council, United Kingdom. The theory behind the BACCO GEM-SA technique can be found by Oakley and O'Hagan (2004); detailed descriptions of the mathematical principles governing the GP emulation are available in Kennedy and O'Hagan (2001), Kennedy (2004) and Oakley and O'Hagan (2004). The use of the Gaussian processes (GP) to model unknown functions in Bayesian statistics dates back to Kimeldorlf & Wahba (1970) and O'Hagan (1978).

Briefly, BACCO GEM-SA implementation consists of two phases: First, a statistically-based representation (i.e. an emulator) of the model is built from training data obtained from simulations derived from the actual model, which have been designed to cover the multi-dimensional input space using a space-filling algorithm. Second, the emulator itself is used to compute a number of statistical parameters to characterise the sensitivity of the targeted model output in respect to its inputs.

BACCO SA implementation starts from a prior belief about the code (i.e. that it has no numerical error) and then based on a GP model, Bayes' theorem and a set of the model code runs this assumption is refined, to yield the posterior distribution of the output, which is the emulator. In building the emulator, the most important prior assumption is that the output emulator is a reasonably smooth function of its inputs. On this basis, the emulator is used to calculate a mean function, which attempts to pass through the observed runs and the same time it quantifies the remaining uncertainty due to the emulator being an approximation to the true code. Within BACCO, various statistical measures are generated automatically when the emulator is built in order to check the accuracy of both types of output.

In simple mathematical terms, the basic SA output from GEM-SA includes a direct decomposition of the model output variance into factorial terms, called 'importance measures' (e.g. Ratto et al., 2001):

$$V(Y) = \sum_{i=1}^{s} D_i + \sum_{i \triangleleft j} D_{ij} + \ldots + D_{1\ldots s} \qquad (1)$$

$$D_i = V(E(Y|X_i)) \qquad (1a)$$

$$D_{ij} = V(E(Y|X_i, X_j)) - V(E(Y|X_i)) - V(E(Y|X_j)) \qquad (1b)$$

- s denotes the number of inputs (so-called 'factors'),
- $V(Y)$ is the total variance of the output variable Y
- D_i is the importance measure for input X_i,
- D_{ij} is the importance measure for the interaction between inputs X_i and X_j
- $D_{1\ldots s}$ denote similar formulae for the higher order terms.
- $E(Y|X_i)$ is the conditional expectation of Y given a value of Xi and the variance of $E(Y|X_i)$ is taken over all inputs factors which are fixed in the conditional expectations.

In addition, in the BACCO method, sensitivity indices are computed by dividing the importance measures from equation 6 by the total output variance as follows:

$$S_i = \frac{D_i}{V(Y)}\ , \quad S_i = \frac{D_{ij}}{V(Y)}, \qquad (3)$$

These ratios S_i for i=1,...,s are called *main effects* or *first order sensitivity indices*, because each S_i delivers a direct measure of the share of the output variance explained by X . The main effect or first order sensitivity index S_i is the expected amount of variance that would be removed from the total output variance if the true value of X_i was known (within its uncertainty range). Thus, this is a measure that quantifies the relative importance of an individual input variable X_i, in driving the total output uncertainty, indicating where to direct future efforts to reduce that uncertainty. Using similar formulae higher order sensitivity indices *(joint effect indices)* are also computed in GEM-SA to compute the sensitivity of the model output to input parameter interactions. However, in practice, because the estimation of S_i or S_{ij} or higher order can be computationally very expensive, the SA is rarely carried out further after the computation of first order interaction indices (i.e. the second term of Equation 3 above). This is also the case with GEM-SA.

Thus, from the definitions of the above indices, and assuming non-correlated inputs, a complete series development of the output variance can be achieved:

$$\sum_{i} S_i + \sum_{i \triangleleft j} S_{ij} + \sum_{i \triangleleft j \triangleleft m} S_{ijm} + \ldots + S_{12\ldots k} = 1 \qquad (4)$$

where higher order indices are defined in a similar way to Equation 7. This decomposition of variance into main effects and interactions is commonly known as *Analysis of Variance-High Dimensional Model Representation (HDMR).*

The percentage variance contribution of each input's main effect is also reported in BACCO, providing a simple means of ranking the inputs in terms of their importance. The percentage variance component associated with each input measures the amount its main effect contributes to the total output variance, based on the uncertainty distributions for all inputs. It should be noted that, in general, summing the main effect contributions will not total to 100 % because of the additional contributions from the interaction effects. However, the total can be used to determine the degree of interactions.

In addition to the above indices, another measure that is computed in GEM-SA is the *total sensitivity index*. This is used to provide a cheaper computational method of investigating the higher order sensitivity effects as it collects all the interactions involving X_i in one single term. The total sensitivity index of a given factor X_i takes into account the main effect and the effect of all its interactions with other model inputs, and is defined as:

$$ST_i = \frac{D_i + D_{i,\sim i}}{V(Y)} \qquad (5)$$

where $D_{i,\sim i}$ indicates all interactions between factor X_i and all the others ($X_{\sim i}$).

The total sensitivity index represents the expected amount of output variance that would remain unexplained (residual variance) if only X_i were left free to vary over its range, the value of all other variables being known. The usefulness of the ST_i is that it is possible to compute them without necessarily evaluating the single indices S_i (and higher order ones), making the analysis computationally affordable. The total sensitivity indices are generally used to identify unessential variables (i.e. those that have no importance neither singularly nor in combination with others) while building a model. The existence of large total effects relative to main effects implies the presence of interactions among model inputs.

The BACCO method has already supplied useful insights in various disciplines and in various SA studies underlying the advantages of this approach (Kennedy and O'Hagan, 2001; Johnson et al., 2011; Kennedy et al., 2012; Parry et al., 2012). Petropoulos et al (2009c) demonstrated for the first time the use of the BACCO method in performing a SA on SimSphere, providing an insight into the model structure. Petropoulos et al. (2010) performed a comparative study of various emulators including BACCO GEM, investigating the effect of sampling method and size on the sensitivity of key target quantities simulated by SimSphere. Their results showed that the sampling size and method did affect the SA results in terms of absolute values, but had no bearing in identifying the most sensitive model inputs and their interactions, for model outputs on which SA was performed.

3 Sensitivity analysis implementation

To ensure consistency and comparability with previous analogous SA studies on SimSphere, the BACCO GEM-SA was implemented herein along the lines of previous similar GSA studies applied to that model (Petropoulos et al., 2009c; 2010; 2013a,b,c). The only difference was the use of a different atmospheric sounding profile derived from a dissimilar location and season. Thus, the sensitivity of the following SimSphere outputs was evaluated:

- Daily Average Net Radiation ($\overline{Rn_{daily}}$)
- Daily Average Latent Heat flux, ($\overline{LE_{daily}}$)
- Daily Average Sensible Heat flux ($\overline{H_{daily}}$),
- Daily Average Tair ($\overline{Tair_{daily}}$)
- Daily Average Surface Moisture Availability ($\overline{Mo_{daily}}$).
- Daily Average Evaporative Fraction ($\overline{EF_{daily}}$)
- Daily Average Non-Evaporative Fraction ($\overline{NEF_{daily}}$)
- Daily Average Radiometric Temperature ($\overline{Trad_{daily}}$).

A design space of 400 SimSphere simulations developed using the LP-tau sampling method. In creating the input space from the 400 model runs, all SimSphere inputs were allowed to vary, except those of the geographical location (latitude/longitude) and atmospheric profile (Figure 2), for which *a priori* real observations for the August 7th, 2002 were used from the Loobos CarboEurope site, located in The Netherlands (52° 10' 04.29" N, 05° 44' 38.25" E). In accordance to previous GSA studies on SimSphere, GEM SA was implemented assuming both normal and uniform probability distribution functions (PDFs) for the inputs/outputs from the model. For all variables, the theoretical ranges of values were defined from the entire possible theoretical range which they could take in SimSphere parameterisation (Table 1). The potential of co-variation between the parameters was assumed negligible, as in previous studies. In addition, the emulator performance was evaluated based on the "leave final 20 % out" method offered in GEM-SA, again in accordance to previous GEM SA studies conducted to the model.

4 Results

4.1 Emulator validation

The uncertainty of the SA due to the performance of the emulator was evaluated on the basis of a number of statistical measures computed internally by GEM-SA. Those included the "cross validation root mean square error", "cross-validation root mean squared relative error" and the "cross-validation root mean squared standardized error (RMSE)". In addition a unitless parameter called "roughness value", also computed internally in GEM SA, was used. This parameter provides an estimate of the changes in model outputs in response to changes in the inputs to the model. Finally, the "sigma-squared" statistical parameter, also computed within GEM-SA, was also used to statistically appreciate the performance of the emulator build. Within BACCO GEM-SA, this expresses the variance of the emulator after standardising the output, and effectively provides a measure of the quality of the fit of the emulator to the original model code.

Tables 2 and 3 summarise the results from the computation of the main statistical measures used to evaluate the performance of the emulator. As can be observed, sigma-squared' values for all parameters were low, as were RMSE values for all model outputs. Cross-validation RMSD varied widely between 3.03 % ($\overline{Tair_{daily}}$) and 41.63 % ($\overline{H_{daily}}$). Roughness values for the majority of the model inputs were reported having very low values for both normal and uniform PDFs, indicating that the built emulator is a very good approximation of the actual model. For thermal inertia, for example, roughness values are 0 for all model outputs with the exception of H flux and daily LE and H fluxes (which are all 0.01). Most roughness values obtained were below 1.0, suggesting that the emulator responded smoothly to variations in model inputs.

Roughness values above 1.0 were rare (eg. for $\overline{H_{daily}}$ were vegetation height and surface soil moisture availability (Mo) and for $\overline{Trad_{daily}}$ were aspect, fractional vegetation cover, vegetation height and Mo). Roughness values above one were rare and indicated some degree of non-linearity between model inputs and outputs. However, these are not significant enough to suggest an extreme level of non-linear relationships. Noticeably, the results obtained herein in regards to the emulator accuracy were largely comparable to previous GSA studies on SimSphere (Petropoulos et al., 2009c; 2013,a,b,c), suggesting a good emulator build, able to emulate the target quantities examined reasonably accurately.

4.2 SA results

Tables 4 and 5 summarise the relative sensitivity of the model outputs with respect to the model inputs, for both the cases of normal and uniform PDFs assumptions for the model inputs/outputs. Input parameters with a main effect > 1 % and/or > 1% total effect are highlighted in grey. Figure 3 exemplifies the main effect and total effects for each model output of which the SA was examined. The following sections systematically describe the main results obtained in terms of the SA for both cases of PDFs assumption, focusing primarily on the analysis of the main and total SA indices computed.

4.2.1 Parameter sensitivity for $\overline{Rn_{daily}}$

Main effects and total effects ranged from 0 to 50.1 % and 0 to 63.6 %, respectively, for normal PDFs (Table 4, Figure 3) and from 0 to 48.1 % and 0 to 65.7 % (Table 5), respectively in the case of uniform PDFs assumption. Under normal PDFs assumption, the inputs with the largest percentage variance contribution were aspect (50.1 %), slope (20.3 %) and Fr (7.2 %), and LAI (2.1 %) and Mo (3.6 %) were also relevant. As Table 4 shows, these parameters also contributed significantly to the total effects, although vegetation height also contributed here (1.2 %). Clearly, changing the PDFs to uniform did not alter the nature or the ranking of the most important model inputs (Table 5, Figure 3). Yet, it is noticeable that for this PDFs assumption, surface roughness input became more important, contributing 1.1 % to the total effects. In summary, the model input parameters with the highest total effects (i.e. those to which $\overline{Rn_{daily}}$ is most sensitive) were aspect, slope, Fr, LAI, Mo, vegetation height and surface roughness. Only nine significant (> 0.1 %) first order interactions were found for this parameter assuming a normal PDFs and assuming a uniform PDFs for the model inputs. Assuming a uniform PDFs, the most significant first order interactions were between slope and aspect (13.4 %) and between Fr and LAI (0.6 %). For normal PDFs the interaction between slope and aspect was, by far the most important (10.20 %). Interactions between aspect and Fr (0.4 %), Fr and LAI (0.3 %) and aspect and Mo (0.3 %) were also significant.

4.2.2 Parameter sensitivity for $\overline{H_{daily}}$

Main effects and total effects were lower in this case and ranged from 0 to 15.2 % and from 0 to 31.1 %, respectively, for normal PDFs (Table 4) and from 0 to 16.6 % and 0 to 30.4 %, respectively, for uniform PDFs (Table 5). Under normal PDFs, the inputs parameters with the largest percentage variance contribution were Fr (15.2 %), Mo (11.7 %), aspect (10.9 %) and vegetation height (10.4 %). Surface roughness (3.5 %) and slope (1.4 %) were also important. In terms of the total effects, aspect was the most important parameter (31.1 %) for the simulation of $\overline{H_{daily}}$ by the model, followed by vegetation height (29.7 %), Mo (26.3 %) and Fr (25.5 %). A number of other parameters also showed significant total effects (Table 4). The nature and rank of significant input parameters to main effects was also not changed by changing the PDFs to uniform (Table 5, Figure 3). In terms of the total effects, however, vegetation height becomes the most important by a small margin (30.4 % compared to 30.1 % for aspect). Numerous important input parameters are seen to influence $\overline{H_{daily}}$ therefore, the most important being aspect, Fr, vegetation height, Mo and surface roughness. A large number of first order interactions with values higher than 0.1% were observed for $\overline{H_{daily}}$ assuming a uniform PDFs (32 in total) and assuming a normal PDFs (39 in total). Assuming a uniform PDFs the most important interactions were between vegetation height and surface roughness (4.76 %), Fr and Mo (2.46 %) and vegetation height (1.95 %), respectively and between aspect and surface roughness (1.67 %) and Mo (1.40 %), respectively. The most significant interaction assuming a normal PDFs was between vegetation height and surface roughness (4.31 %), but interactions between aspect and surface roughness (2.52 %), Mo (1.71 %), vegetation height (1.13 %) and O_3 in the air (0.72 %) respectively and between Fr and Mo (2.26 %) and vegetation height (1.91 %) were also found. In terms of second order or higher interactions, a higher level of significant interactions were found, with 16.8 % and 21.9 % noted assuming normal and uniform PDFs, respectively.

4.2.3 Parameter sensitivity for $\overline{LE_{daily}}$

As regards the $\overline{LE_{daily}}$, SA results showed ranges in main effects and total effects ranging from 0 to 36.0 % and 0 to 51.9 %, respectively, for normal PDFs assumption (Table 4) and from 0 to 29.8 % and 0 to 48.0 %, respectively, for uniform PDFs (Table 5, Figure 3). Under normal PDFs, the model inputs with the highest percentage variance contribution were those of aspect (36.0 %), Mo (17.6 %), Fr (8.1 %), slope (8.0 %) and cuticle resistance (1.0 %). This is also mirrored in the total effects results obtained, yet at higher percentage contributions (e.g. 51.9 % for the aspect). Both PSI and substrate maximum volumetric water content contributed > 1 % to the total effects also. Once again, the nature and rank of significant model input parameters was mirrored when the PDFs was changed to uniform, but additional parameters contribute to the total effects, including [Ca], [O_3] in the air, ground emissivity, RKS, CosbyB, and THM. In summary, results suggest that the most important model inputs influencing the simulation of $\overline{LE_{daily}}$ were aspect, Mo, Fr and slope. Assuming uniform PDFs for the model inputs, two first order interactions dominate for this parameter – those between slope and aspect once more (6.8 %) and those between Fr and Mo (6.8 %). Interactions between aspect and Mo (1.0 %) and Fr (4.6 %), respectively, are also important. When normal PDFs for model inputs/outputs was assumed, twenty four first order interactions with values higher than 0.1% were observed, and once again, the interaction between slope and aspect (6.1 %) were the most important. However, important interactions between Fr and Mo (4.6 %), aspect and Mo (1.2 %) and between aspect and Fr (0.8 %) were also observed.

4.2.4 Parameter sensitivity for $\overline{Trad_{daily}}$

Main effects and total effects for $\overline{Trad_{daily}}$ simulation by SimSphere ranged from 0 to 34.9 % and 52.0 % respectively, assuming normal PDFs for the model inputs (Table 4, Figure 3) and from 0 to 29.6 % and 49.2 %, respectively for the case of uniform PDFs (Table 5). For normal PDFs the most important model inputs were aspect (34.9 %), Mo (16.9 %) and slope (12.7 %), with Fr and vegetation height also important. This is mirrored in the total effects, but here LAI, [O_3] in the air, surface roughness, obstacle height and THM also contributed more than 1 %. The nature and ranking of the model inputs contributing significant main effects under uniform PDFs was largely similar to that of normal PDFs. In common with the parameters discussed above, therefore, aspect, slopes, Mo and vegetation characteristics (Fr and height) exert the most influence on $\overline{Trad_{daily}}$. Assuming a uniform PDFs twenty one first order interactions with values higher than 0.1% were reported. The most important was between slope and aspect (9.5 %), followed by some less important interactions e.g. between Fr and Mo (1.2 %), and between aspect and Mo (0.8 %). On the other, assuming a normal PDFs twenty four significant first order interactions with values higher than 0.1% were returned. The two most important were once again between slope and aspect (8.9 %) and between aspect and Mo (0.9 %). Interactions between Fr and Mo (0.9 %) and aspect and Fr (0.7 %) were also important. Second order or higher interactions contributed 5.2 % and 8.0 % in the total variance decomposition for the normal and uniform PDFs, respectively.

4.2.5 Parameter sensitivity for $\overline{Mo_{daily}}$

For main effects and total effects for normal PDFs, a similar range was observed for $\overline{Mo_{daily}}$ as for other parameters, from 0 to 28.5 % and 50.2 %, respectively (Table 4, Figure 3). However, a much larger range was observed for these values under uniform PDFs – from 0 to 96.4 % and 97.6 % for main and total effects, respectively (Table 5). For normal PDFs the most important model input parameters were aspect (28.5 %), slope (17.1 %) and LAI (12.0 %) in the main effects. These were also important in terms of total effects but in addition many other factors also become important in that case, the most significant being Mo (7.1 %), Fr (6.7 %) and station height (4.9 %). In this case therefore, although the most significant parameters were, once again, aspect and slope, many other parameters also appear to contribute to the sensitivity of $\overline{Mo_{daily}}$. Evidently, a marked difference in terms of sensitivity was observed when a uniform PDFs is assumed for this parameter (Table 5, Figure 3). In this case, the sensitivity is dominated by Mo in both the main and total effects – 96.4 % and 97.6 %, respectively. In the total effects, substrate maximum volumetric water content and PSI both contributed to a much lesser degree. For the case of uniform PDFs, only one first order interaction with values higher than 0.1% was observed between Mo and substrate maximum volumetric water content (0.2 %). Thirty two first order interactions with values higher than 0.1% were reported assuming a normal PDFs for the model inputs/outputs. The interaction between slope and aspect was once again the most significant (8.5 %), followed by that between Fr and LAI (2.18 %). Interactions between aspect and LAI (1.4 %) and Mo (1.2 %), respectively, were also important.

4.2.6 Parameter sensitivity for $\overline{Tair_{daily}}$

Ranges of main and total effects for this parameter were found to be comparable to the majority of the other parameters discussed previously. For normal PDFs these range from 0 to 21.89 % and from 0 to 43.8 %, respectively (Table 4, Figure 3) and for uniform PDFs these range from 0 to 18.1 % and 0 to 43.8 % (Table 5), respectively. For main effects under normal PDFs the most significant model input parameters were, once again, aspect (21.9 %), Fr (16.7 %), vegetation height (7.8 %), surface Mo (7.0 %) and surface roughness (6.5 %). The total effects were broadly similar, but surface roughness became the third most important parameter, whereas other inputs (e.g. station height, [O_3] in the air, obstacle height and PSI) become important. Under uniform PDFs, the most important parameters were aspect (18.1 %), Fr (16.9 %), Mo (8.2 %), vegetation height (5.9 %), and surface roughness (4.8 %). Under total effects, once again, surface roughness becomes more important, and the same additional model parameters as were observed under normal PDFs also contributed greater than 1 %. Once again, aspect and Fr, vegetation height and surface roughness seem to be the most important variables influencing $\overline{Tair_{daily}}$.

Twenty three first order interactions with values higher than 0.1% were found for this parameter, and once again, the interaction between slope and aspect is the most important (5.2 %), although it is closely followed by interactions between vegetation height and surface roughness (4.4 %) and between Fr and vegetation height (2.0 %) and between aspect and surface roughness (1.9 %). Of the twenty three first order interactions higher than 0.1% also found assuming a normal PDFs for model inputs/outputs, the most important was between slope and aspect (5.0 %), closely followed by the interactions between vegetation height and surface roughness (4.1 %) inputs, but a number of other important interactions are evident. These include interactions between aspect and surface roughness (2.3 %), vegetation height (1.5 %), Fr (1.4 %) and Mo (0.7 %), respectively and between Fr and vegetation height (1.9 %) and surface roughness (1.0 %), respectively.

4.2.7 Parameter sensitivity for $\overline{EF_{daily}}$

Once again, the ranges of main and total effects reported for the sensitivity of $\overline{EF_{daily}}$ were to a large degree similar to most of the other parameters already discussed. For normal PDFs, main effects of the inputs ranged widely from 0 to 38.2% and from 0 to 49.5%, respectively (Table 4, Figure 3) and for the case of uniform PDFs from 0 to 35.7% and from 0 to 49.1%, respectively

(Table 5). Mo was found to be the most important model input parameter here in terms of main effects under normal PDFs (38.2%), followed by Fr (10.4%), vegetation height (8.2%) and aspect (4.3%). As Table 4 shows, many additional parameters become important contributors to total effects although the nature and rank of the most significant parameters does not change. Once again, Table 5 shows very little differences in terms of the nature and ranking of the main and total effects under a uniform PDFs assumption for the model inputs/outputs. Therefore, for this parameter, the most important model input parameters are Mo, Fr, vegetation height and aspect. Assuming a uniform PDFs, thirty two first order interactions with values higher than 0.1% were observed for this parameter, with the most important being between Fr and Mo (5.4%) and vegetation height (4.2%), respectively, and between vegetation height and surface roughness (1.9%). Thirty one first order interactions with values higher than 0.1% were found assuming ormal PDFs. The two most important are those between Fr and Mo (4.8%) and vegetation height (3.7%), respectively. Other important interactions included those between vegetation height and surface roughness (1.9%) and Mo (0.8%), respectively and between Fr and cuticle resistance (0.7%). Second or higher order interactions for this parameter assuming normal PDFs were largely similar to those observed for other parameters.

4.2.8 Parameter sensitivity for $\overline{NEF_{daily}}$

The main and total effects for this parameter assuming both normal (Table 4, Figure 3) and uniform PDFs (Table 5) were very similar (if not identical) to those observed for $\overline{LE_{daily}}$. The first order interactions with values higher than 0.1% B for this parameter were very similar to those for $\overline{EF_{daily}}$ with respect to the nature and ranking of the most important interactions assuming both normal and uniform PDFs, as were the contributions of second order or higher interactions.

5 Discussion

The aim of this study was to undertake a SA on the SimSphere SVAT model using different atmospheric sounding data from another location compared to previous SA studies on the model, in order to identify whether this had any impact on the model sensitivity to a set of input parameters. The most important implication of this study is that the same input parameters (in broadly the same ranking of importance) have been identified as the most significant influences on model outputs despite the SA using sounding data from a different site, in a different region and under a different climatic regime. The fact that this has not shown any major differences in the nature of the model sensitivity, especially the ranking of importance is a significant step forward in terms of the model use, in that it demonstrates the applicability of the model at different sites. It has also shown that although the complex combinations of slope, aspect, vegetation and soil characteristics that are unique to each site will introduce some site-specific results (Ellis and Pomeroy, 1975), in broad terms, the most important parameters governing the sensitivity of model outputs do not change. This further confirms the findings of Petropoulos et al. (2013b,c) that by fixing the relatively unimportant model inputs to typical value ranges, the dimensionality of SimSphere could be reduced and its robustness could thus be further improved. The fact that a large number of significant first order interactions have been found for almost all the model outputs, as well as substantial contributions of higher order interactions is important since it further confirms that the model is coherent. This also suggests that no parts of the model are redundant and that there is no need to remove any element of the model architecture.

In common with the other recent SA experiments undertaken on SimSphere (e.g. Petropoulos et al., 2009c; 2013a-c), this article has shown that slope and aspect are the two most significant input parameters in terms of their influence on the model outputs, even assuming different PDFs. As has been outlined in these previous works, the influence of these topographic parameters is a result of their control on the amount of incoming solar radiation reaching the surface of the earth (Oliphant et al., 2003; Sabetraftar et al., 2011). As a result they will also influence LE and H fluxes surface temperature by providing energy for evapotranspiration and heat transfer through the surface energy budget. High levels of incoming solar radiation can be translated into high sensible heat transfers and into high surface temperatures. First order interactions between slope and aspect that were higher than all other first order interactions for numerous model outputs further demonstrate the sensitivity of the model outputs to these parameters.

Once again, in common with other SA undertaken on the model, vegetation parameters have been shown to be important, and the reasons for this have been analysed/discussed previously by Petropoulos et al., (2009c; 2013b,c). In summary, both Fr and vegetation height may influence the surface energy budget by influencing the proportion of incoming solar radiation that reaches the surface of the earth. Large Fr shade the Earth surface, and as such will influence surface temperatures. The proportion of vegetation can affect the fluxes of both LE and H fluxes through its influence on evapotranspiration, for example, as well as the proportion of incoming solar radiation which is reflected and emitted by the surface. By reducing wind speed and evaporation and increasing plant transpiration, vegetation height and surface roughness can influence surface temperatures as well as the proportion of incoming solar radiation that is converted into latent or sensible heat. The influence of Mo on $\overline{LE_{daily}}$ is to be expected, as is its influence on LE fluxes. Previous SA works on SimSphere have shown that Mo can influence air temperature (Carlson and Boland, 1978; Petropoulos et al., 2009c, Petropoulos et al., 2013c) because it can exert a significant control on evapotranspiration (Santanello et al., 2009; Dirmeyer, 2011; Lockart et al., 2012) and, therefore the partitioning of net radiation into LE and H fluxes. The importance of Fr is important since it is one of the two parameters in the “triangle” method (Gillies et al., 1997) and its more recent modifications (Chauhan et al., 2003) for deriving LE and H fluxes as well as SMC from EO data (Petropoulos et al., 2009c) and this work has shown once again that this method correctly identifies Fr and Mo as an important variables.

The results of this study have significant implications for the development of successful modelling approaches involving the use of SimSphere either as a standalone application or synergistically with EO data. These results evidently further confirm the model coherence and solid structure in estimating land surface interactions, supporting on-going work with the model on a global scale. Results obtained herein can be used practically to assist in future model parameterisation and implementation in diverse ecosystem conditions allowing better understanding of Earth system and feedback processes. In particular the synergistic use of SimSphere with EO data via the “triangle” method implementation appears to be a promising direction in this respect in providing regional estimates of key parameters characterising land surface interactions at different observational scales exploiting EO technology.

6 Conclusions

This study represents a significant step forward in the validation of the coherence of the SimSphere SVAT model, an effort currently on-going globally. Whereas previous work has examined the influence of different parameters and PDFs against real observations collected in Italy, this study examines the sensitivity of the model against data collected from a different region with a different climatic regime. In common with previous works, results confirmed that once again, model outputs are only significantly sensitive to a small group of model inputs. Slope and aspect were the most important, but the influence of vegetation parameters (vegetation height, Fr and surface roughness) and soil moisture content are also important influences on a number of output parameters. Significant interactions have also been found to exist between the input parameters.. The latter suggests that the model is a coherent representation of real-world processes and in that natural feedbacks and interactions between, for example vegetation and soil moisture, are being represented.

In common with previous SA on SimSphere, this study has examined runs of the model at 11am. Examining the sensitivity of the model outputs at different times would be a very important direction in which future studies on SimSphere SA can be conducted. In combination with direct comparisons of the model outputs against *in-situ* "reference" estimates diurnally, conducted at different ecosystem and environmental conditions, this can assist to further extend our understanding of the SimSphere structure and establish further its coherence and correspondence to the behaviour of natural systems. It will also provide information that will be of key scientific and practical value as regards the model use, particularly as the use of SimSphere is at present expanding around the globe.

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Table 1. *Summary of the SimSphere inputs considered in the GSA implementation. Units of each of the model inputs, where appropriate, are provided in brackets.*

Model input short name	Actual name of the model input	Process in which each parameter is involved	Min value	Max value
X1	Slope *(degrees)*	time & location	0	45
X2	Aspect *(degrees)*	time & location	0	360
X3	Station Height *(meters)*	time & location	0	4.92
X4	Fractional Vegetation Cover *(%)*	vegetation	0	100
X5	LAI *(m^2m^{-2})*	vegetation	0	10
X6	Foliage emissivity *(unitless)*	vegetation	0.951	0.990
X7	[Ca] (external [CO_2] in the leaf) *(ppmv)*	vegetation	250	710
X8	[Ci] (internal [CO_2] in the leaf) *(ppmv)*	vegetation	110	400
X9	[03] (ozone concentration in the air) *(ppmv)*	vegetation	0.0	0.25
X10	Vegetation height *(meters)*	vegetation	0.021	20.0
X11	Leaf width *(meters)*	vegetation	0.012	1.0
X12	Minimum Stomatal Resistance *(sm^{-1})*	plant	10	500
X13	Cuticle Resistance *(sm^{-1})*	plant	200	2000
X14	Critical leaf water potential *(bar)*	plant	-30	-5
X15	Critical solar parameter *(Wm^{-2})*	plant	25	300
X16	Stem resistance *(sm^{-1})*	plant	0.011	0.150
X17	Surface Moisture Availability *(vol/vol)*	hydrological	0	1
X18	Root Zone Moisture Availability *(vol/vol)*	hydrological	0	1
X19	Substrate Max. Volum. Water Content *(vol/vol)*	hydrological	0.01	1
X20	Substrate climatol. mean temperature *(^oC)*	surface	20	30
X21	Thermal inertia *($Wm^{-2}K^{-1}$)*	surface	3.5	30
X22	Ground emissivity *(unitless)*	surface	0.951	0.980
X23	Atmospheric Precipitable water *(cm)*	meteorological	0.05	5
X24	Surface roughness *(meters)*	meteorological	0.02	2.0
X25	Obstacle height *(meters)*	meteorological	0.02	2.0
X26	Fractional Cloud Cover *(%)*	meteorological	1	10
X27	RKS (satur. thermal conduct.*(Cosby et al., 1984)*	soil	0	10
X28	Cosby B *(see Cosby et al., 1984)*	soil	2.0	12.0
X29	THM (satur.vol. water cont.) *(Cosby et al., 1984)*	soil	0.3	0.5
X30	PSI (satur. water potential) *(Cosby et al., 1984)*	soil	1	7

Table 2. Emulator accuracy statistics for the SA tests conducted in our study (under both normal and uniform PDFs assumptions for the model inputs/outputs).

Fitted model parameters (based on standardised input/output)	$\overline{Rn_{daily}}$	$\overline{H_{daily}}$	$\overline{LE_{daily}}$	$\overline{Trad_{daily}}$	$\overline{Mo_{daily}}$	$\overline{Tair_{daily}}$	$\overline{EF_{daily}}$	$\overline{NEF_{daily}}$
Sigma-squared:	0.413	1.619	1.057	0.875	1.240	1.630	1.483	1.483
Emulator accuracy:								
Cross-validation root mean squared-error (wm-2):	25.060	34.776	28.798	2.771	31.012	0.491	0.082	0.082
Cross-validation root mean squared relative error (%):	6.349	41.633	23.485	7.913	13.814	3.030	20.033	25.292
Cross-validation root mean squared standardised error:	1.111	1.790	1.484	1.117	1.474	1.505	1.717	1.717

Table 3. Summarised statistics concerning the emulator accuracy evaluation for the different SimSphere model outputs examined in our study. Shading highlights the roughness values of the model inputs with values greater than 1.0. Rows X1 to X30 show roughness values for the different model outputs examined (for normal and uniform PDFs).

Model Inputs	$\overline{Rn_{daily}}$	$\overline{H_{daily}}$	$\overline{LE_{daily}}$	$\overline{Trad_{daily}}$	$\overline{Mo_{daily}}$	$\overline{Tair_{daily}}$	$\overline{EF_{daily}}$	$\overline{NEF_{daily}}$
X1	1.842	0.092	0.479	0.755	0.688	0.488	0.049	0.049
X2	12.728	4.317	8.451	8.557	7.638	7.247	0.617	0.617
X3	0.156	0.289	0.105	0.013	0.611	0.187	0.043	0.043
X4	0.643	0.672	0.931	1.307	0.668	0.838	1.845	1.845
X5	0.608	0.065	0.062	0.223	1.027	0.035	0.150	0.150
X6	0.022	0.053	0.000	0.015	0.010	0.000	0.000	0.000
X7	0.001	0.102	0.094	0.000	0.012	0.000	0.091	0.091
X8	0.000	0.007	0.016	0.000	0.038	0.005	0.035	0.035
X9	0.174	0.172	0.121	0.338	0.018	0.201	0.002	0.002
X10	0.377	2.389	0.000	1.036	0.137	2.272	4.396	4.396
X11	0.019	0.054	0.040	0.034	0.156	0.030	0.030	0.030
X12	0.000	0.008	0.003	0.000	0.000	0.000	0.386	0.386
X13	0.022	0.048	0.161	0.043	0.030	0.040	0.217	0.217
X14	0.014	0.000	0.001	0.010	0.004	0.019	0.037	0.037
X15	0.016	0.000	0.000	0.071	0.000	0.009	0.000	0.000
X16	0.011	0.023	0.048	0.058	0.047	0.000	0.033	0.033
X17	1.197	2.146	1.416	1.048	0.408	0.422	1.346	1.346
X18	0.025	0.000	0.056	0.007	0.131	0.000	0.135	0.135
X19	0.000	0.000	0.077	0.004	0.048	0.000	0.070	0.070
X20	0.012	0.006	0.054	0.000	0.107	0.005	0.000	0.000
X21	0.005	0.013	0.000	0.000	0.000	0.002	0.011	0.011
X22	0.007	0.000	0.101	0.041	0.000	0.000	0.010	0.010
X23	0.004	0.000	0.042	0.104	0.055	0.003	0.098	0.098
X24	0.176	3.328	0.064	0.185	0.329	4.195	1.384	1.384
X25	0.030	0.000	0.053	0.145	0.169	0.070	0.000	0.000
X26	0.008	0.089	0.058	0.032	0.000	0.000	0.105	0.105
X27	0.000	0.000	0.092	0.000	0.026	0.000	0.000	0.000

X28	0.012	0.046	0.125	0.034	0.222	0.000	0.091	0.091
X29	0.079	0.178	0.092	0.102	0.204	0.026	0.022	0.022
X30	0.079	0.006	1.710	0.083	0.054	0.174	0.003	0.003

Table 4. Summarised results from the implementation of the BACCO GEM SA method on the different outputs simulated by SimSphere using the normal PDFs. Computed main (ME) and total effect (TE) indices by the GEM tool (expressed as %) for each of the model parameters are shown whereas the last three lines summarise the percentages of the explained total output variance of the main effects alone and after including the interaction effects. Input parameters with a variance decomposition of greater than 1 % are highlighted in grey.

Model Input	$\overline{Rn}_{daily}$		$\overline{H}_{daily}$		$\overline{LE}_{daily}$		$\overline{Trad}_{daily}$		$\overline{Mo}_{daily}$		$\overline{Tair}_{daily}$		$\overline{EF}_{daily}$		$\overline{NEF}_{daily}$	
	ME	**TE**	**ME**	**TE**	**ME**	**TE**	**ME**	**TE**	**ME**	**TE**	**ME**	**TE**	**ME**	**TE**	**ME**	**TE**
X1	20.294	31.964	1.388	3.078	7.969	16.245	12.676	24.032	17.129	29.450	1.846	10.150	0.991	1.613	0.991	1.613
X2	50.095	63.626	10.944	31.147	36.024	51.870	34.857	52.048	28.462	50.207	21.877	43.797	4.283	8.883	4.283	8.882
X3	0.016	0.353	0.469	4.245	0.066	0.825	0.031	0.150	1.278	4.853	0.411	2.482	0.130	0.610	0.130	0.610
X4	7.161	8.916	15.239	25.509	8.132	16.975	5.586	10.606	0.704	6.702	16.655	25.647	10.362	26.932	10.362	26.932
X5	2.060	3.357	0.135	1.710	0.184	0.709	0.049	1.462	12.028	20.080	0.071	0.672	0.060	1.824	0.060	1.824
X6	0.014	0.094	0.142	1.136	0.027	0.028	0.048	0.177	0.030	0.151	0.020	0.022	0.032	0.034	0.032	0.034
X7	0.010	0.015	0.090	2.166	0.049	0.855	0.028	0.029	0.054	0.198	0.037	0.039	0.065	1.086	0.065	1.086
X8	0.008	0.008	0.120	0.262	0.031	0.181	0.020	0.021	0.065	0.474	0.102	0.200	0.060	0.544	0.060	0.544
X9	0.029	0.465	0.093	3.309	0.098	0.898	0.149	1.703	0.032	0.222	0.067	2.669	0.093	0.120	0.093	0.120
X10	0.427	1.234	10.357	29.664	0.015	0.016	3.293	7.415	0.803	2.066	7.832	22.447	8.155	24.214	8.155	24.214
X11	0.021	0.095	0.275	1.401	0.350	0.677	0.127	0.432	0.177	2.093	0.044	0.500	0.308	0.759	0.308	0.759
X12	0.006	0.007	0.137	0.306	0.065	0.091	0.026	0.027	0.033	0.034	0.058	0.060	0.442	3.400	0.442	3.400
X13	0.134	0.203	0.158	1.041	1.546	2.699	0.609	0.922	0.151	0.490	0.247	0.929	1.652	4.295	1.653	4.295
X14	0.013	0.066	0.088	0.090	0.037	0.052	0.074	0.155	0.131	0.174	0.097	0.395	0.155	0.599	0.155	0.599
X15	0.024	0.077	0.037	0.039	0.041	0.042	0.070	0.506	0.030	0.031	0.122	0.260	0.025	0.026	0.025	0.026
X16	0.021	0.057	0.242	0.717	0.021	0.422	0.168	0.563	0.042	0.648	0.055	0.057	0.042	0.477	0.042	0.477
X17	3.554	5.219	11.669	26.284	17.567	27.166	16.911	21.465	3.563	7.129	7.010	11.169	38.200	49.518	38.199	49.518
X18	0.071	0.160	0.099	0.101	0.251	0.707	0.095	0.159	0.054	1.229	0.143	0.145	0.835	2.507	0.835	2.507
X19	0.010	0.010	0.054	0.056	0.643	1.300	0.056	0.090	0.284	0.735	0.033	0.035	0.286	1.055	0.286	1.056
X20	0.083	0.125	0.190	0.308	0.098	0.538	0.346	0.347	0.749	1.608	0.167	0.256	0.036	0.038	0.036	0.038
X21	0.032	0.050	0.228	0.487	0.029	0.030	0.043	0.044	0.035	0.037	0.105	0.137	0.072	0.234	0.072	0.234
X22	0.016	0.043	0.119	0.121	0.130	0.841	0.043	0.449	0.055	0.057	0.094	0.096	0.045	0.194	0.045	0.194
X23	0.009	0.025	0.052	0.054	0.032	0.378	0.042	0.718	0.124	0.653	0.025	0.081	0.066	1.239	0.066	1.239
X24	0.285	0.745	3.509	24.425	0.222	0.707	0.853	2.332	1.391	4.019	6.465	23.644	1.318	9.913	1.318	9.913
X25	0.010	0.129	0.049	0.051	0.044	0.552	0.051	1.067	0.061	1.551	0.042	1.070	0.075	0.076	0.075	0.076
X26	0.030	0.059	0.264	2.020	0.079	0.625	0.087	0.368	0.051	0.052	0.047	0.049	0.050	1.240	0.050	1.240
X27	0.005	0.005	0.043	0.045	0.032	0.909	0.017	0.018	0.053	0.330	0.031	0.033	0.026	0.028	0.026	0.028

X28	0.035	0.075	0.072	1.019	0.044	0.882	0.049	0.321	0.374	2.540	0.082	0.084	0.224	1.261	0.224	1.261
X29	0.058	0.289	0.402	2.995	0.028	0.866	0.344	1.024	0.103	2.105	0.206	0.585	0.118	0.404	0.118	0.404
X30	0.036	0.276	0.074	0.199	0.285	5.121	0.096	0.781	0.042	0.661	0.071	2.333	0.052	0.099	0.052	0.099
Main effects Only	**84.568**		**56.735**		**74.138**		**76.844**		**68.091**		**64.061**		**68.258**		**68.258**	
1st Order Interactions Only	**13.486**		**26.454**		**19.706**		**17.916**		**24.610**		**24.309**		**22.129**		**22.129**	
2nd or Higher Order Interactions	**1.946**		**16.810**		**6.155**		**5.240**		**7.299**		**11.630**		**9.613**		**9.613**	

Table 5. Summarised results from the implementation of the BACCO GEM SA method on the different outputs simulated by SimSphere using the uniform PDFs. Computed main (ME) and total effect (TE) indices by the GEM tool (expressed as %) for each of the model parameters are shown whereas the last three lines summarise the percentages of the explained total output variance of the main effects alone and after including the interaction effects. Input parameters with a variance decomposition of greater than 1 % are highlighted in grey.

Model Input	$\overline{Rn_{daily}}$		$\overline{H_{daily}}$		$\overline{LE_{daily}}$		$\overline{Trad_{daily}}$		$\overline{Mo_{daily}}$		$\overline{Tair_{daily}}$		$\overline{EF_{daily}}$		$\overline{NEF_{daily}}$	
X1	ME	TE	ME	TE	ME	TE	ME	TE	ME	TE	ME	TE	ME	TE	ME	TE
X2	12.975	28.482	1.275	3.143	4.924	14.568	8.652	21.467	0.004	0.137	1.629	11.437	1.060	1.835	1.060	1.836
X3	48.063	65.740	8.488	30.090	29.778	48.045	29.559	49.160	0.030	0.225	18.069	43.831	2.378	7.725	2.378	7.725
X4	0.011	0.486	0.493	4.965	0.062	1.103	0.054	0.207	0.005	0.064	0.227	3.012	0.126	0.747	0.126	0.747
X5	9.495	12.012	16.600	28.455	8.924	21.070	5.572	12.051	0.069	0.106	16.940	28.347	9.465	30.328	9.465	30.328
X6	2.588	4.589	0.190	1.926	0.255	0.920	0.046	2.046	0.002	0.002	0.073	0.835	0.043	2.241	0.043	2.241
X7	0.010	0.121	0.122	1.265	0.030	0.031	0.044	0.210	0.004	0.004	0.023	0.025	0.035	0.037	0.035	0.037
X8	0.013	0.020	0.078	2.519	0.044	1.150	0.032	0.033	0.004	0.019	0.042	0.044	0.043	1.353	0.043	1.353
X9	0.010	0.010	0.096	0.253	0.042	0.234	0.023	0.025	0.006	0.093	0.098	0.218	0.045	0.653	0.045	0.653
X10	0.035	0.646	0.148	3.845	0.072	1.130	0.140	2.224	0.001	0.020	0.165	3.944	0.100	0.134	0.100	0.134
X11	0.459	1.614	8.144	30.406	0.017	0.018	2.941	8.203	0.002	0.003	5.886	23.266	7.743	27.736	7.743	27.737
X12	0.041	0.140	0.325	1.595	0.342	0.765	0.209	0.603	0.003	0.032	0.046	0.651	0.287	0.857	0.287	0.857
X13	0.008	0.008	0.150	0.341	0.072	0.104	0.030	0.031	0.003	0.003	0.065	0.068	0.341	4.153	0.341	4.153
X14	0.179	0.277	0.249	1.234	1.791	3.330	0.689	1.110	0.014	0.038	0.418	1.263	1.885	5.225	1.885	5.225
X15	0.014	0.088	0.087	0.089	0.041	0.060	0.085	0.191	0.005	0.022	0.105	0.496	0.135	0.699	0.135	0.699
X16	0.035	0.111	0.037	0.039	0.046	0.047	0.077	0.682	0.003	0.003	0.149	0.326	0.027	0.029	0.027	0.029
X17	0.026	0.076	0.280	0.811	0.023	0.536	0.172	0.699	0.002	0.002	0.062	0.065	0.060	0.620	0.060	0.620
X18	4.907	7.116	11.788	28.159	20.154	33.046	22.206	28.072	96.361	97.557	8.174	13.430	35.735	49.092	35.735	49.092
X19	0.073	0.196	0.098	0.100	0.321	0.921	0.112	0.195	0.346	0.472	0.162	0.164	0.635	2.692	0.635	2.692
X20	0.012	0.013	0.053	0.055	0.708	1.564	0.061	0.105	0.950	2.090	0.037	0.039	0.297	1.262	0.297	1.262
X21	0.092	0.151	0.188	0.319	0.117	0.693	0.396	0.398	0.001	0.002	0.181	0.294	0.039	0.041	0.039	0.041
X22	0.038	0.062	0.192	0.480	0.032	0.034	0.049	0.051	0.002	0.009	0.116	0.156	0.079	0.280	0.079	0.280
X23	0.027	0.065	0.117	0.120	0.120	1.052	0.026	0.532	0.002	0.002	0.106	0.108	0.048	0.233	0.048	0.233
X24	0.011	0.034	0.051	0.054	0.036	0.495	0.048	0.955	0.003	0.003	0.028	0.099	0.071	1.620	0.071	1.620
X25	0.405	1.081	3.761	27.617	0.281	0.913	1.136	3.181	0.006	0.015	4.772	26.161	1.217	12.448	1.217	12.448

X26	0.009	0.184	0.049	0.051	0.031	0.687	0.041	1.452	0.009	0.019	0.080	1.392	0.081	0.083	0.081	0.083
X27	0.031	0.073	0.250	2.123	0.079	0.774	0.067	0.429	0.004	0.004	0.053	0.055	0.041	1.584	0.041	1.584
X28	0.006	0.007	0.042	0.045	0.041	1.128	0.020	0.021	0.015	0.454	0.035	0.037	0.028	0.030	0.028	0.030
X29	0.049	0.106	0.082	1.130	0.040	1.145	0.091	0.446	0.058	0.797	0.093	0.095	0.373	1.682	0.372	1.682
X30	0.092	0.436	0.470	3.459	0.090	1.130	0.488	1.384	0.010	0.417	0.201	0.687	0.115	0.480	0.115	0.480
	0.022	0.361	0.082	0.220	0.137	6.415	0.046	0.956	0.026	1.103	0.060	3.286	0.055	0.113	0.055	0.113
Main effects Only	79.736		53.985		68.651		73.112		97.950		58.096		62.586		62.586	
1st Order Interactions Only	17.077		24.146		22.103		18.889		0.830		24.932		22.731		22.731	
2nd or Higher Order Interactions	3.187		21.869		9.246		7.999		1.220		16.972		14.683		14.683	

List of Figures:

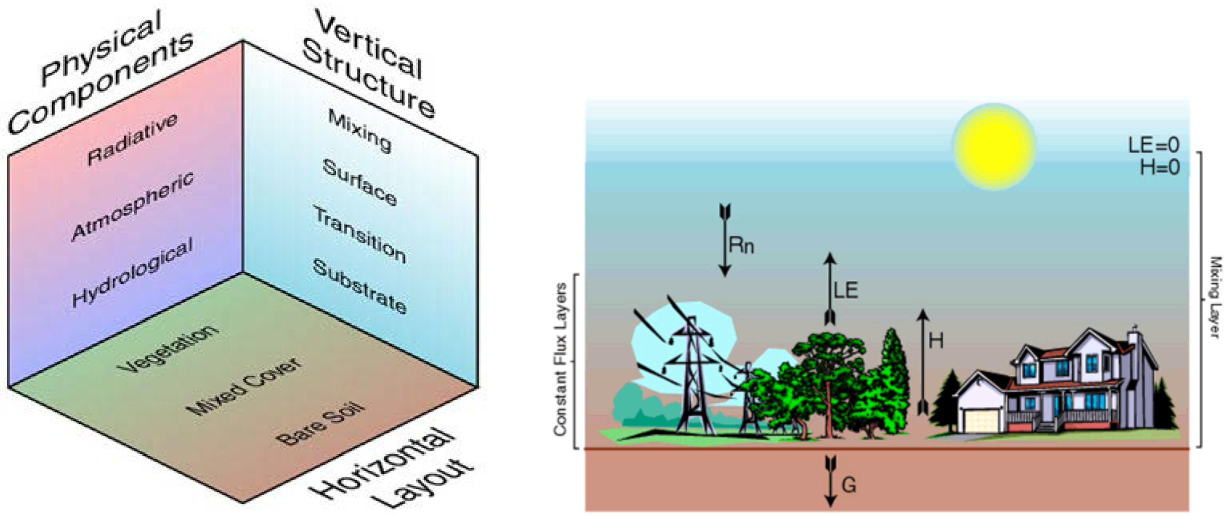
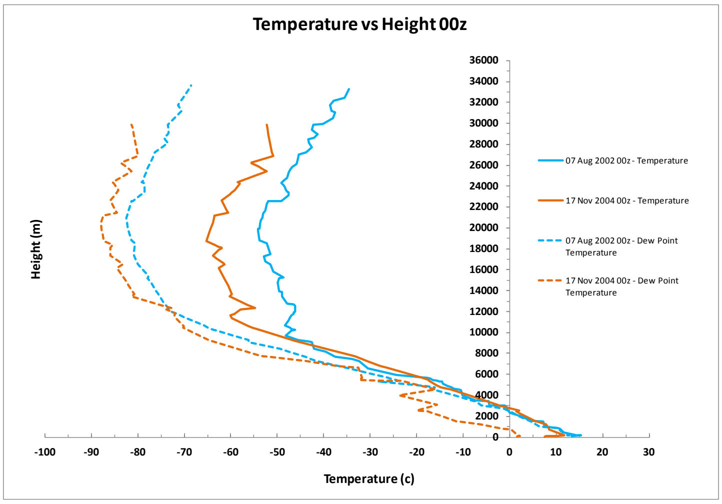
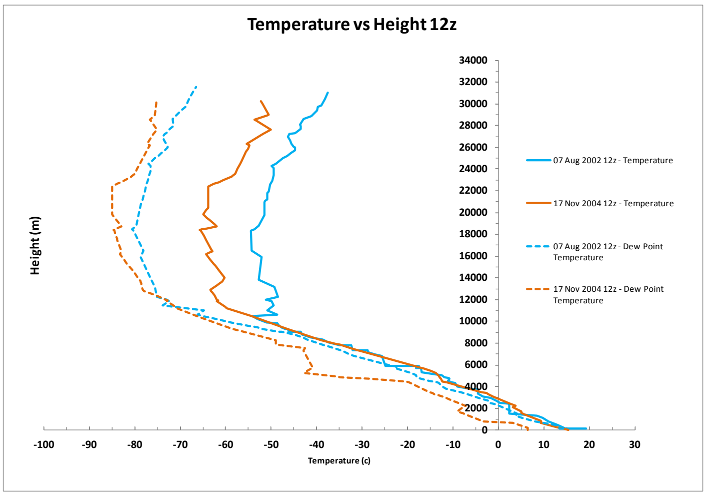
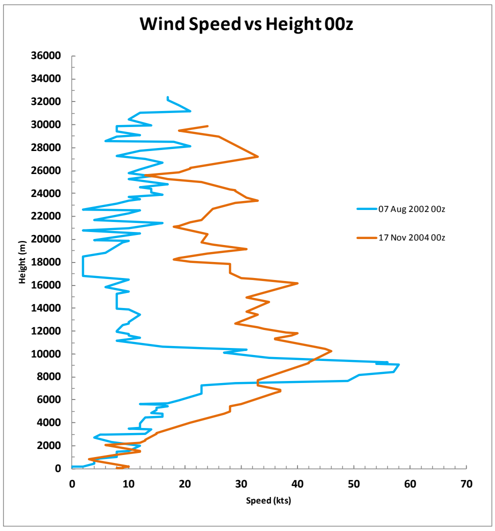


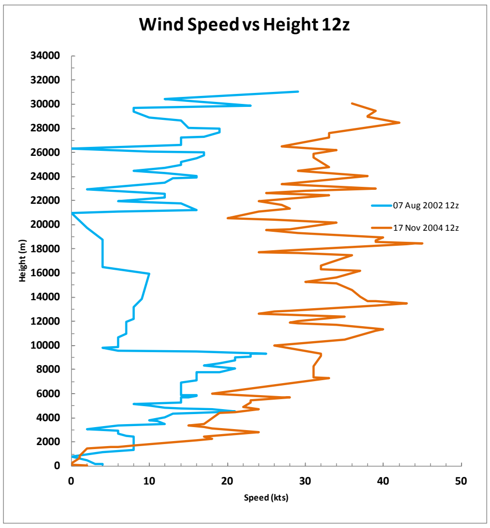
Figure 1. Left: The different layers of the SVAT model in the vertical domain; Right: a schematic representation of the surface energy balance components computation in the SVAT model (after SimSphere User's manual available at http://www.aber.ac.uk/en/iges/research-groups/earth-observation-laboratory/simsphere/workbook/preface/).



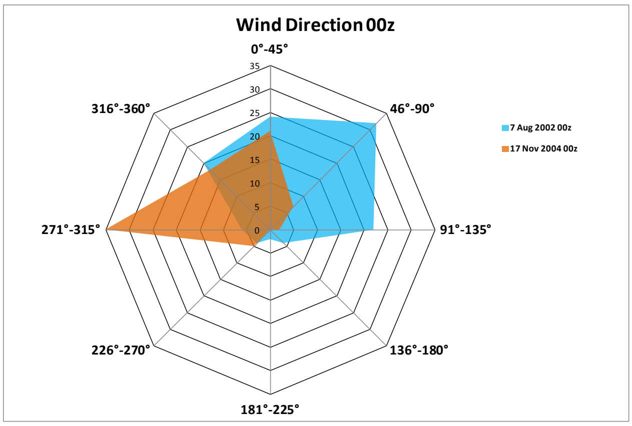


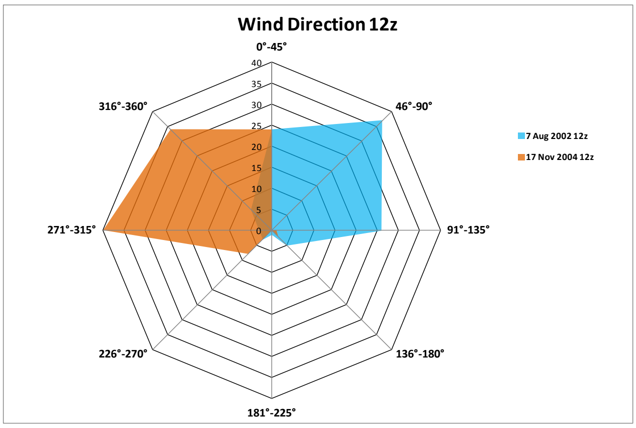
(a). (b).





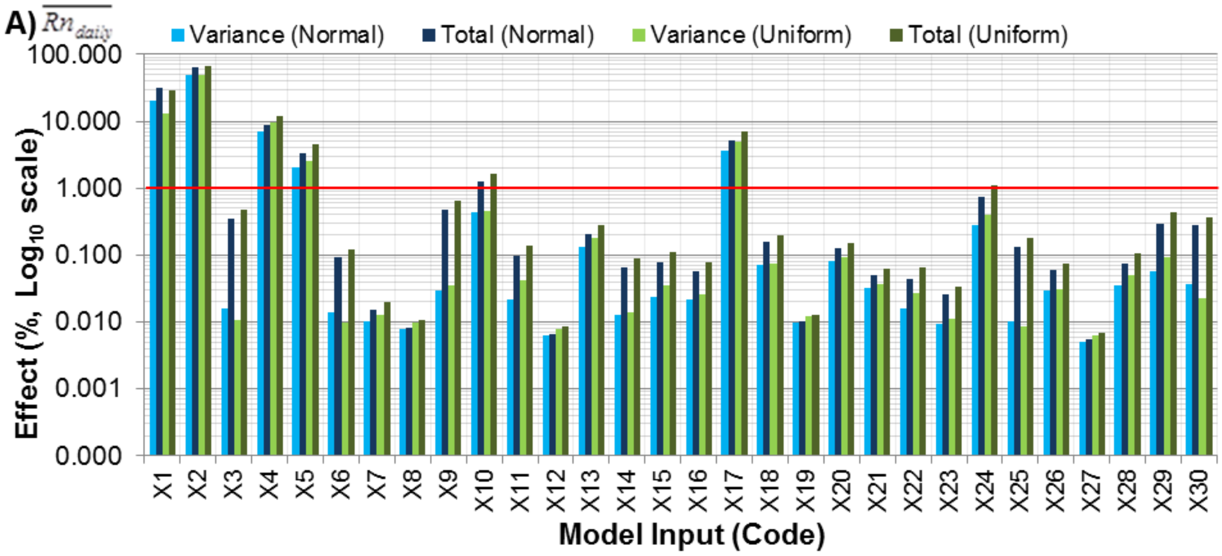
(c). (d).

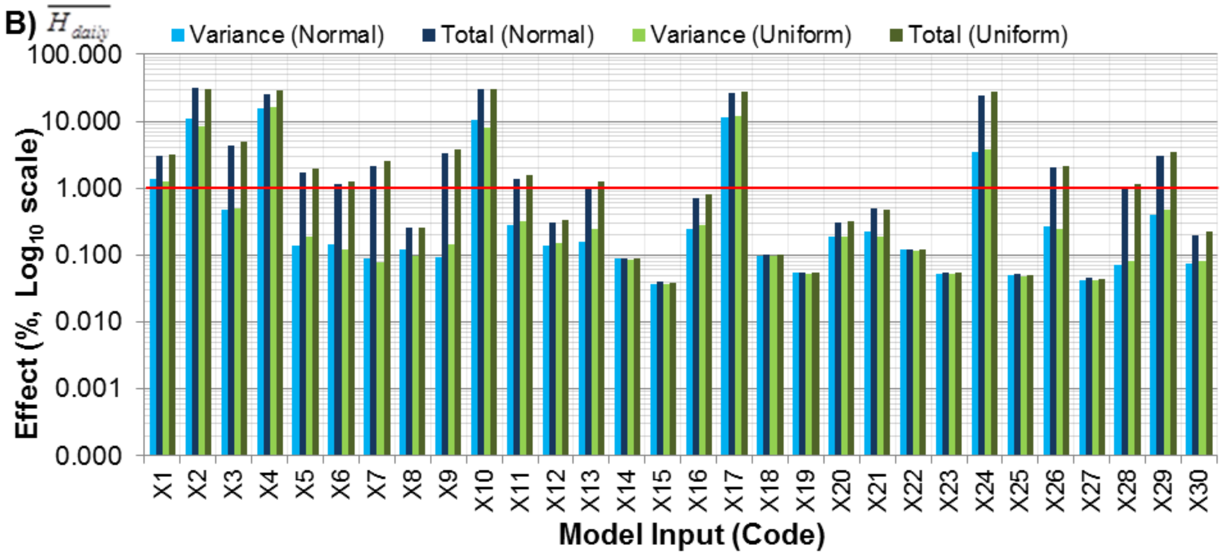


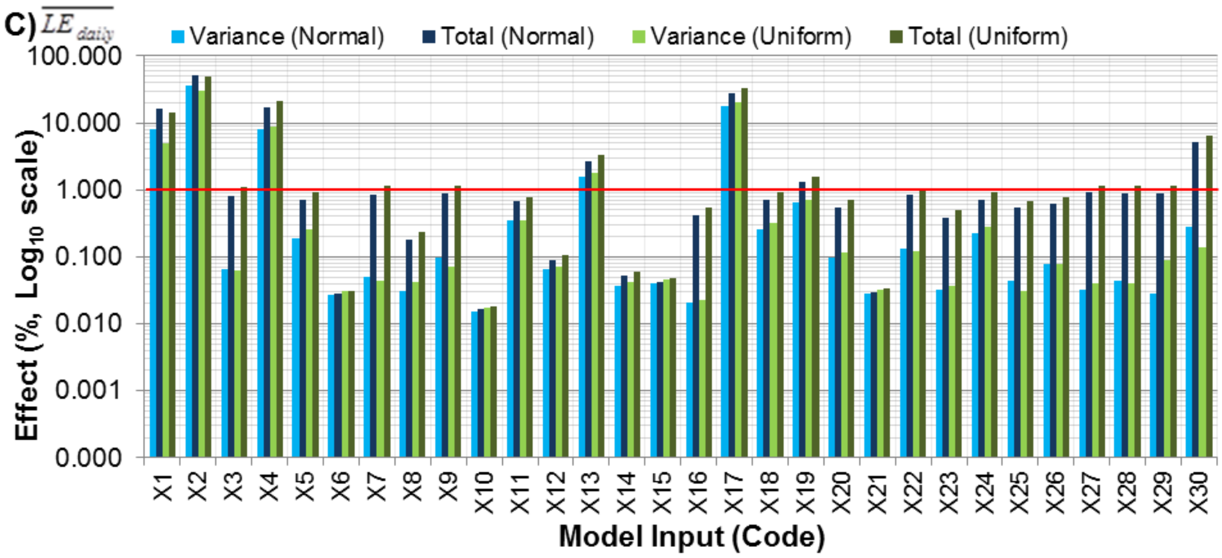


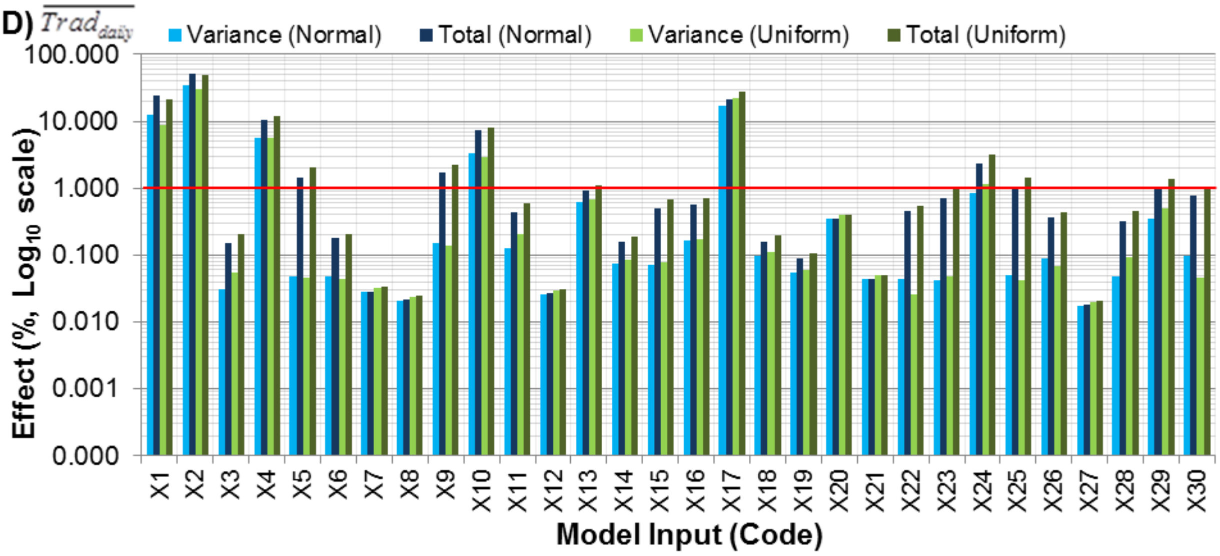
(e). (f).

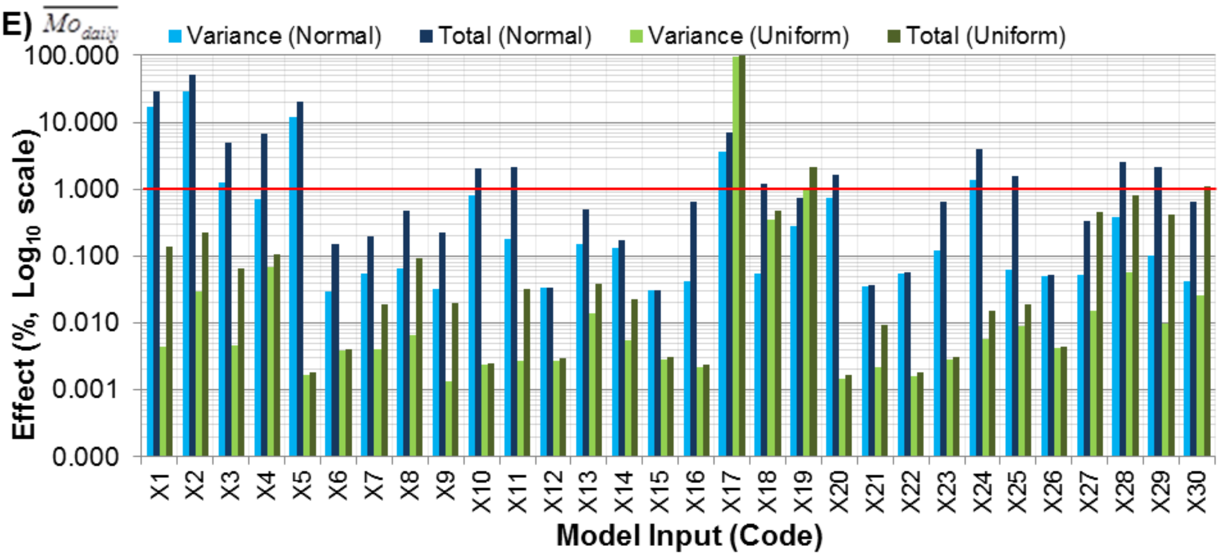
Figure 2: Atmospheric soundings used in the present study in comparison to the Petropoulos et al., (2009d) study for temperature (a,b), wind direction (c-d) and wind speed (e,f).

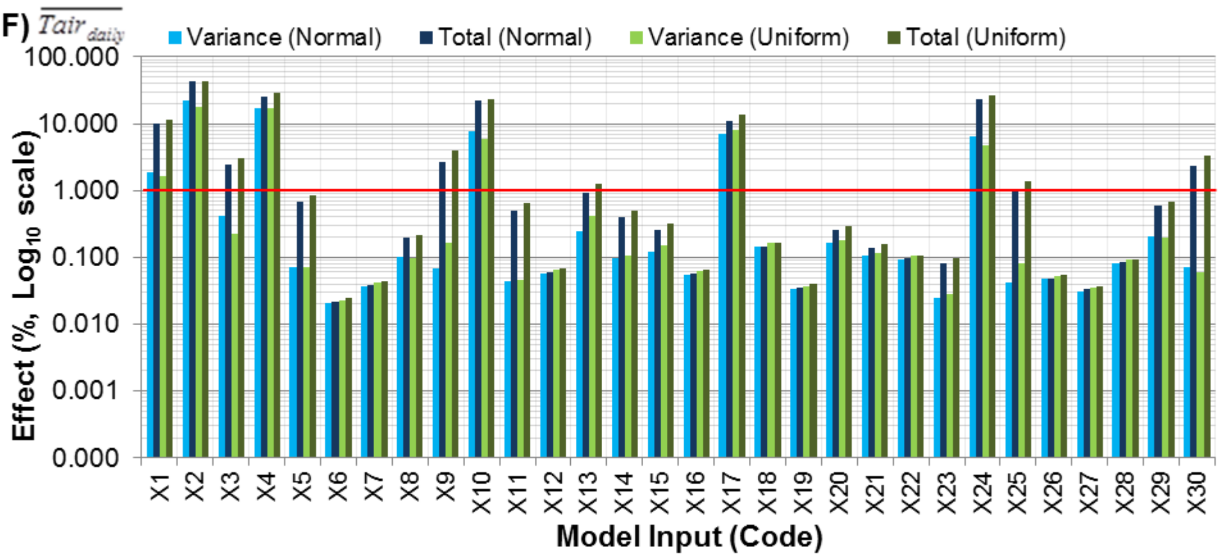

A) $\overline{Rn_{daily}}$
Variance (Normal)
Total (Normal)
Variance (Uniform)
Total (Uniform)
100.000
10.000
1.000
0.100
0.010
0.001
0.000
Effect (%, Log_{10} scale)
X1 X2 X3 X4 X5 X6 X7 X8 X9 X10 X11 X12 X13 X14 X15 X16 X17 X18 X19 X20 X21 X22 X23 X24 X25 X26 X27 X28 X29 X30
Model Input (Code)

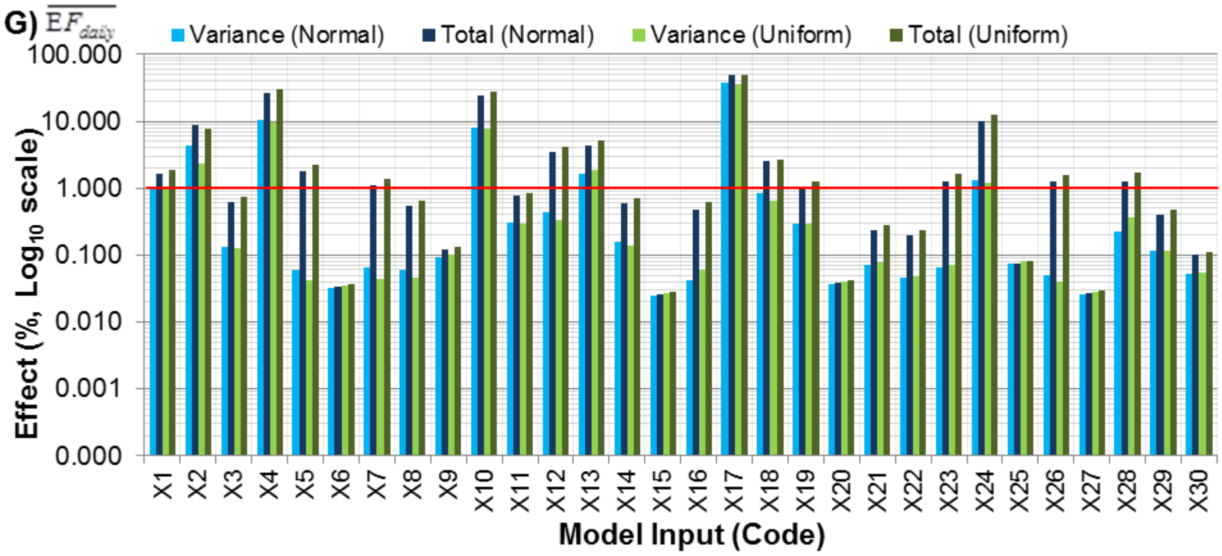

B) $\overline{H_{daily}}$
Variance (Normal)
Total (Normal)
Variance (Uniform)
Total (Uniform)
100.000
10.000
1.000
0.100
0.010
0.001
0.000
Effect (%, Log_{10} scale)
X1 X2 X3 X4 X5 X6 X7 X8 X9 X10 X11 X12 X13 X14 X15 X16 X17 X18 X19 X20 X21 X22 X23 X24 X25 X26 X27 X28 X29 X30
Model Input (Code)


C) $\overline{LE_{daily}}$
Variance (Normal)
Total (Normal)
Variance (Uniform)
Total (Uniform)
100.000
10.000
1.000
0.100
0.010
0.001
0.000
Effect (%, Log_{10} scale)
X1 X2 X3 X4 X5 X6 X7 X8 X9 X10 X11 X12 X13 X14 X15 X16 X17 X18 X19 X20 X21 X22 X23 X24 X25 X26 X27 X28 X29 X30
Model Input (Code)


D) $\overline{Trad_{daily}}$
Variance (Normal)
Total (Normal)
Variance (Uniform)
Total (Uniform)
100.000
10.000
1.000
0.100
0.010
0.001
0.000
Effect (%, Log_{10} scale)
X1 X2 X3 X4 X5 X6 X7 X8 X9 X10 X11 X12 X13 X14 X15 X16 X17 X18 X19 X20 X21 X22 X23 X24 X25 X26 X27 X28 X29 X30
Model Input (Code)


E) $\overline{Mo_{daily}}$
Variance (Normal)
Total (Normal)
Variance (Uniform)
Total (Uniform)
100.000
10.000
1.000
0.100
0.010
0.001
0.000
Effect (%, Log_{10} scale)
X1 X2 X3 X4 X5 X6 X7 X8 X9 X10 X11 X12 X13 X14 X15 X16 X17 X18 X19 X20 X21 X22 X23 X24 X25 X26 X27 X28 X29 X30
Model Input (Code)


F) $\overline{Tair_{daily}}$
Variance (Normal)
Total (Normal)
Variance (Uniform)
Total (Uniform)
100.000
10.000
1.000
0.100
0.010
0.001
0.000
Effect (%, Log_{10} scale)
X1 X2 X3 X4 X5 X6 X7 X8 X9 X10 X11 X12 X13 X14 X15 X16 X17 X18 X19 X20 X21 X22 X23 X24 X25 X26 X27 X28 X29 X30
Model Input (Code)



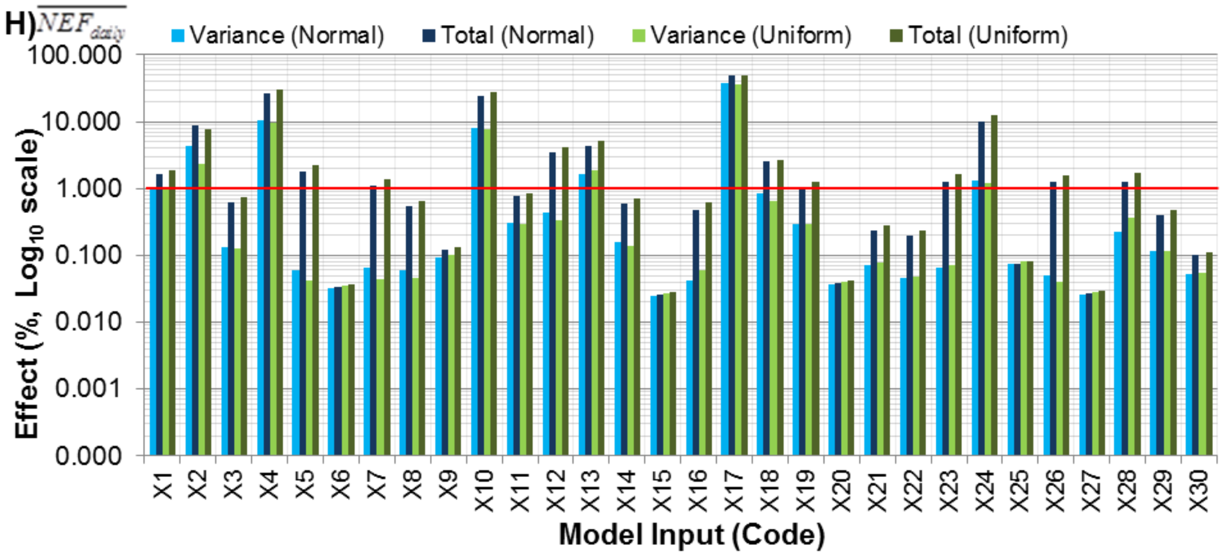


Figure 3. Variance Decomposition and total effects of the model inputs examined for (A) $\overline{Rn_{daily}}$, (B) $\overline{H_{daily}}$, (C) $\overline{LE_{daily}}$, (D) $\overline{Trad_{daily}}$, (E) $\overline{Mo_{daily}}$, (F) $\overline{Tair_{daily}}$, (G) $\overline{EF_{daily}}$ and (H) $\overline{NEF_{daily}}$. Vertical axis is logarithmic (Log_{10}), with the red line across the graphs at 1% signifying those parameters that are highlighted in Tables 3 and 4.