Improvement of Simulated Soil Moisture and Temperature from HRLDAS: A Case Study in East Asia by Parameter Uncertainty Quantification

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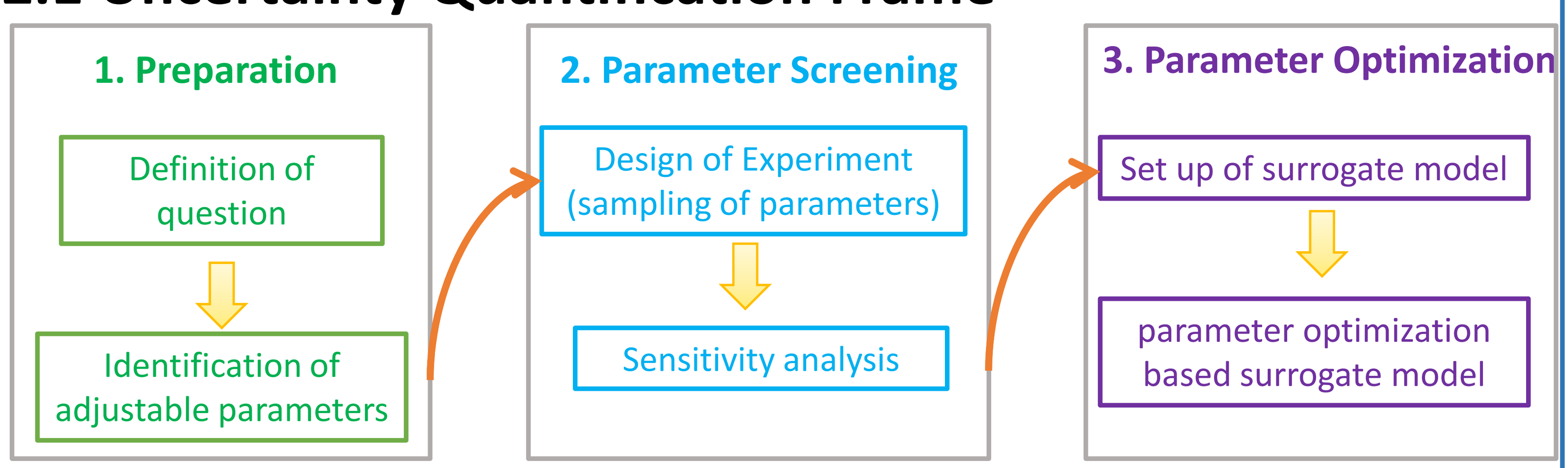
1. Introduction

In face of incomplete observations, reanalysis products covering the globe with consistent spatial and temporal resolution are the most important data tools to identify causes of climate variations and change, and to prepare more reliable predictions. Data assimilation, which works by updating model state variables with related observations, is a commonly used approach to create reanalysis products. On the other hand, model calibration, which works to improve model representation of physical processes by adjusting model parameters, can be a complementary approach to improve reanalysis products.

However, calibrating the parameters of land surface models is a challenging task which may consume unbearable computational time. Sensitivity analysis (SA) is one of the methods to help resolve this problem. SA shortens the calibration time by reducing the number of parameters needed to be calibrated. By optimizing only the sensitive parameters, we can reduce calibration time dramatically while improving model simulations. In this study, three qualitative methods are used to identify the sensitive parameters of the Noah-MP land surface model in East Asia continent. Sensitivities of different fluxes to the specification of 19 adjustable parameters in Noah-MP on different land cover types are evaluated.

2. Method

2.1 Uncertainty Quantification Frame



2.2 Sampling Method

The GLP design is generated by the following equations:

$$\begin{cases} q_{ki} = kh_i \pmod n \\ x_{ki} = (2q_{ki} - 1)/n \end{cases}, \quad k = 1, \ldots, n; \; i = 1, \ldots, s$$

If the lattice point set of $P_n = \{\mathbf{x}_k = (x_{k1}, \ldots, x_{ks}), k = 1, \ldots, n\}$ has the lowest discrepancy among all possible generating vectors, the point set is called GLP set.

2.3 Sensitivity Analysis Methods

Sum-Of-Trees (SOT) (Breiman, 2001; Chipman et al., 2010) is a classification and regression tree-based method. The importance of a variable is measured by the total split number for it.

Multivariate Adaptive Regression Splines (MARS) (Friedman, 1991) builds localized regression models (first-order linear or second-order nonlinear) instead of step functions.

$$GCV(\lambda) = \frac{\sum_{i=1}^{n} \left(y_i - \hat{f}_\lambda(x_i) \right)^2}{\left(1 - M(\lambda)/n \right)^2}$$

The importance of the removed variable is measured by the increase in GCV values between the pruned model and the over-fitted model (Steinberg et al., 1999).

Delta Test (DT) (Pi and Peterson,1994) is based on the nearest neighbor approach. The subset of variables corresponding to the minimum $\delta(\mathbf{S}) = \frac{1}{2N} \sum_{i=1}^{N} \left(y_{s(i)} - y_i \right)^2$ among all variable combinations are taken as the most sensitive ones.

3. Experimental Setup

3.1 Study Area and Forcing Data

The study area is located between 60-160°E and 0-65°N (Figure 1). CLDAS forcing data, hourly, 0.0625°×0.0625°, 2013 to 2014. Downward longwave radiation is by Idso (1981).

3.2 Noah-MP and Adjustable Parameters

Noah-MP was enhanced from the original Noah land surface model through the improved biophysical and hydrological processes, and the addition of multiparameterization options (Niu et al., 2011; Yang et al., 2011). The parameterizations used in this study shown in Table 2. Nineteen time-invariant parameters in Noah-MP are chosen as adjustable parameters (Table 3)

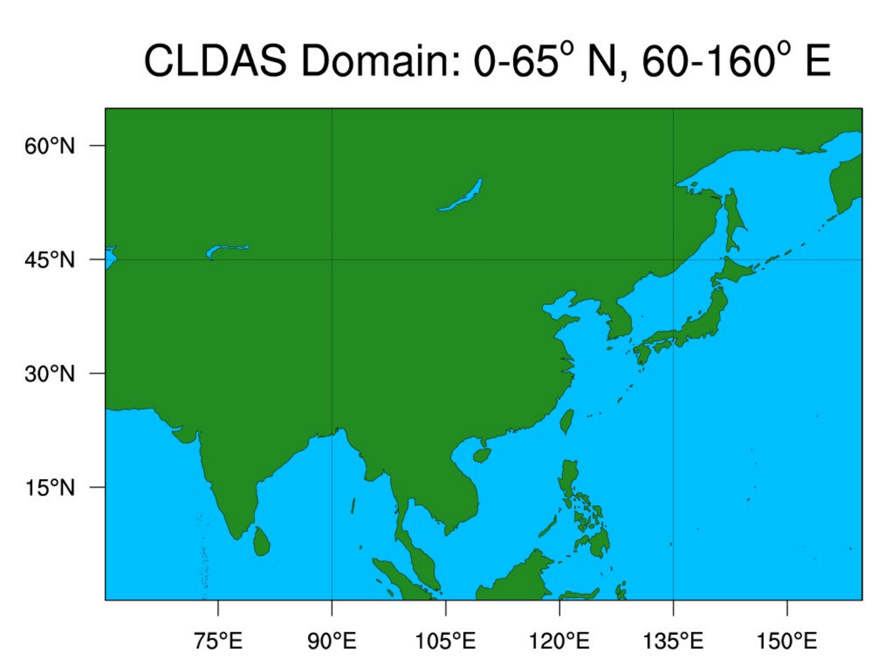


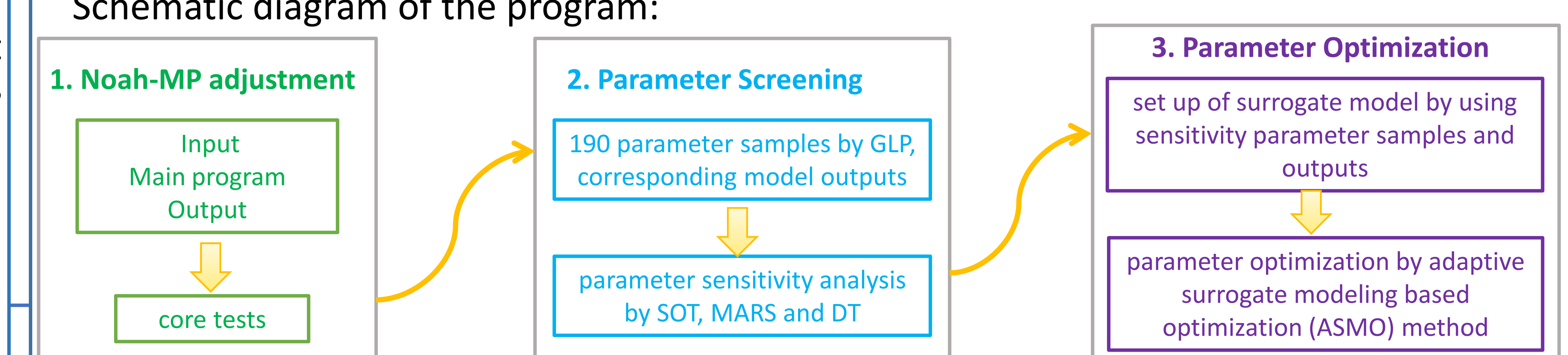
Fig 1. CLDAS domain

Table 3. Adjustable parameters in land use of irrigated cropland

Index	Parameter	Physical meaning	Category	Unit	Range
P1	CH2OP	maximum intercepted H_2O per unit (leaf area + stem area) index	canopy	mm	[0.4, 4]
P2	DLEAF	characteristic leaf dimension	canopy	m	[0.018, 0.04]
P3	Z0MVT	momentum roughness length	canopy	m	[0.01, 0.3]
P4	RC	tree crown radius	canopy	m	[0.01, 0.09]
P5	SLA	single-side leaf area per Kg	canopy	m^2/kg	[30, 80]
P6	VCMX25	maximum rate of carboxylation at 25℃	canopy	umol $CO_2/(m^2 \cdot s)$	[29, 194]
P7	CWPVT	empirical canopy wind parameter	canopy	-	[0.01, 0.99]
P8	TDLEF	characteristic temperature for leaf freezing	canopy	K	[268, 278]
P9	XL	leaf/stem orientation index	canopy	-	[-0.4, 0.6]
P10	SMCWLT	wilting point soil moisture	soil	-	[0.5, 1.2]
P11	SMCDRY	dry soil moisture threshold where direct evap from top layer ends	soil	-	[1.3, 2]
P12	SMCREF	field capacity	soil	-	[0.8, 1.05]
P13	SMCMAX	porosity, saturated value of soil moisture	soil	-	[0.98, 1.2]
P14	BEXP	Clapp and Hornberger "b" parameter	soil	-	[0.5, 1.5]
P15	PSISAT	saturated soil matric potential	soil	m	[0.5, 1.5]
P16	DKSAT	saturated soil hydraulic conductivity	soil	m/s	[0.5, 1.5]
P17	DWSAT	saturated soil hydraulic diffusivity	soil	m/s	[0.5, 1.5]
P18	REFKDT	surface runoff parameter	soil	-	[0.5, 5]
P19	CSOIL	Soil heat capacity	soil	$J/(m^3 \cdot K)$	[10^6, 3.4×10^6]

3.3 Design of Experiment:

Schematic diagram of the program:



4. Preliminary Results and Discussions

In the study, sensitivity parameters are screened out only on land cover type 3 with 190 sample points.

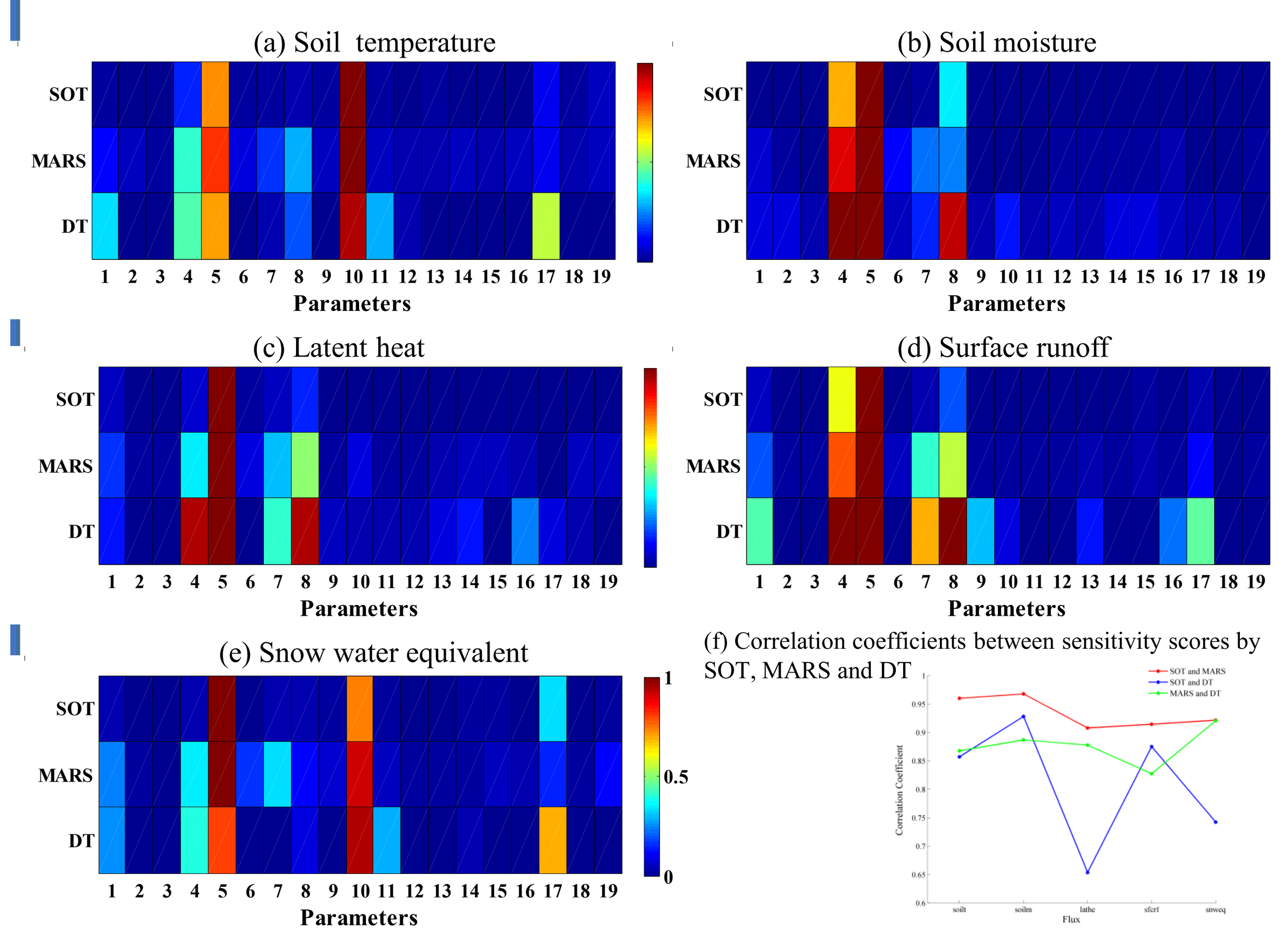


Fig 2. The qualitative sensitivity analysis results of different methods.

SOT and MARS give the similar sensitive analysis results, while DT tends to label less sensitive parameters as more sensitive parameters.

Sensitive parameters are determined and classified by the average value of sensitive scores obtained by three sensitivity analysis method.

Flux	High sensitive [0.66, 1)	Medium sensitive [0.33, 0.66)	Low sensitive [0.1,0.33)
Soil temperature	P5,P10	P4	P1,P8, P11, P17
Soil moisture	P4,P5	P8	P7
Latent heat	P5	P4,P8	P1,P7
Surface runoff	P4,P5	P7,P8	P1,P9,P17
Snow water equivalent	P5,P10	P17	P1,P4,P7,P11

P14, P3 identified as sensitive parameters in the study of Li et al. (2013) are non sensitive to soil temperature and moisture in our study. None of P11, P16, and P13 (Cai et al., 2014) is identified as sensitive parameter for surface runoff. Sensitive parameters in Chaney et al. (2016) are not included in the adjustable parameter list.

5. Conclusions

1. Soil temperature, soil moisture, latent heat, surface-runoff and snow water equivalent are highly sensitive to P5. Besides, P10 and P4 are identified as sensitive parameters for different fluxes.
2. SOT and MARS give the similar sensitive analysis results, while DT labels more sensitive parameters;
3. More samples are needed to give a reliable sensitive analysis result.

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Research interested : Land surface model calibrating.