Land Surface Model Parameter Sensitivity Analysis and Estimation in the Amazon Basin

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Outline

Paper #1 (Parameter Sensitivity Analysis): Assess parameter sensitivity analysis across all sites using SiB3' model using a newly proposed approach based on variance-based Sobol method accounting for full multi-output nature of land surface models

Paper #2 (Parameter Estimation): Substantial improvement (10-30% reduction of RMSE) in energy, water and CO₂ flux simulations after calibration but also identifying the sources of uncertainty

How could these ideas be applied to LBA-DMIP models?
Sobol application: Conventional approach

RMSE

LBA sites

RMSE

LBA sites

RMSE

LBA sites

Morphological
Optical
Physiological
Soil Properties
Carbon Properties

SiB3 parameters
Sobol application: New multi-objective approach

Example:

Carbon flux (NEE) for K67 site

Relative Sensitivity

S_{Ti} for F_2

RANK 1

RANK 2

RANK 3

RANK 4

RANK 5

RANK 6

RANK 7

RANK 8

RANK 9

RANK 10

Linear Correlation Coefficient, R

Number of Parameters, Npar
Sobol application: New multi-objective approach
Sobol application: New multi-objective approach

Relative Sensitivity

Number of Parameters, Npar

Linear Correlation Coefficient, R

S_{Ti} for F_1

S_{Ti} for F_2

Rank 1

Rank 2

Rank 3

Rank 4

Rank 5

RANK 1

RANK 2

RANK 3

RANK 4 ... RANK N

Example:

Carbon flux (NEE) for K67 site.
Sobol application: New multi-objective approach
Sobol application: New multi-objective approach
Sobol application: New multi-objective approach

The lower the rank (darker), the more sensitive a parameter is for a given site (taking into account the contribution from all objective functions; i.e. fluxes).

The top row is the weighted average results based on distinct biome types.
Common set of sensitive parameters to all biome types

“Influential Ranks” (H, LE, and NEE fluxes)

Physiological Properties = 8 parameters (vmaxO, effcon, gradm, binter, trop, shti, hlti, hhti)
Soil Properties = 6 parameters (bee, phsat, satco, poros, wssp and scalez)
Morphological = 2 parameters (z2 and vcovr)
Optical = 2 parameters (tran21 and ref21)
Soil Respiration = 2 parameters (wopt and respref)
Improved evolutionary optimization from genetically adaptive multimethod search

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In the last few decades, evolutionary algorithms have emerged as a revolutionary approach for solving search and optimization problems involving multiple conflicting objectives. Beyond their ability to search intractably large spaces for multiple solutions, these algorithms are able to maintain a diverse population of solutions and exploit similarities of solutions by recombination. However, existing theory and numerical experiments have demonstrated that it is impossible to develop a single algorithm for population evolution that is always efficient for a diverse set of optimization problems. Here we show that significant improvements in the efficiency of evolutionary search can be achieved by running multiple optimization algorithms simultaneously using new concepts of global information sharing and genetically adaptive offspring creation. We call this approach a multialgorithm, genetically adaptive multiobjective, or AMALGAM, method, to evoke the image of a procedure that merges the strengths of different optimization algorithms. Benchmark results using a set of well known multiobjective test problems show that AMALGAM approaches a factor of 10 improvement over current optimization algorithms for the more complex, higher dimensional problems. The AMALGAM method provides new opportunities for solving previously intractable optimization problems.

A Multi-Algorithm Genetically Adaptive Multiobjective method - AMALGAM
(Vrugt and Robinson, 2007)
We select a \textbf{‘compromise’} solution, for which average normalized RMSE of errors in matching all three fluxes is minimum. This solution provides a balanced (\textbf{equally weighted}) reproduction of all three fluxes.
Improvement RMSE for simulated fluxes at seasonal-scale

- **RJA**
  - Improvement: 
    - **ALL = 41%**
    - **WET = 40%**
    - **DRY = 43%**

- **K83**
  - Improvement: 
    - **ALL = 14%**
    - **WET = 7%**
    - **DRY = 21%**

- **K67**
  - Improvement: 
    - **ALL = 30%**
    - **WET = 31%**
    - **DRY = 28%**
Improvement RMSE for simulated fluxes at seasonal-scale

![Graph showing carbon fluxes for different months with seasonal-scale RMSE improvements.]

- **Default**
  - Blue line: An
  - Red line: Rs
  - Green line: NEE

- **Calibrated**
  - Blue line: An
  - Red line: Rs
  - Green line: NEE

The graphs illustrate the improvement in RMSE for carbon fluxes at seasonal-scale, with a focus on the months of January to December. The y-axis represents carbon (kg ha$^{-1}$), and the x-axis represents the months from January to December.
Consistency of calibrated parameters:
Canopy Height & Total Soil Depth

Evergreen Broadleaf Forest
- Default
- Calibrated

Deciduous Broadleaf Forest
- Default
- Calibrated

Savanna
- Default
- Calibrated

Cropland Pastureland
- Default
- Calibrated
Consistency of calibrated parameters:
Soil Water Stress Curvature Parameter

SiB3 originally assumes this to be a constant (wssp = 0.20)

K77 (cropland/pastureland) \(\rightarrow\) wssp = 0.65
K83 (selectively-logged forest) \(\rightarrow\) wssp = 0.21
K67 (undisturbed forest) \(\rightarrow\) wssp = 0.01
Mean-Squared-Error (MSE) Decomposition (Gupta et al. 2009)

\[
MSE = \left( \mu_s - \mu_o \right)^2 + \left( \sigma_s - \sigma_o \right)^2 + 2 \cdot \sigma_s \cdot \sigma_o \cdot (1-r)
\]

- Error in Signal Mean
- Error in Signal Variability
- Error in Timing and shape

\[
\begin{align*}
\mu_s & \approx \mu_o \\
3\sigma_s & \approx 3\sigma_o \\
r & \approx 0
\end{align*}
\]
Mean-Squared-Error (MSE) Decomposition (Gupta et al. 2009)

\[
MSE = \left(\mu_s - \mu_o\right)^2 + \left(\sigma_s - \sigma_o\right)^2 + 2 \cdot \sigma_s \cdot \sigma_o \cdot (1 - r)
\]

- Error in Signal Mean
- Error in Signal Variability
- Error in Timing and shape

Rearranging terms so individual signals are directly related to cross-correlation coefficient \((r)\):

\[
MSE_{\text{non-dimensional}} = \frac{MSE}{2 \cdot \sigma_s \cdot \sigma_o} = \frac{\left(\mu_s - \mu_o\right)^2}{2 \cdot \sigma_s \cdot \sigma_o} + \frac{\left(\sigma_s - \sigma_o\right)^2}{2 \cdot \sigma_s \cdot \sigma_o} + (1 - r)
\]

- Signal Mean
- Signal Variability
- Timing and shape
MSE Decomposition: Reduced error in signal mean and signal variability

Signal Mean

Signal Variability

Timing and shape

Percent contribution to overall uncertainty from individual components

- 2% 3% 95%
- 9% 23% 68%
- 2% 9% 89%
- 6% 12% 82%
- 1% 10% 90%
- 11% 9% 80%
Summary

1. Newly proposed parameter sensitivity analysis approach based on variance-based Sobol method accounting for full multi-output nature of land surface models.

2. Substantial improvement (10-30% reduction of RMSE) in energy, water and CO₂ flux simulations after calibration.

Additional:

- Deeper effective soil depth needed;
- Soil water stress curvature parameter different among biome types;
- Improvement in model performance is achieved by reducing the signal mean and signal variability components of parameter uncertainty but the timing/shape (i.e., system dynamics) is little affected.
Uncertainty sources at seasonal and diurnal scales

This is another optimization exercise (randomly generated parameters) and parameter set is selected based on individual minimization of each flux.