Improving the Performance of an Eco-Hydrological Model to Estimate Soil Moisture and Vegetation Dynamics by Assimilating Microwave Signal

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the University of Tokyo

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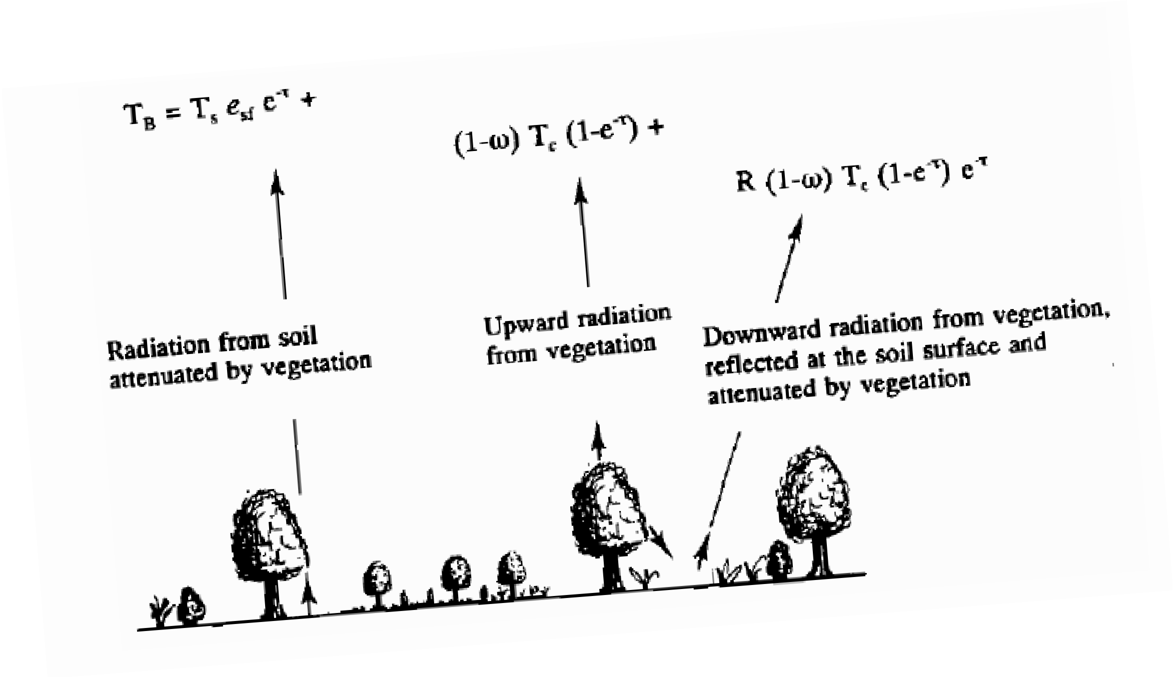
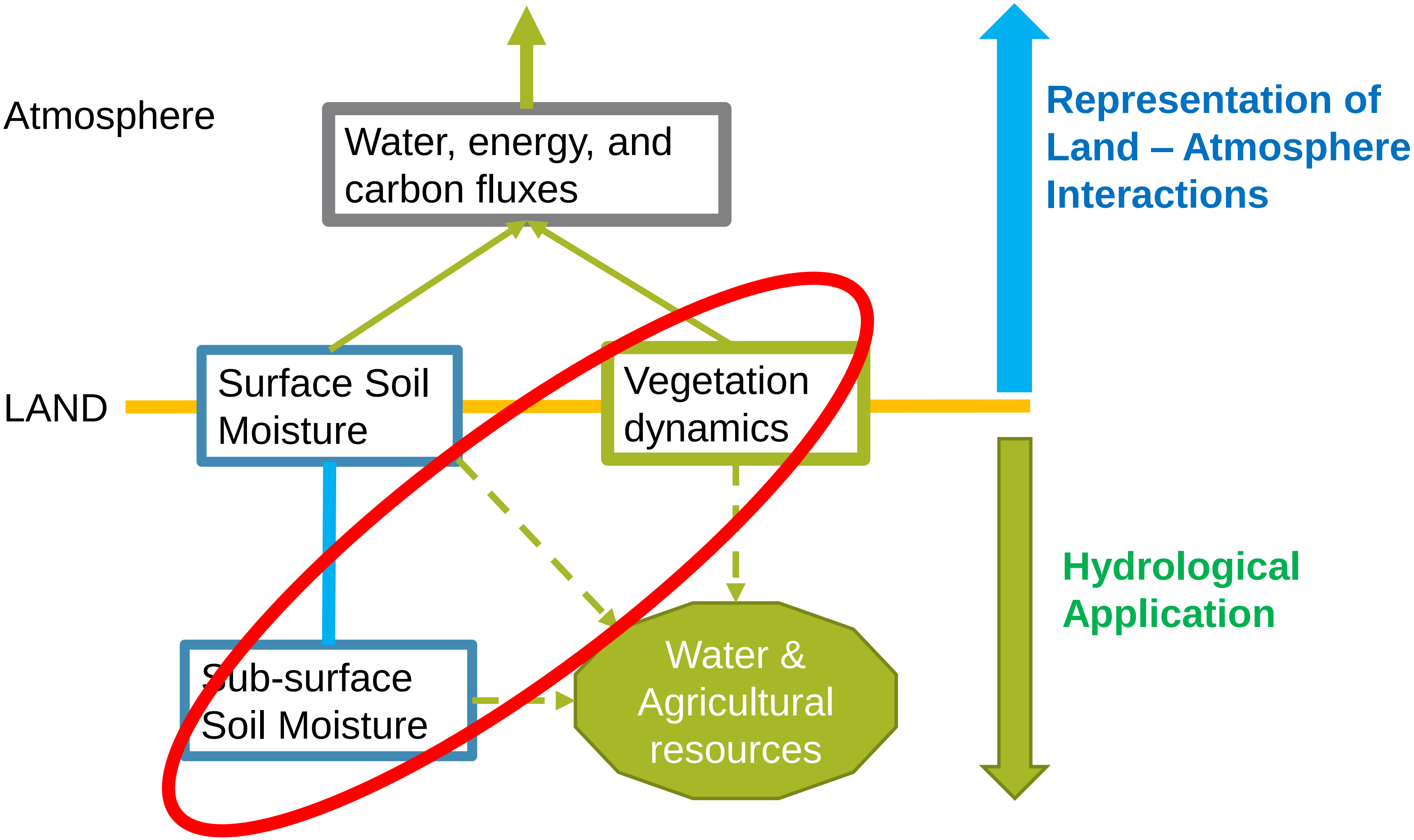


1. Introduction

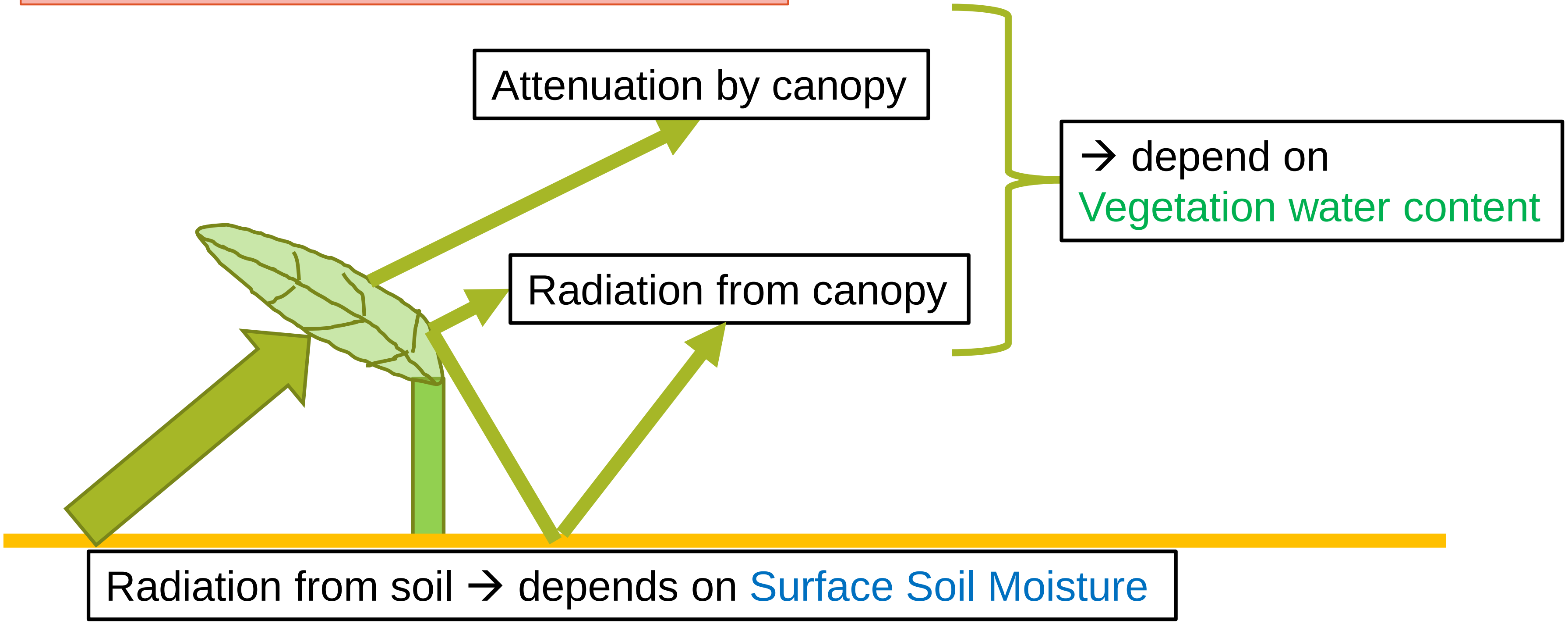
1.1. Motivation



→ A microwave land data assimilation system that can address the interactions between subsurface soil moisture and vegetation dynamics has yet to be established.

1.2. Application of Passive Microwave Remote Sensing

Radiative Transfer in microwave region



Attenuation by canopy

Radiation from canopy

→ depend on Vegetation water content

Radiation from soil → depends on Surface Soil Moisture

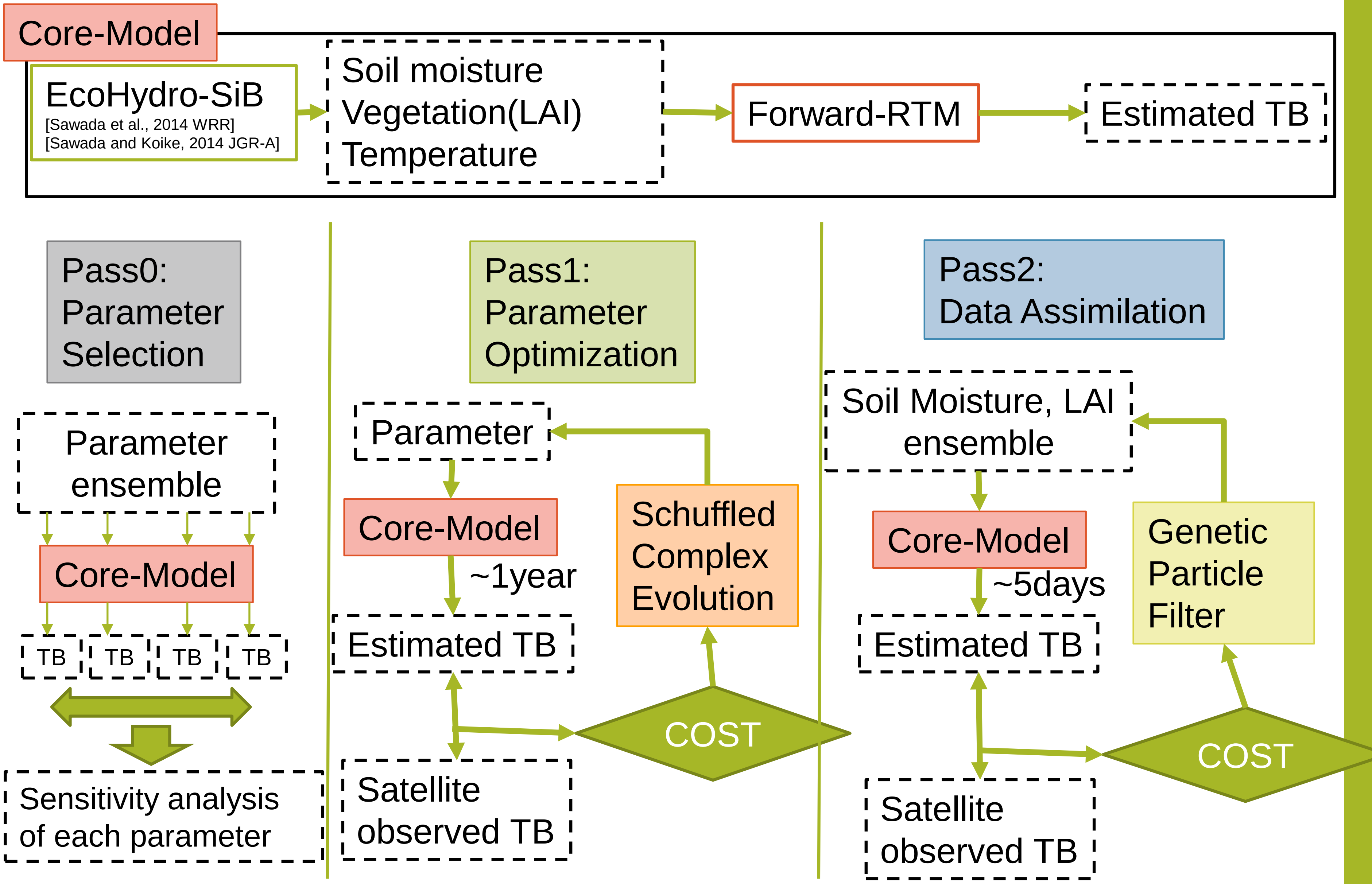
- Microwave brightness temperature is influenced by surface soil moisture, vegetation water content, and temperature [e.g., Paloscia and Pampaloni, 1988]

→ By assimilating this data, we can improve the skill of eco-hydrological model to simultaneously calculate soil moisture and vegetation dynamics.

1.3. GOAL

- Estimating both hydrological and ecological unknown parameters in eco-hydrological model that can simulate both soil moisture and vegetation dynamics.
- Obtaining initial conditions of soil moisture vertical profile and biomass for prediction by assimilating microwave brightness temperatures.

1.4. Coupled Land and Vegetation Data Assimilation System (CLVDAS)



Core-Model

EcoHydro-SiB
[Sawada et al., 2014 WRR]
[Sawada and Koike, 2014 JGR-A]

Soil moisture
Vegetation(LAI)
Temperature

Forward-RTM

Estimated TB

Pass0:
Parameter
Selection

Parameter
ensemble

Core-Model

TB TB TB TB

Sensitivity analysis
of each parameter

Pass1:
Parameter
Optimization

Parameter

Core-Model

~1year

Estimated TB

Satellite
observed TB

COST

Schuffled
Complex
Evolution

Pass2:
Data Assimilation

Soil Moisture, LAI
ensemble

Core-Model

~5days

Estimated TB

Satellite
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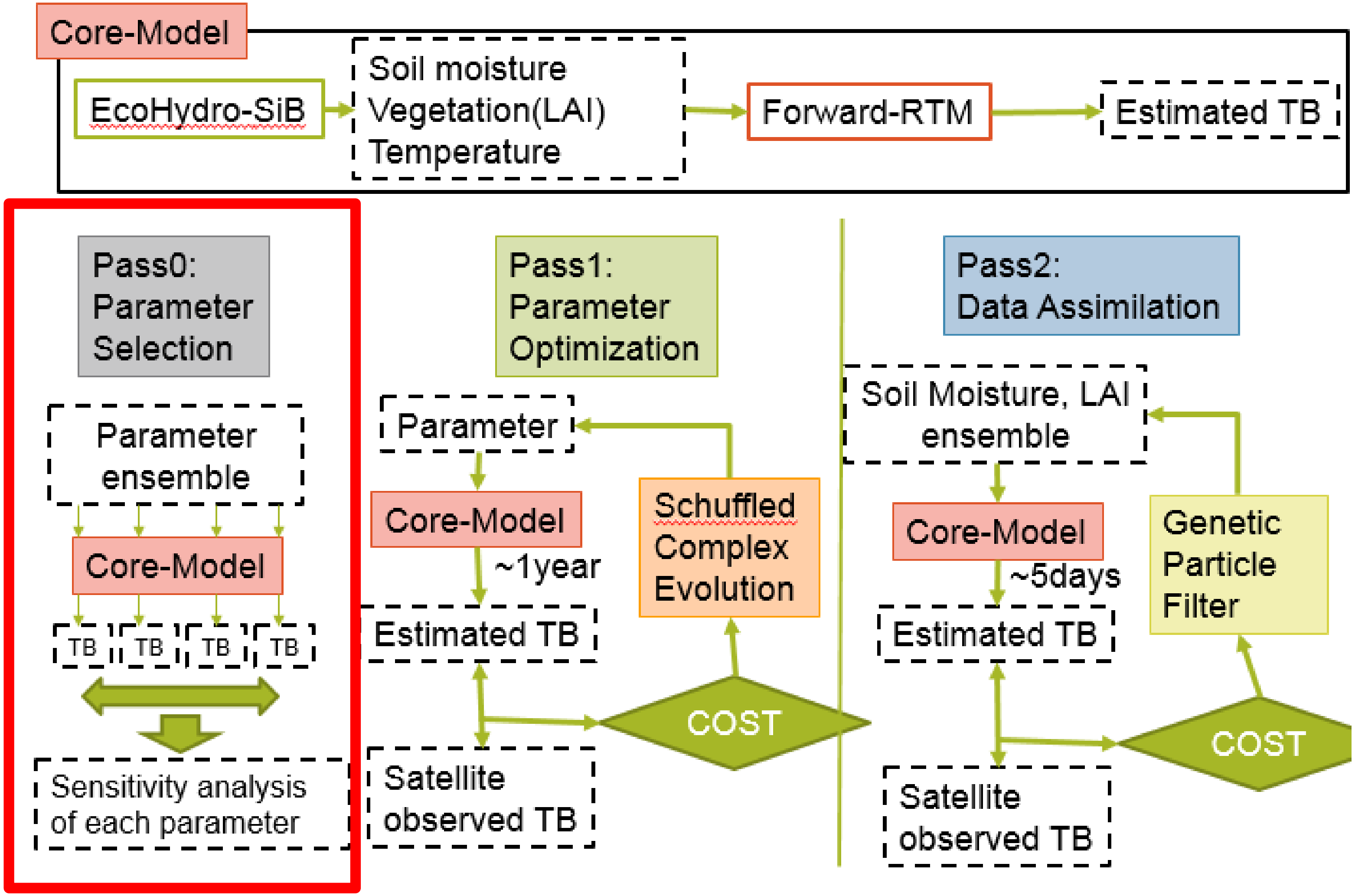
COST

Genetic
Particle
Filter

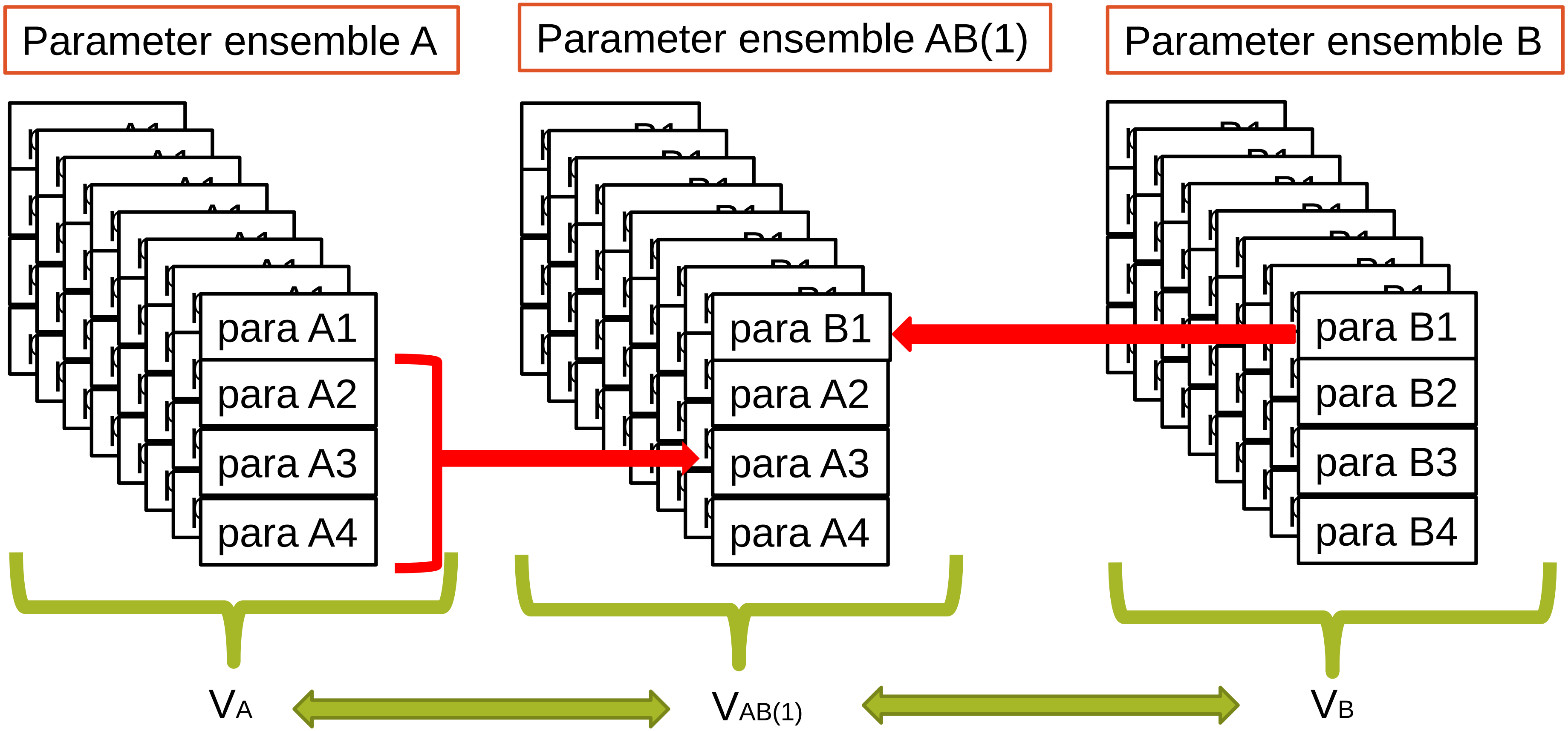


2. Parameter Selection Strategy

2.1. Global Sensitivity Analysis (GSA) [Saltelli et al., 2010]

$$V_Y = \sum_i V_i + \sum_{i<j} V_{ij} + \sum_{i<j<k} V_{ijk} + \ldots\ldots + V_{12\ldots n}$$

→ Total variance of the model's output is decomposed to the variance that come from each parameter uncertainty.



Parameter ensemble A

para A1
para A2
para A3
para A4

Parameter ensemble AB(1)

para B1
para A2
para A3
para A4

Parameter ensemble B

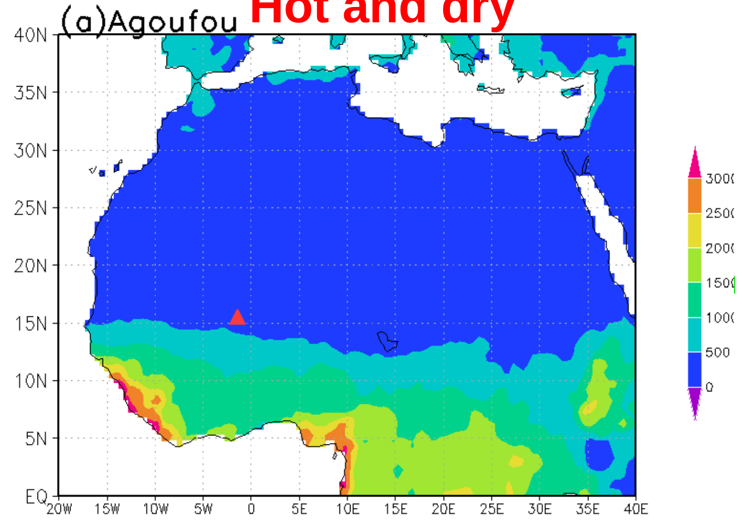
para B1
para B2
para B3
para B4

V_A

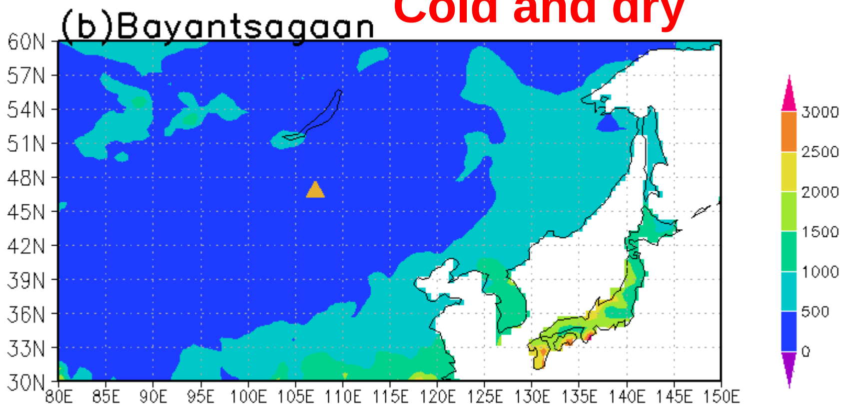
$V_{AB(1)}$

V_B

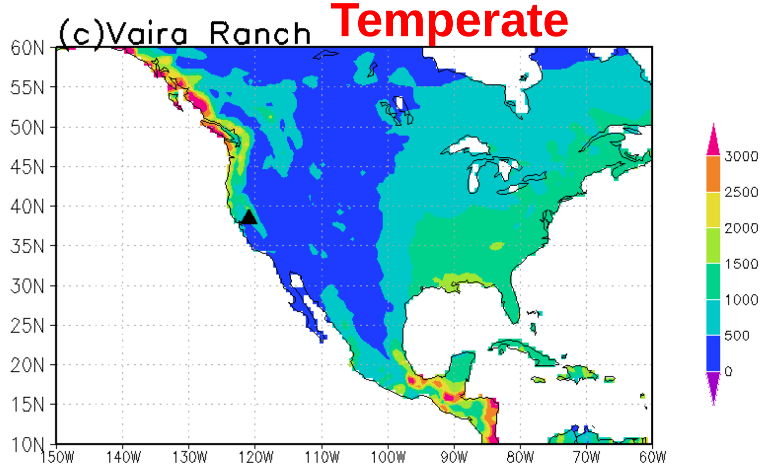
2.2. Study area & Experiment design



Hot and dry



Cold and dry

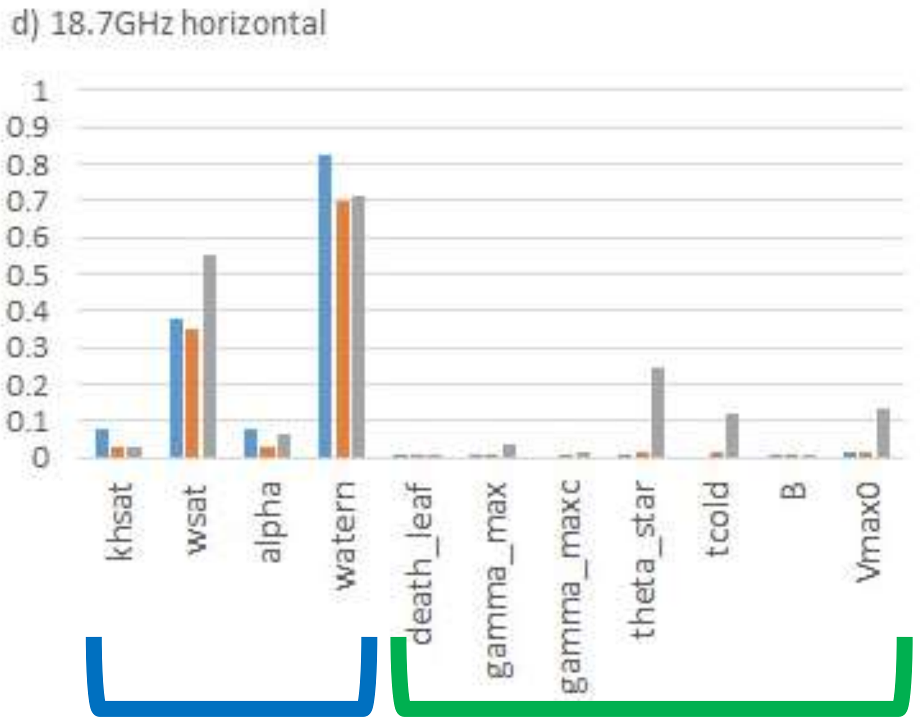


Temperate

- CLVDAS is applied to three in-situ sites that have different hydroclimatic conditions.
- All land use are grassland.
- Model is driven by in-situ meteorological forcings.

2.3. Results

Parameter Sensitivity to TBs (18.7GHz Horizontal)



Hydrological parameters （e.g., hydraulic conductivity）

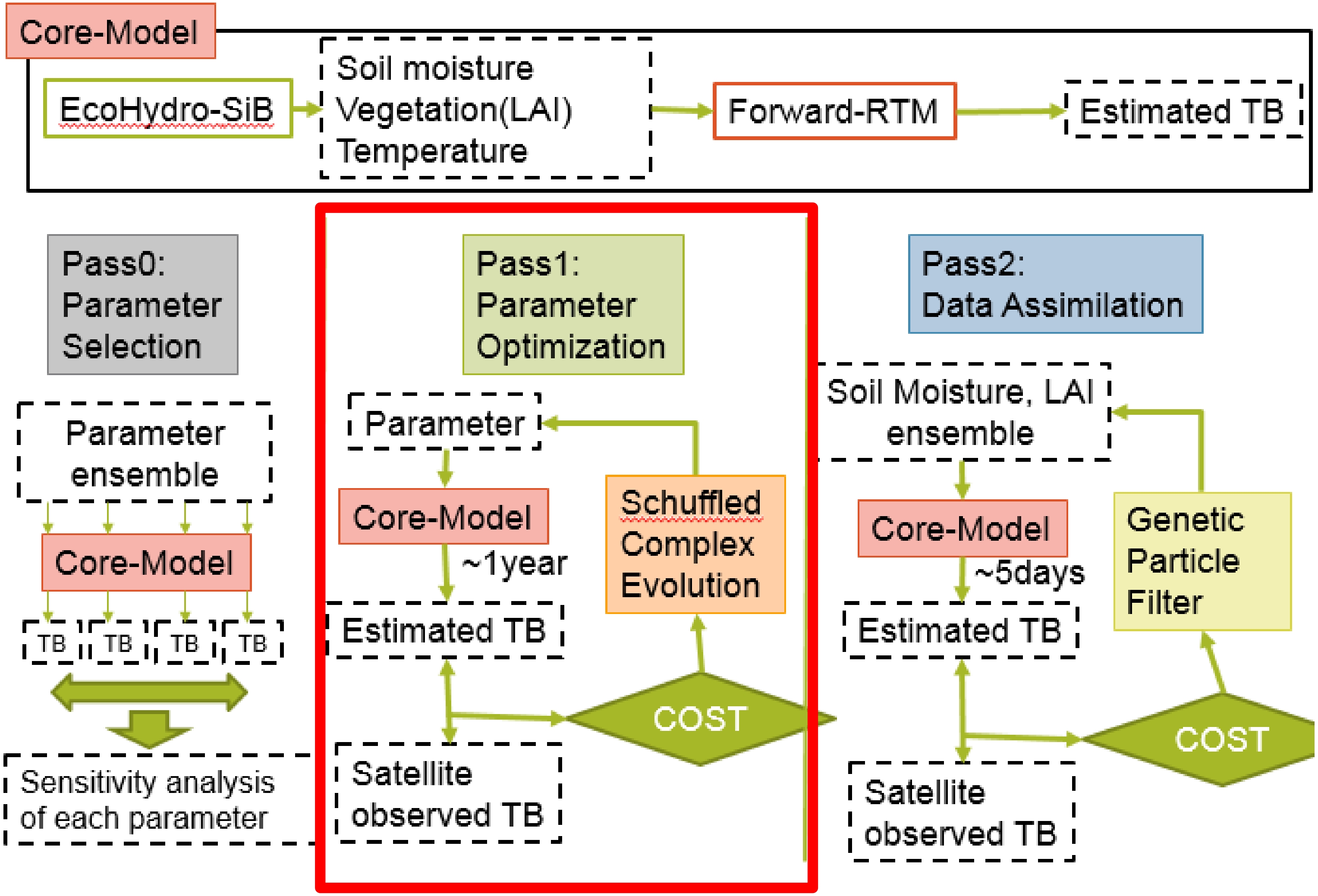
Ecological parameters （Maximum efficiency of Rubisco）

Blue：West Africa (Hot and dry)
Orange：Mongolia (cold and dry)
Gray：California (US) (temperate)

→ In dry area, we can improve the performance by tuning only hydrological parameters

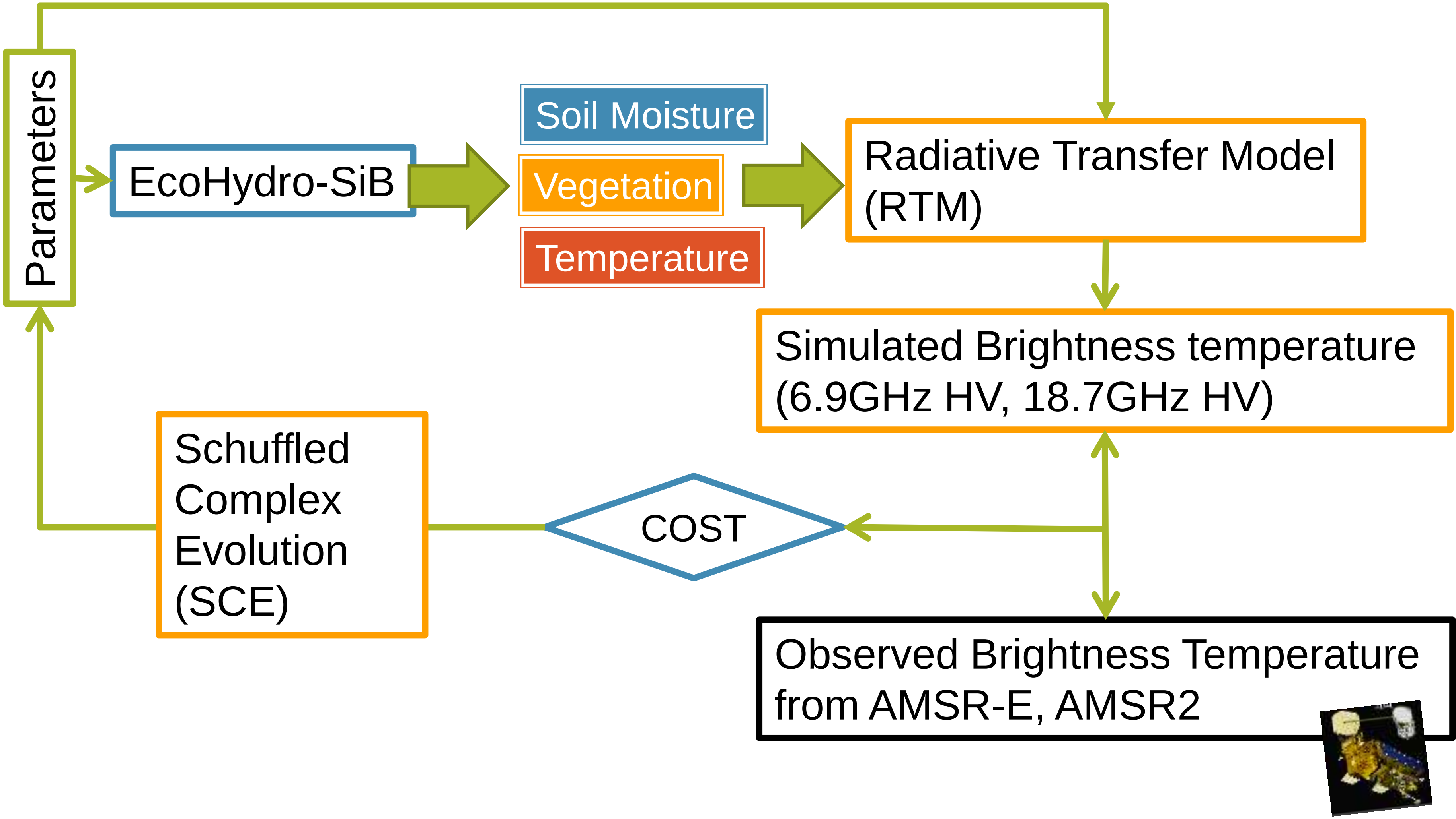
→ We can reduce the number of the calibrated parameters by using GSA.

[Sawada and Koike, 2014 JGR-A]



3. Parameter Optimization

3.1. Pass 1 : Parameter Optimization



Parameters

EcoHydro-SiB

Soil Moisture

Vegetation

Temperature

Radiative Transfer Model (RTM)

Simulated Brightness temperature (6.9GHz HV, 18.7GHz HV)

Schuffled Complex Evolution (SCE)

COST

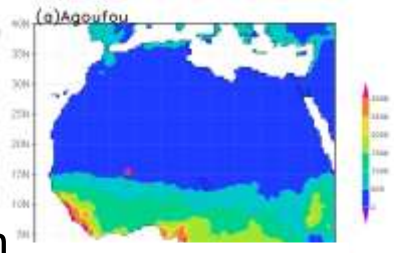
Observed Brightness Temperature from AMSR-E, AMSR2

→ CLVDAS optimizes parameters by minimizing the difference between modeled and observed brightness temperature.

3.2 Results @ West Africa

Green: Optimized, Black：Default,

Red：Observed, Yellow：Observed (Microwave VOD (NASA LPRM))

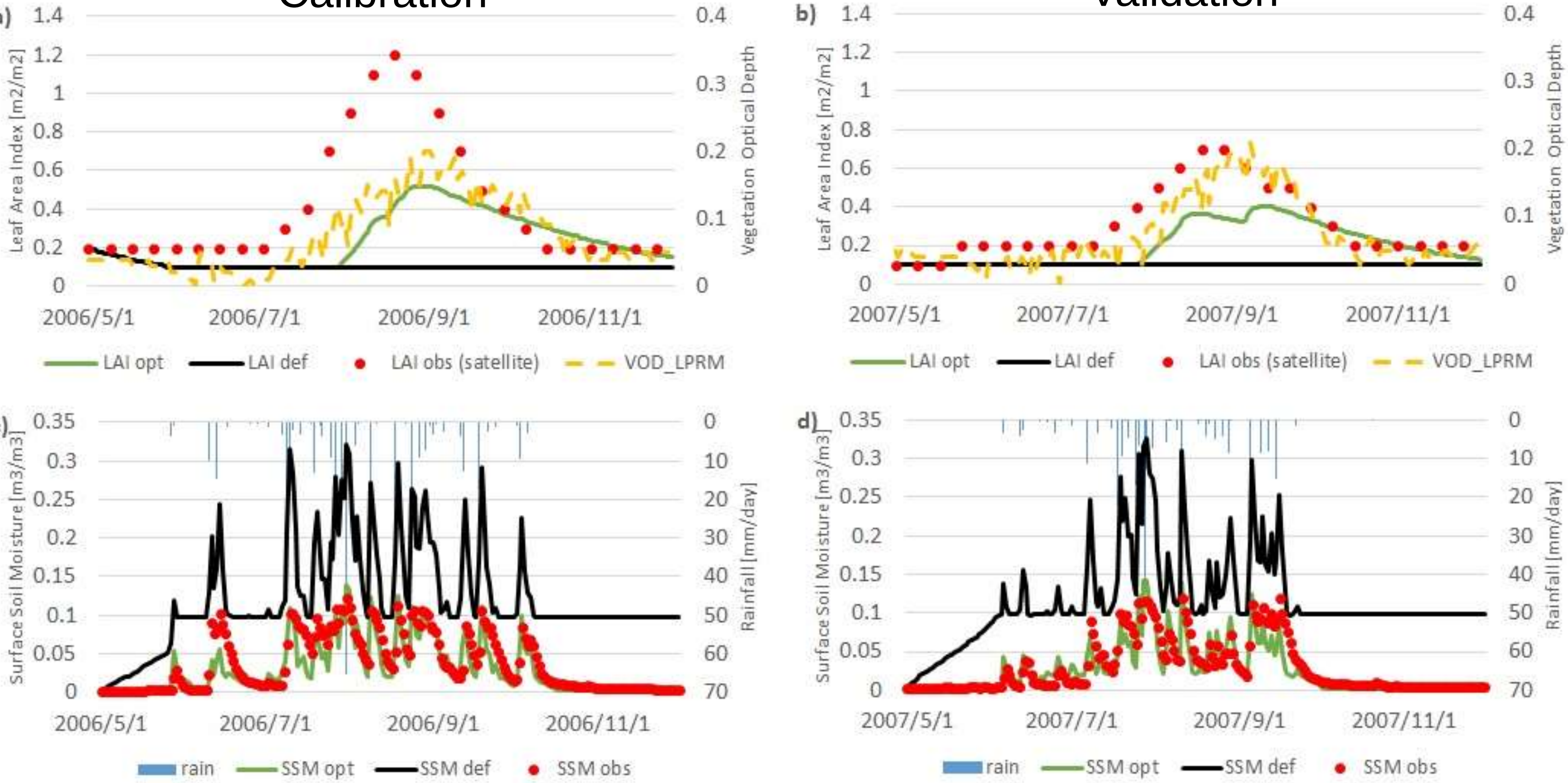


Calibration

Validation

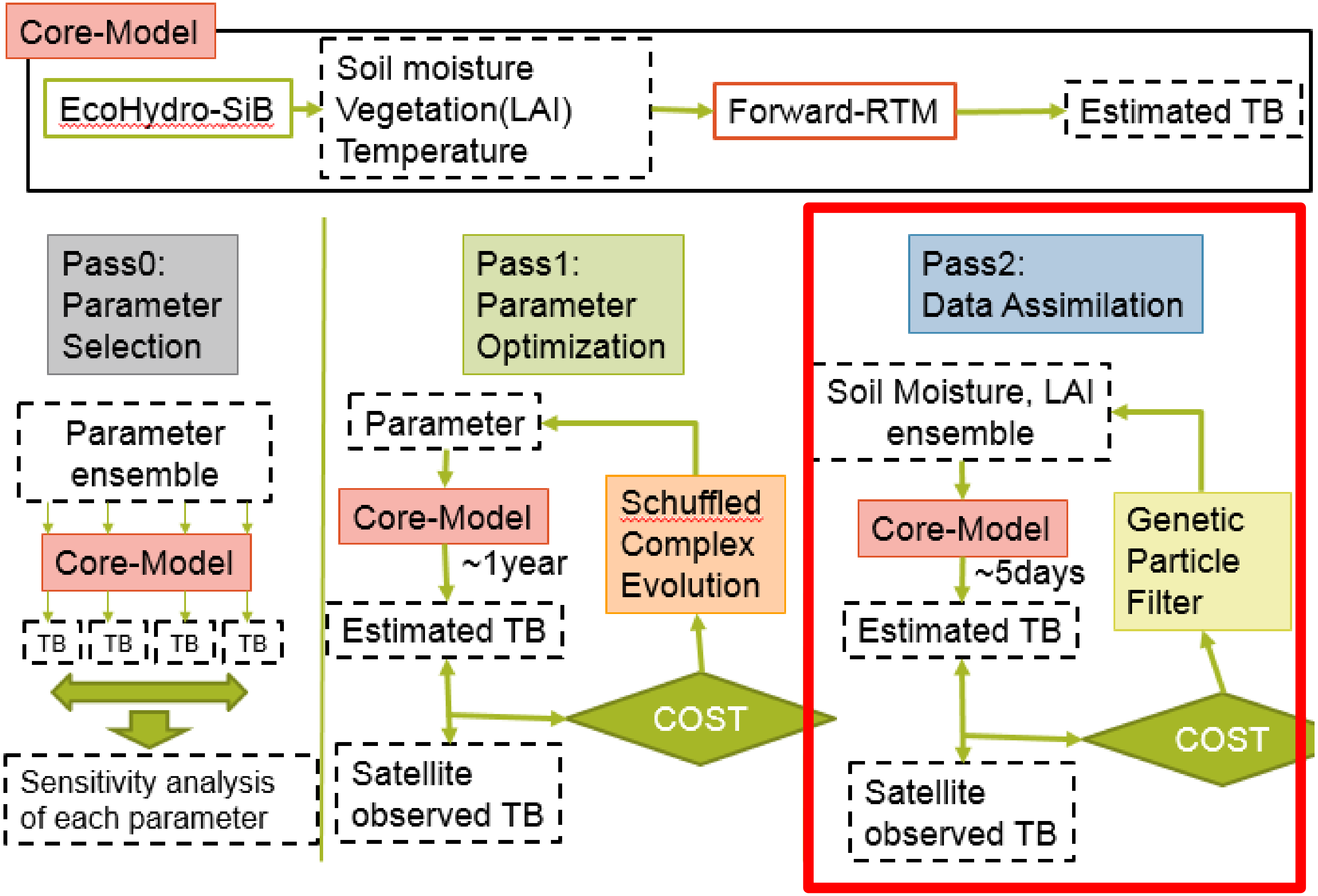
LAI

Surface Soil Moisture



[Sawada and Koike, 2014 JGR-A]

- **Optimization improves the skill of estimating surface soil moisture and vegetation dynamics at the same time.**



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Soil Moisture, LAI
ensemble

Core-Model

~5days

Estimated TB

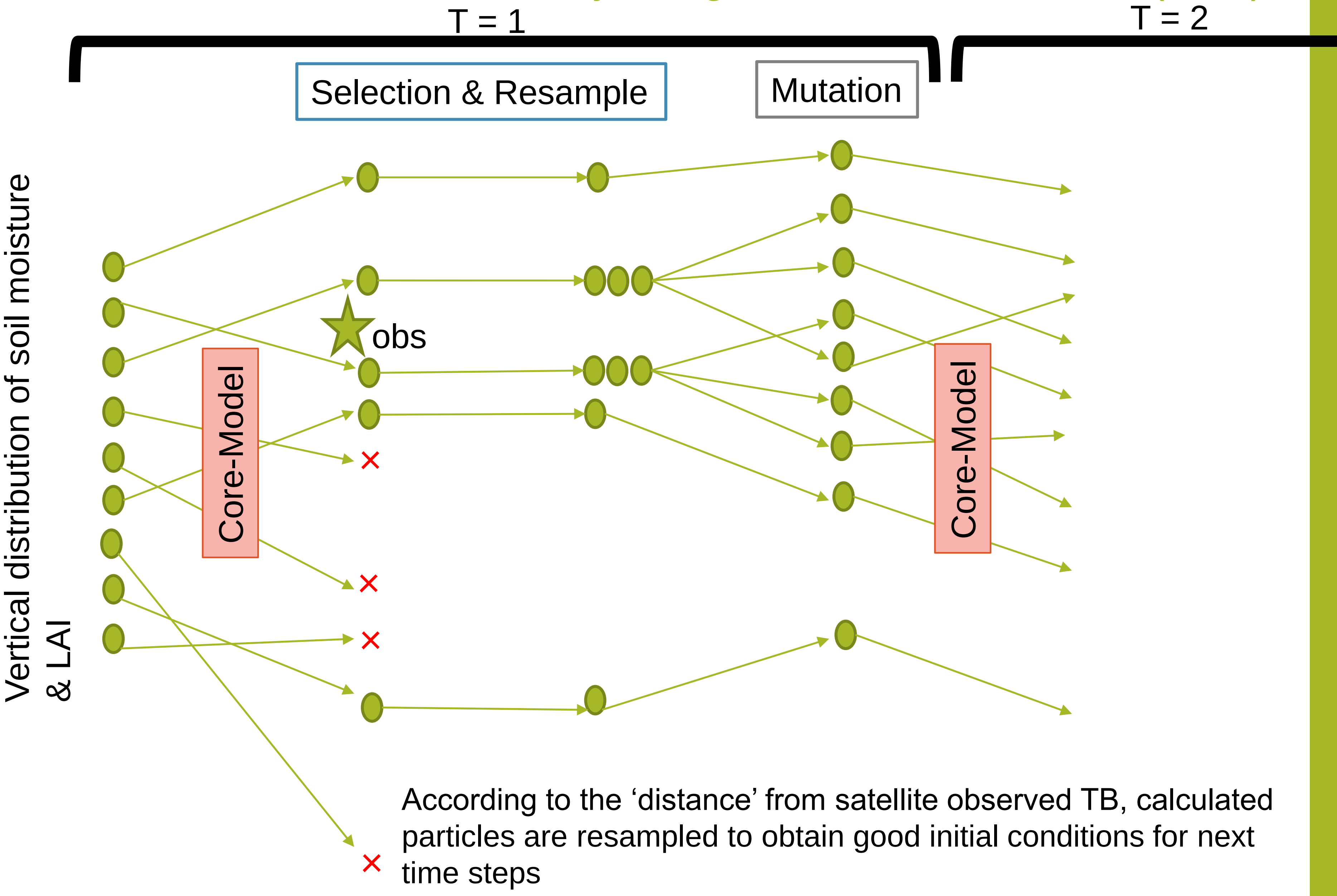
Satellite
observed TB

Genetic
Particle
Filter

COST

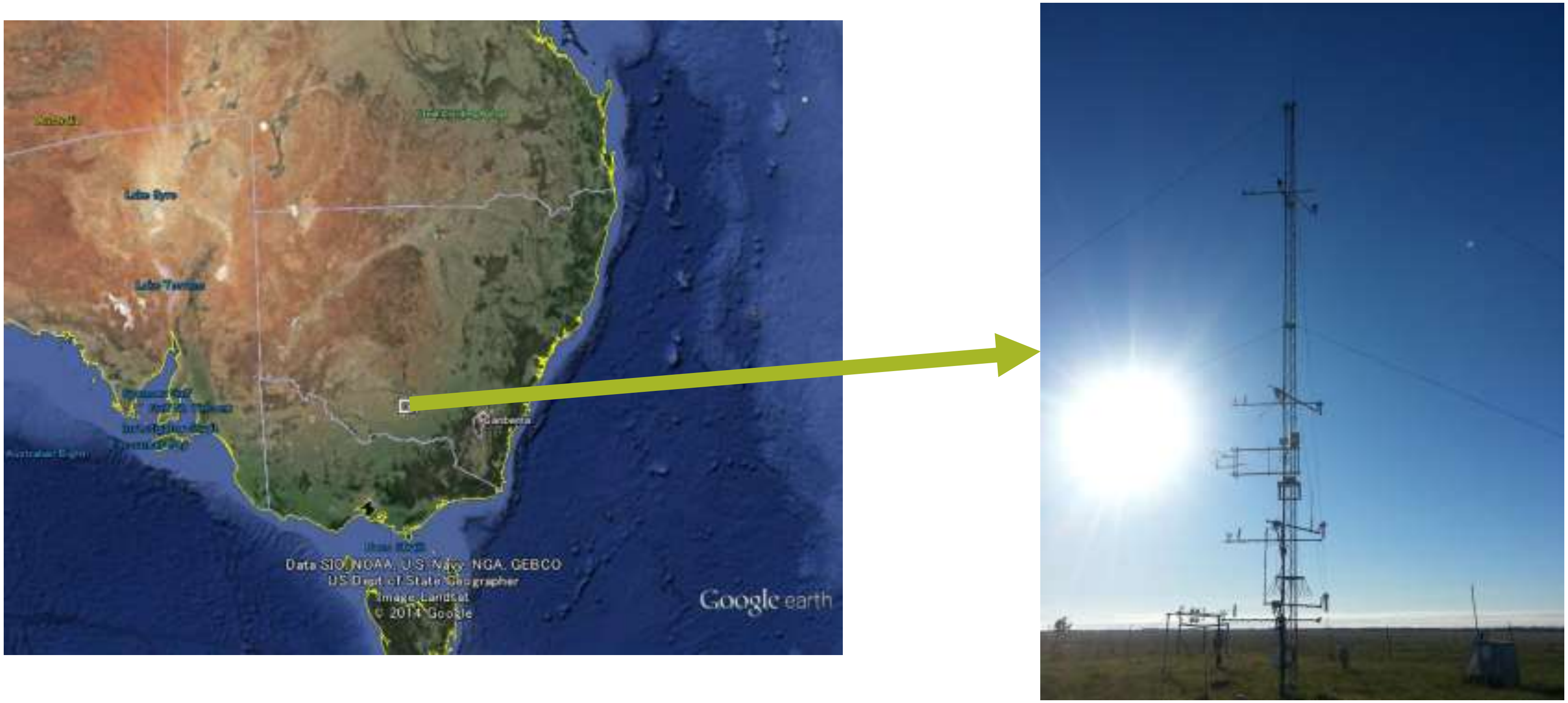
4. Data Assimilation

4.1 Pass 2 : Data Assimilation by using Genetic Particle Filter (GPF)



According to the ‘distance’ from satellite observed TB, calculated particles are resampled to obtain good initial conditions for next time steps

4.2. Study area & Experiment design



Yanco JAXA flux tower site is for validation of AMSR2 soil moisture product. We use AMSR2 brightness temperature and meteorological forcings to run the model.

4.3 Results @ Yanco, AUS

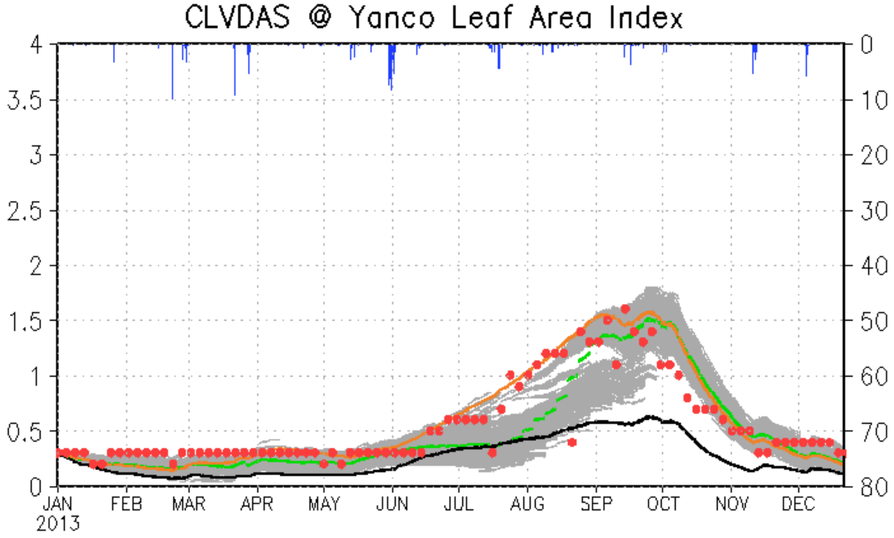
Black: Open loop

Orange: Open loop with parameter optimization

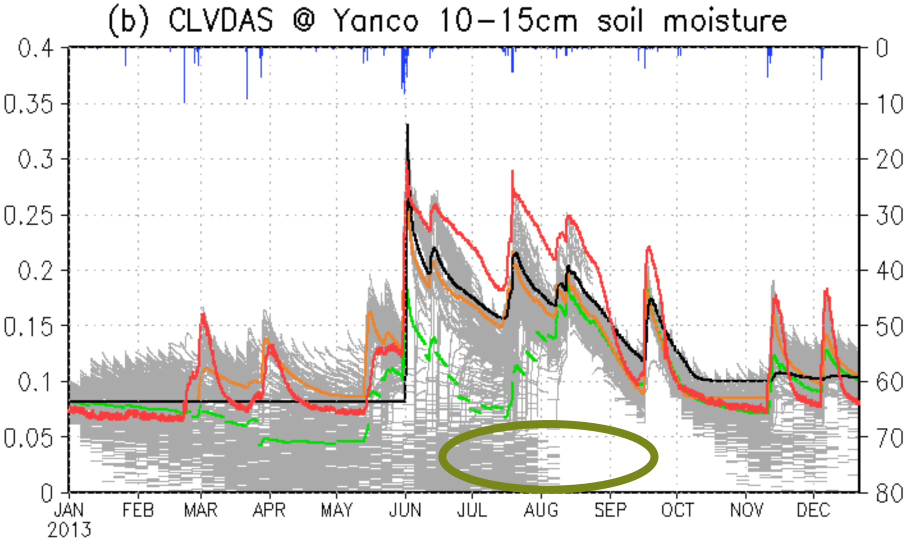
Grey: Assimilation (particles)

Green: assimilation (Ensemble mean)

Red: observation


CLVDAS @ Yanco Leaf Area Index

→ Data assimilation improves the skill of simulating LAI.


(b) CLVDAS @ Yanco 10–15cm soil moisture

→ In growing season, we can effectively confine subsurface soil moisture by particle filtering because subsurface water and vegetation growth are explicitly connected in the model.

5. Discussion and Conclusion

- Microwave satellite data assimilation has the potential to simultaneously estimate the optimal parameters of both hydrological and ecosystem models.

- Data assimilation contributes to improve the performance to estimate sub-surface soil moisture profile as well as land surface conditions.

- Multi-frequency observation of AMSR series makes it possible.

- To further improve the skills, we should consider to assimilate other satellite data (e.g., GRACE, MODIS, SMOS, SMAP,…) to be assimilated.