Plant growth-based modelling improves the estimation of evapotranspiration in tropical regions.

A modelling framework based on evapotranspiration and plant growth for a robust water balance assessment in a sub-tropical and data-scarce region in Western Africa

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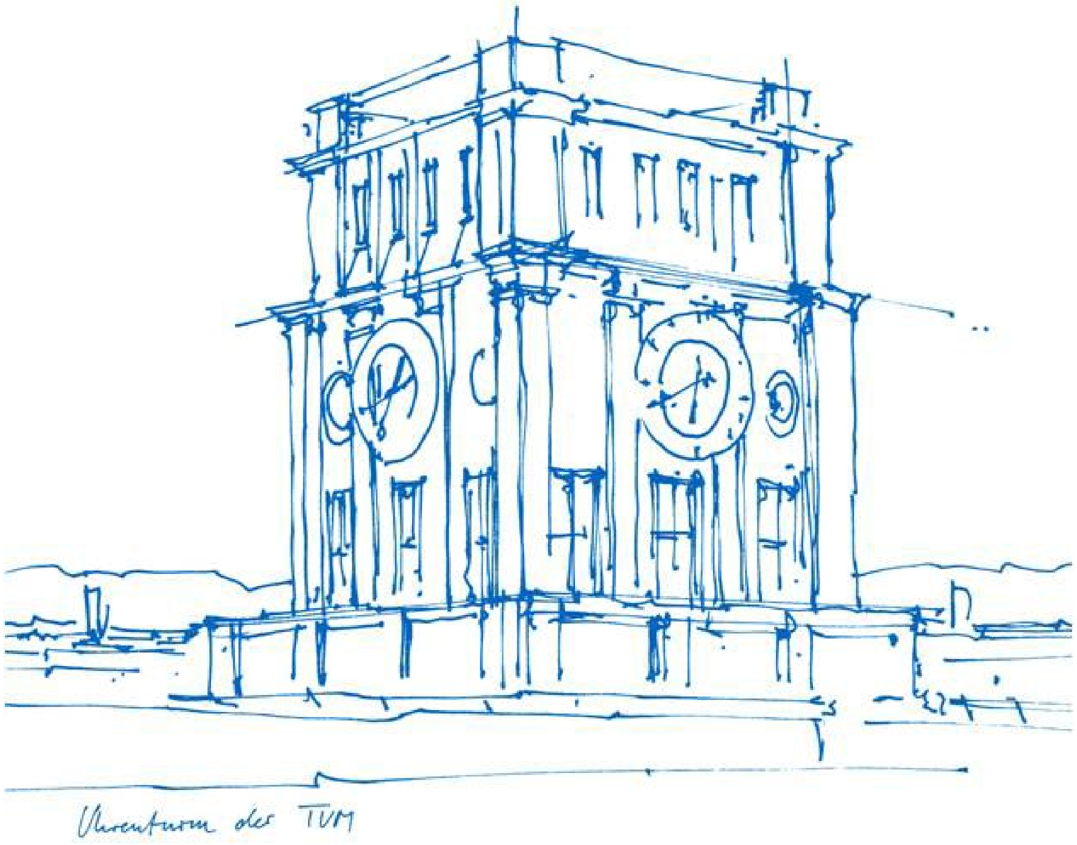
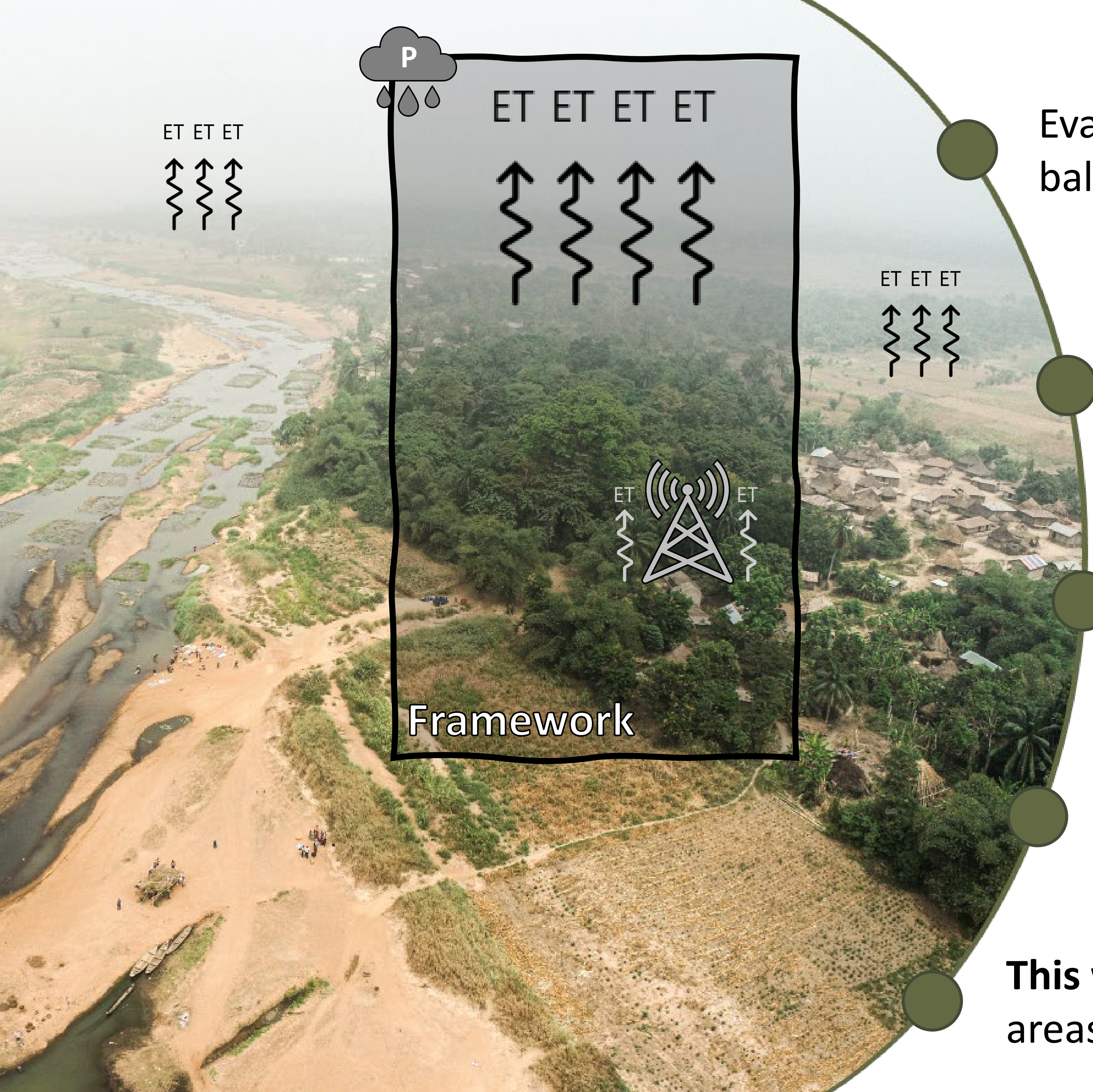
June 2023



Motivation and Background



Evapotranspiration (ET) is essential water balance process in the tropics: **ET/P ≈ 70%**

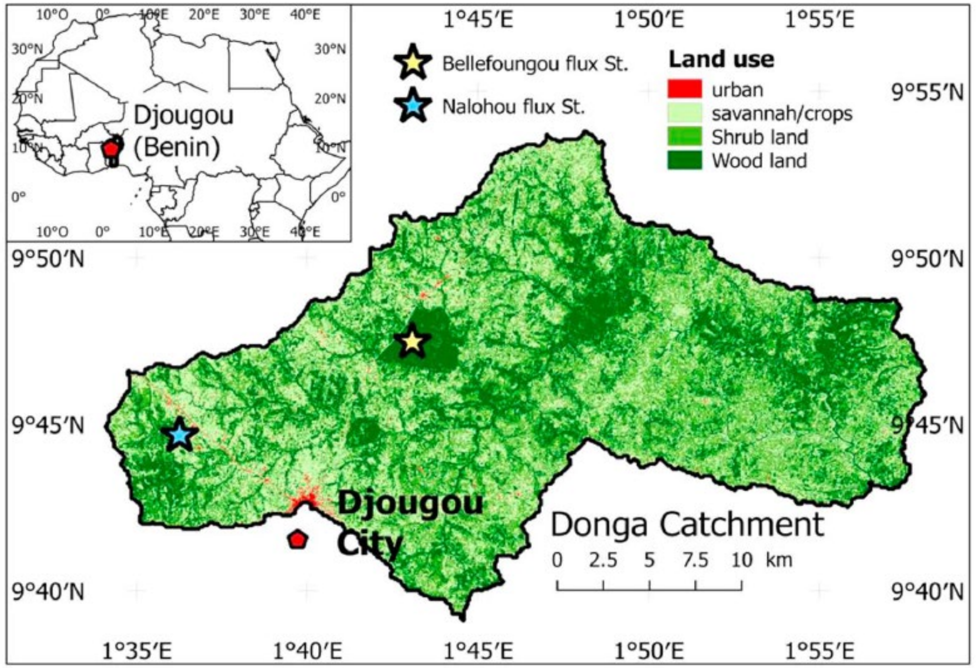
ET is dynamic in space and time: Monitored ET from e.g., eddy flux towers

ET computation in hydrological models dependent on **plant growth (LAI)**

Hypothesis:
Robust ET enables reliable water balance

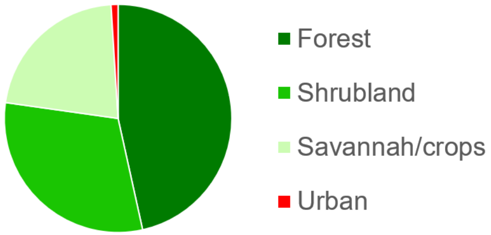
This work: Modelling framework for forested areas **for actual evapotranspiration**

Study Site: Donga catchment, Benin, Western Africa

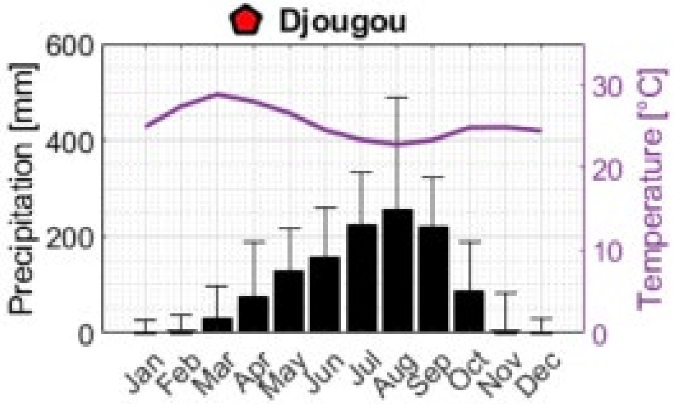


Mamadou et al. (2016)

Land use share



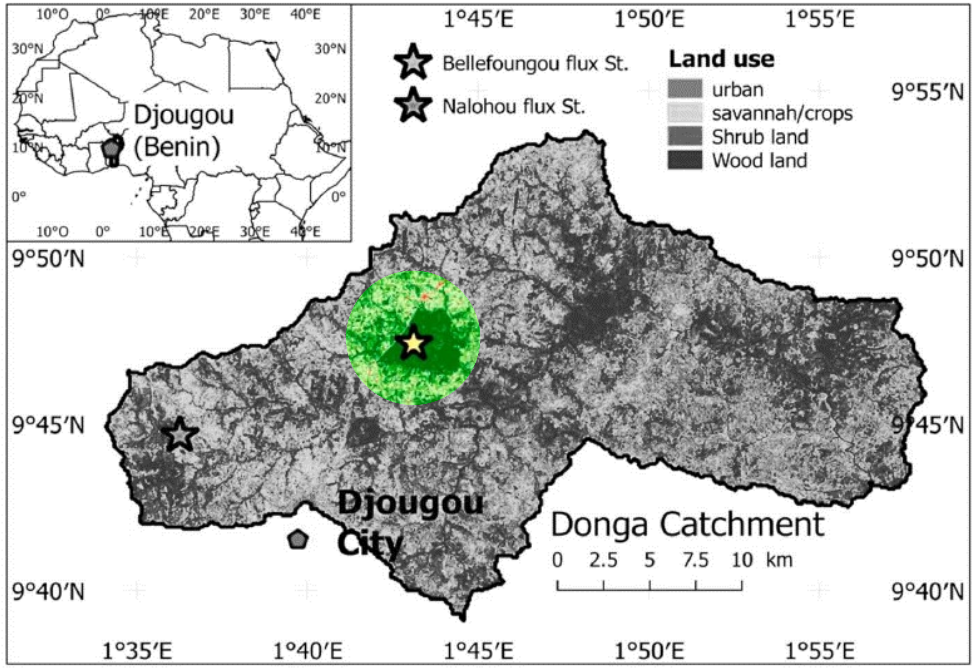
Tropical climate



Monitored Data

Eddy flux towers (ET)

Study Site: Donga catchment, Benin, Western Africa

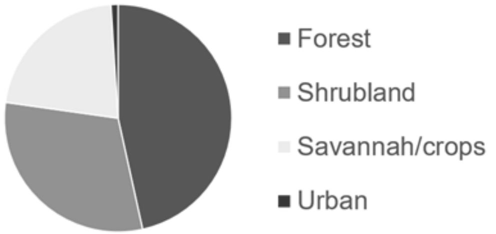


Mamadou et al. (2016)

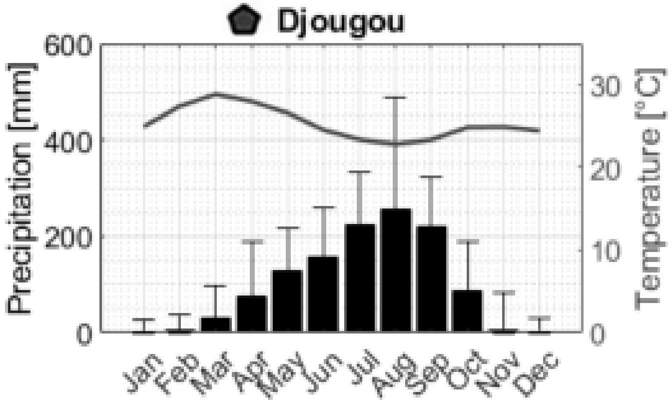
Focus on tower in forested area

Mamadou et al. (2016)

Land use share



Tropical climate



Monitored Data

Eddy flux towers (ET)

Methodology

Methodology

SWAT-T for plant growth modelling

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Plant growth parameters

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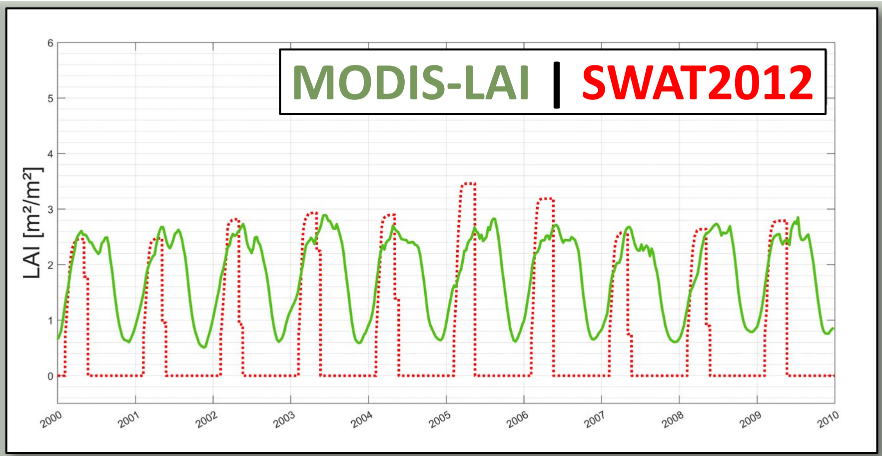
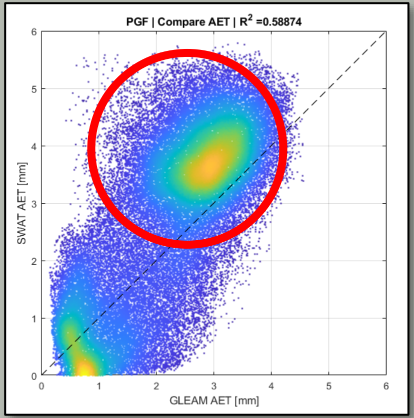
Parameter estimation with ROPE

Test with eddy covariance footprint



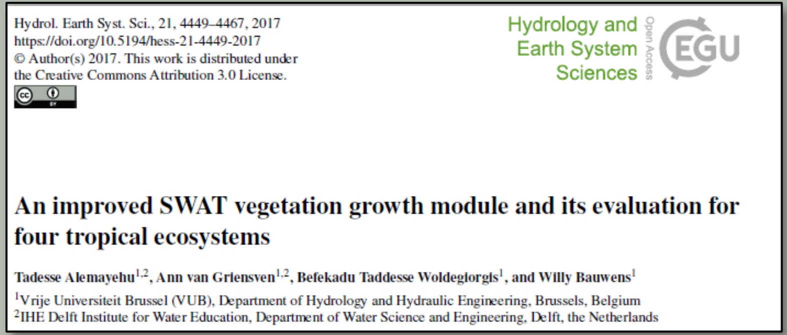
SWAT2012 fails to model plant growth (leaf-area-index) in the tropics

SWAT-ET



Reference-ET

→ Overestimation of ET


Hydrol. Earth Syst. Sci., 21, 4449–4467, 2017
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Hydrology and Earth System Sciences

An improved SWAT vegetation growth module and its evaluation for four tropical ecosystems

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[2]IHE Delft Institute for Water Education, Department of Water Science and Engineering, Delft, the Netherlands

→ Application of SWAT-T

Presented by Alemayehu et al. (2017)
Vegetation module: plant growth is P driven
Leaf senescence like Strauch & Volk (2013)

Methodology

SWAT-T for plant growth modelling

↓

Plant growth parameters

↓

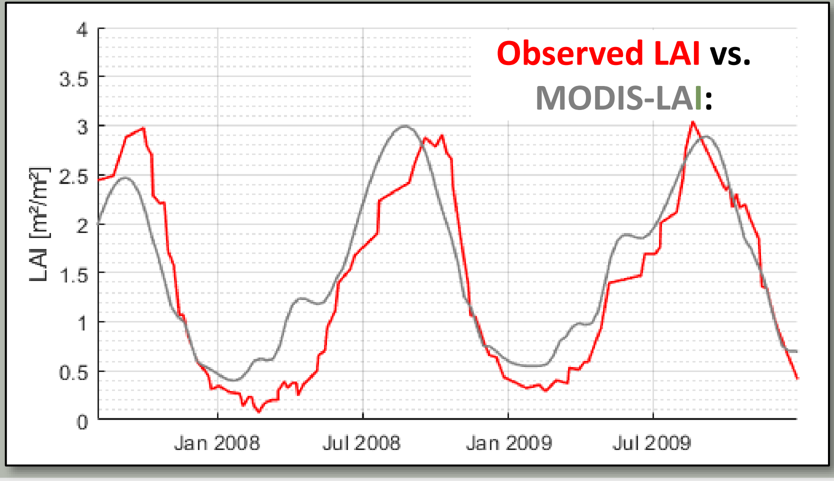
Parameter estimation with ROPE

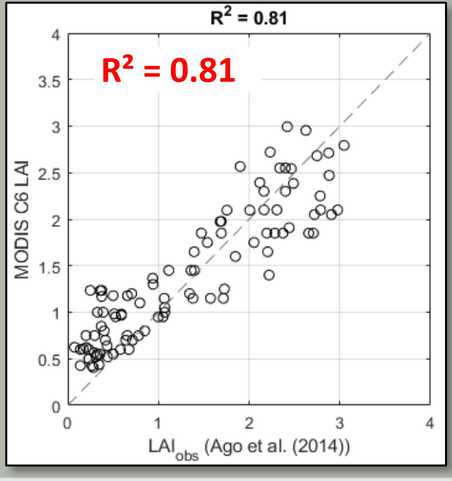
Test with eddy covariance footprint

- 11 parameters for plant growth and the LAI
- **Latin hypercube sampling** with N=10.000

- Evaluation **with MODIS C6 LAI**
  - Optimal value for objective function
  - Included: α***NSE, β*logNSE, KGE, PBIAS**

Fit of MODIS C6 LAI (observed LAI from Ago et al., 2014)





Methodology

SWAT-T for plant growth modelling

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Plant growth parameters

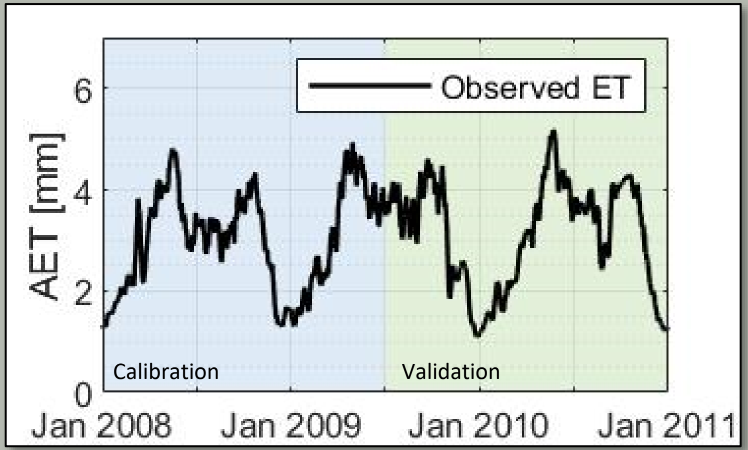
↓

Parameter estimation with ROPE

Test with eddy covariance footprint

- **RO**bust **P**arameter **E**stimation (ROPE) by Bárdossy and Singh (2008)
- **Iterative** approach:
  - Random parameter sampling
  - Good sets according to **KGE** and **depth function**
  - Multi-parameter and thus multi-dimensional
  - Depth function gives **robustness**

Application:
- 11 SWAT parameters
- 3 years of (daily) ET
- PET: Hargreaves
- 5 iterations



Methodology

SWAT-T for plant growth modelling

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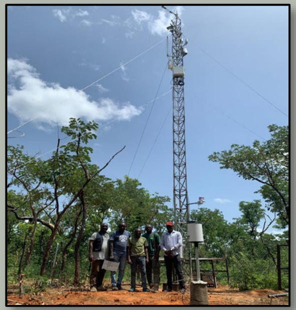
Parameter estimation with ROPE

Test with eddy covariance footprint

Different energy fluxes



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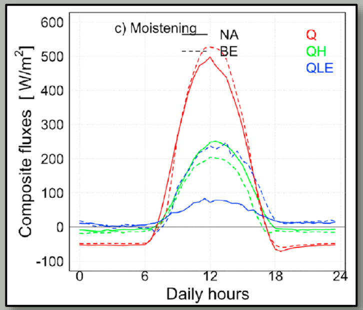
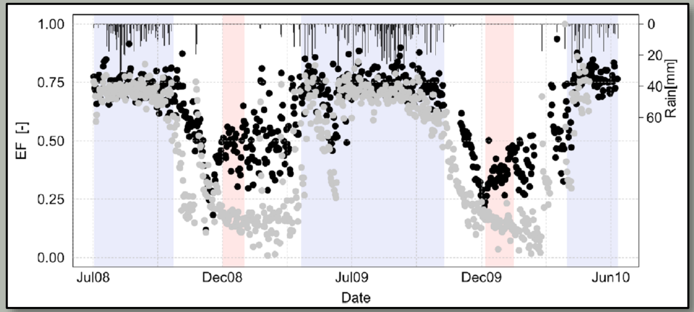


Mamadou et al. (2016)

Measured ET is derived



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Methodology

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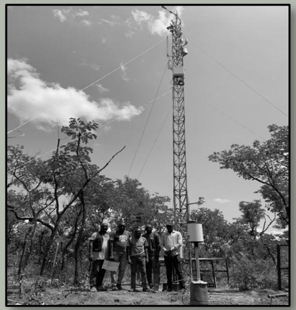
Different energy fluxes



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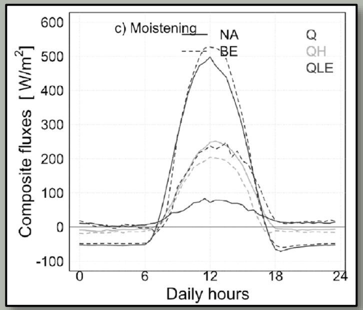
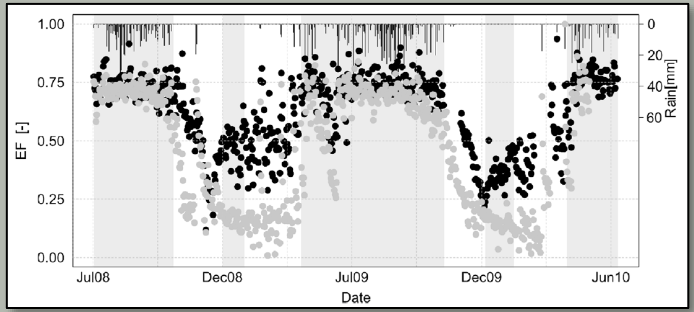


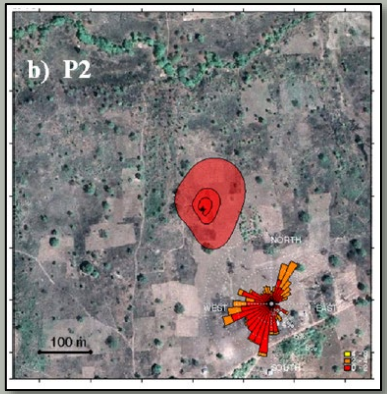
Mamadou et al. (2016)

Measured ET is derived



Mamadou et al. (2016)

Reliability = *footprint*



Example from Mamadou et al. (2014)

Micro-scale SWAT-T model

Orthophoto from ESRI

1 land use
1 soil type
1 HRU

Results

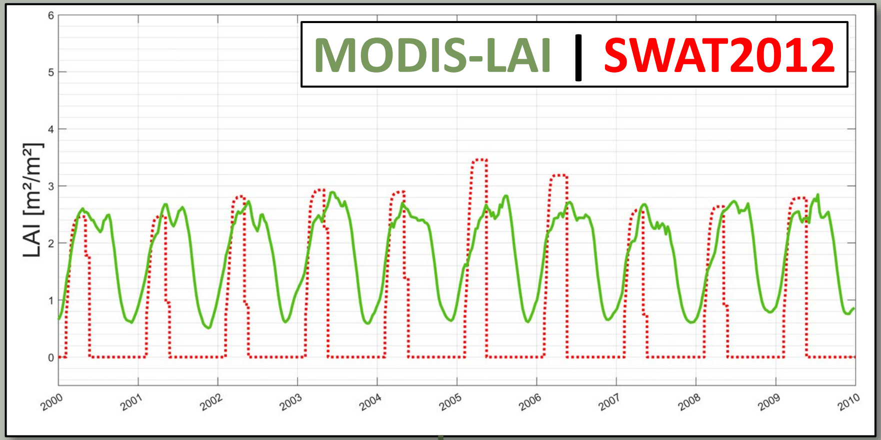
Methodology - Results

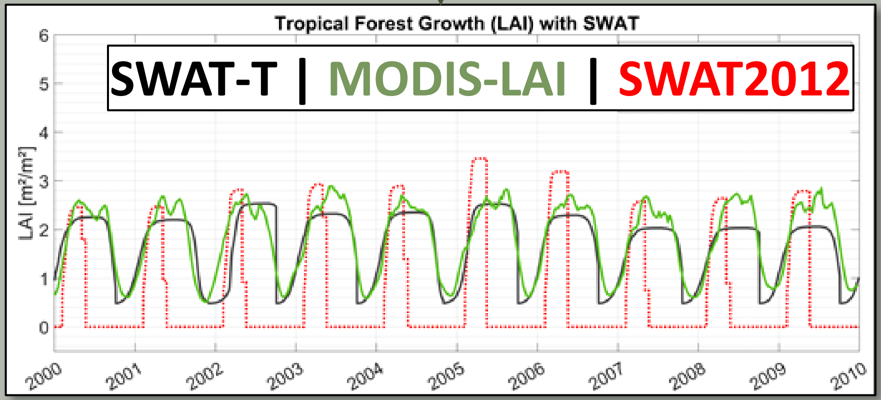
SWAT-T for plant growth modelling

Plant growth parameters

Parameter estimation with ROPE

Test with eddy covariance footprint





SWAT-T outperforms SWAT2012 for plant growth modelling (LAI)

Methodology - Results

SWAT-T for plant growth modelling

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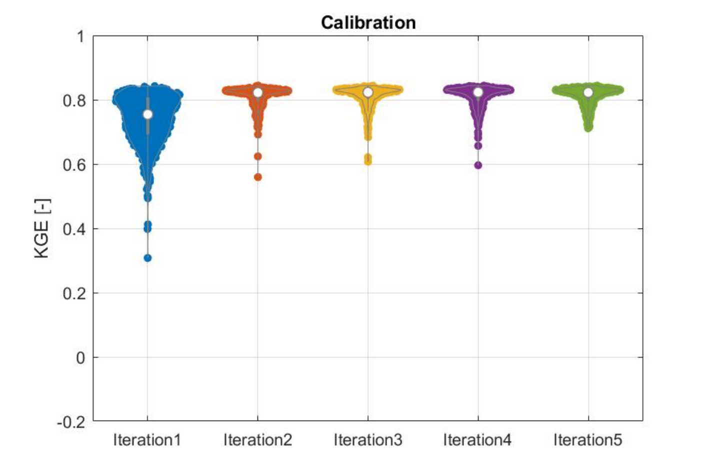
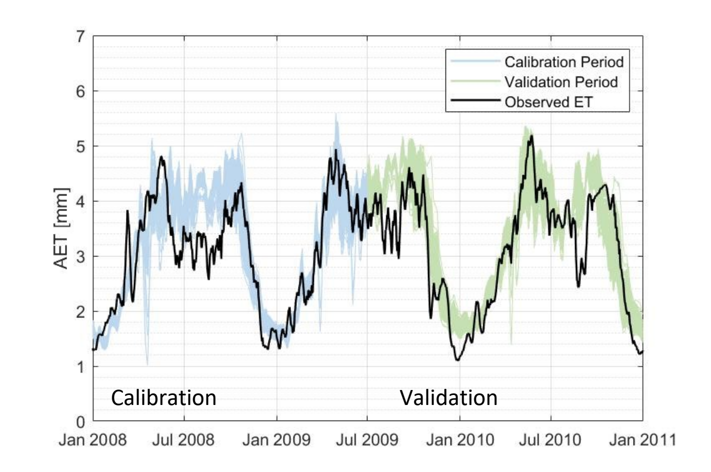
Plant growth parameters

↓

Parameter estimation with ROPE

Test with eddy covariance footprint





→ Mean KGE = 0.83

→ Best set is found quickly

→ For 3 years of data

→ **Good fit in dry and wet period**

Methodology - Results

SWAT-T for plant growth modelling

↓

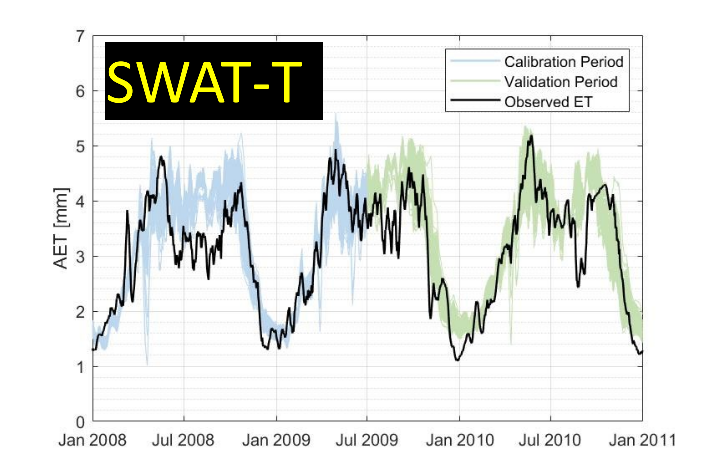
Plant growth parameters

↓

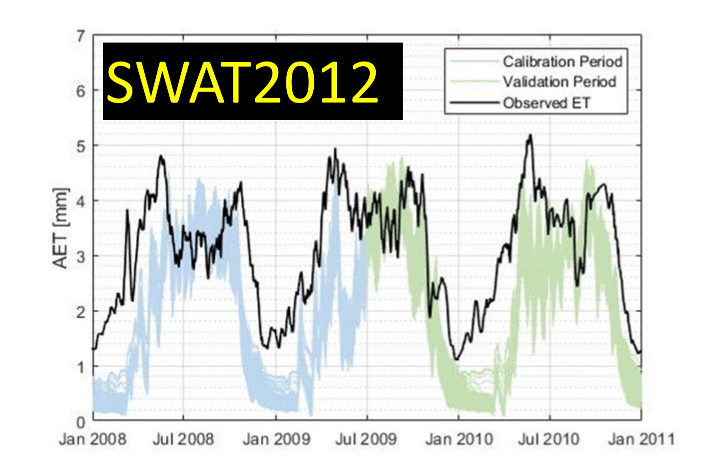
Parameter estimation with ROPE

Test with eddy covariance footprint

Detailed LAI modelling, improved ET modelling?
→ Comparison of SWAT-T with SWAT2012
→ Application of ROPE with identical settings



Mean KGE = 0.83



Mean KGE = 0.46

SWAT-T and a tailor-suited ET modelling outperforms SWAT2012 for ET estimation

Conclusion and Outlook

Conclusion and Outlook

Plant growth-based modelling improves the estimation of evapotranspiration in tropical regions.

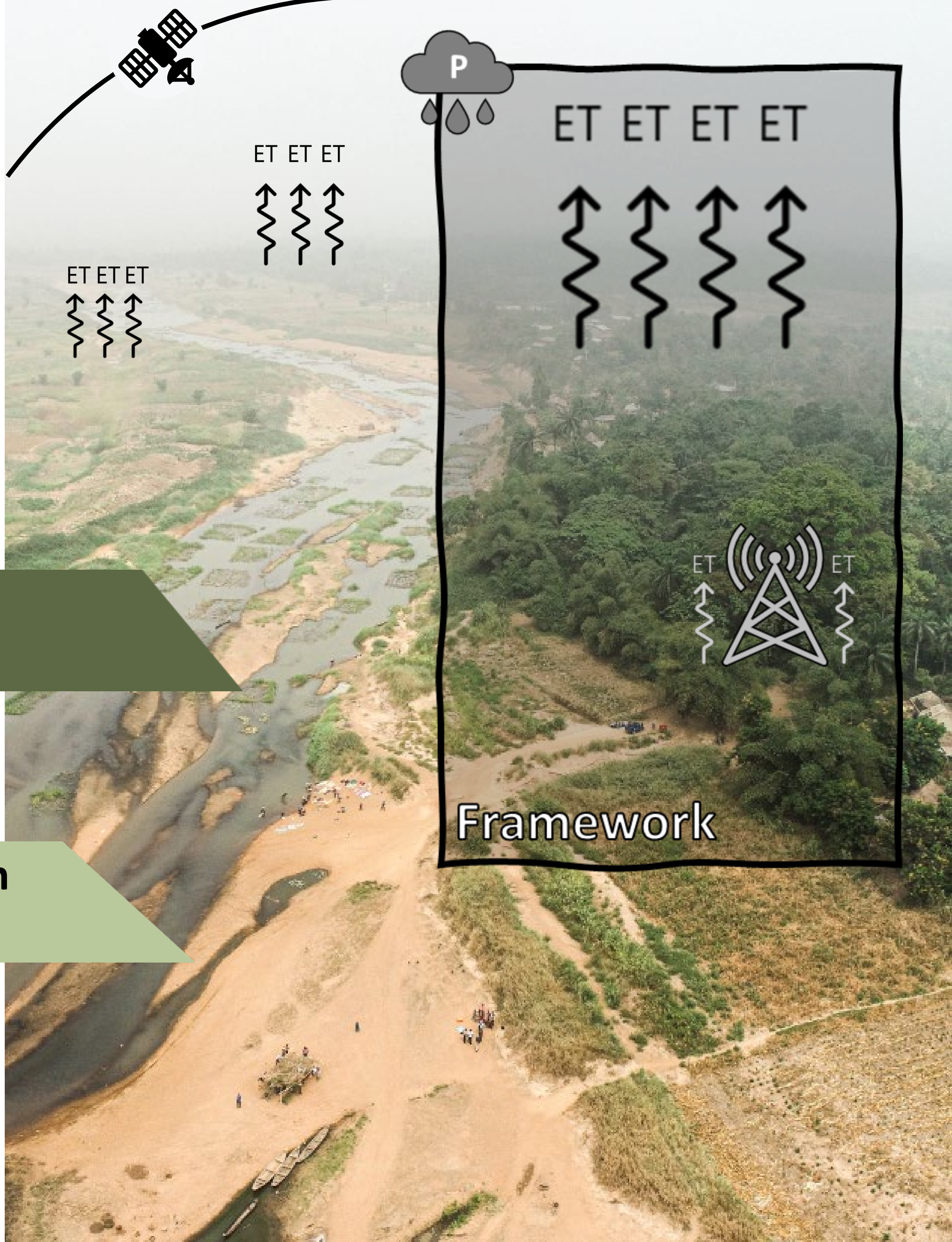
Modelling framework **combining LAI and ET**
→ LAI calibration with MODIS, ET with observed ET

For the first time: SWAT-T benchmarked with eddy flux data

SWAT-T outperforms SWAT2012 for LAI

Plant growth-based modelling (LAI) improves ET estimation
Limitation: tropical and sub-humid regions

Data-scarcity: application of earth observation data
Also applicable for other vegetation, e.g., shrubland



Thank you for your attention!

More information, or:
fabian.merk@tum.de

Funding and support:

Federal Ministry of Education and Research

FONA
Research for Sustainability

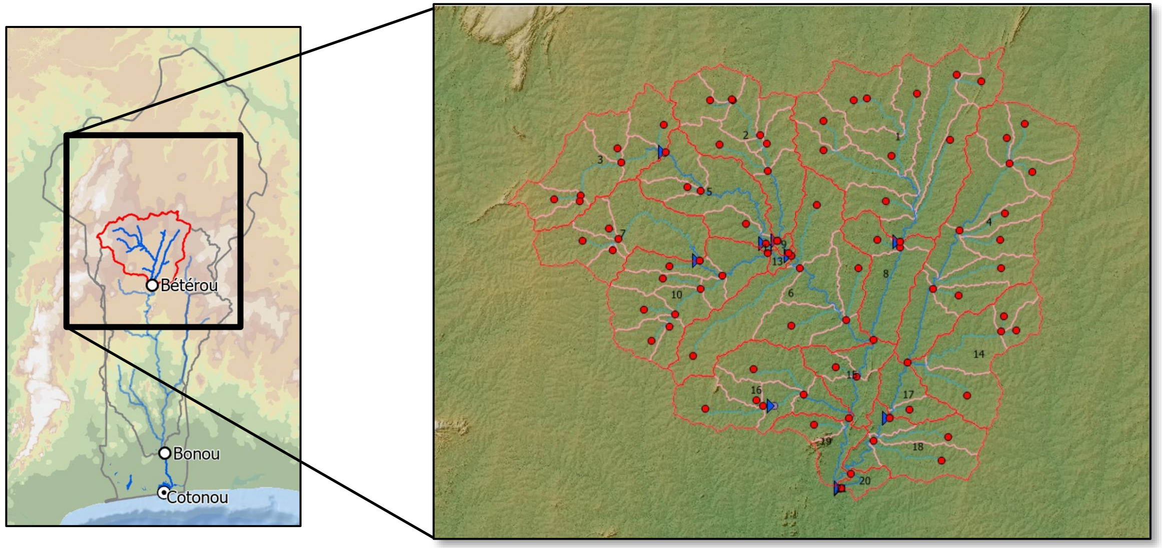
Backup

The case of SWAT+

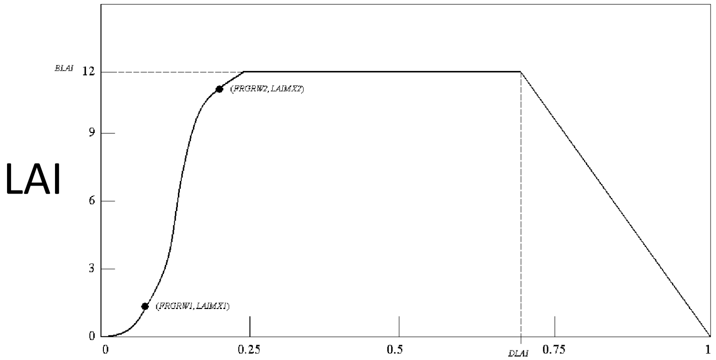
- SWAT+ model for Bétérou

From user manual:

  - 10 parameters for LAI modelling
  - PHU is not needed anymore



LAI in SWAT



Annual cycle based on heat units

If PHU is not needed anymore…How is plant growth triggered in SWAT+?

If PHU is not needed anymore…How is plant growth triggered in SWAT+?

→ From the weather generator data (cli_initwgn.f90)

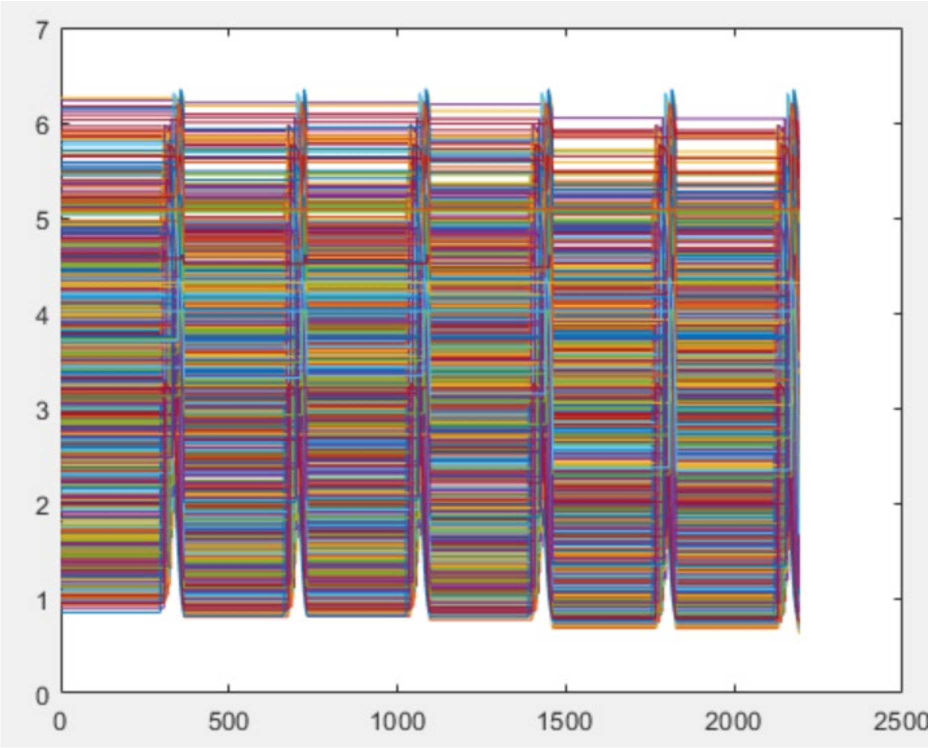
```
!! calculate missing values and additional parameters
summx_t = 0.
summn_t = 0.
summm_p = 0.
tmin = 100.
tmax = 0.
do mon = 1, 12
  mdays = 0
  tav = 0.
  mdays = ndays(mon+1) - ndays(mon)
  tav = (wgn(iwgn)%tmpmx(mon) + wgn(iwgn)%tmpmn(mon)) / 2.
  if (tav > tmax) tmax = tav
  if (tav < tmin) tmin = tav
  summx_t = summx_t + wgn(iwgn)%tmpmx(mon)
  summn_t = summn_t + wgn(iwgn)%tmpmn(mon)

  !! calculate total potential heat units
  if (tav > 0.) wgn_pms(iwgn)%phutot = wgn_pms(iwgn)%phutot + tav * mdays
```

```
!! update base zero total heat units
if (tmpav(j) > 0. .and. wgn_pms(iwgn)%phutot > 0.01) then
  phubase(j) = phubase(j) + tmpav(j) / wgn_pms(iwgn)%phutot
end if
```

Some examples:

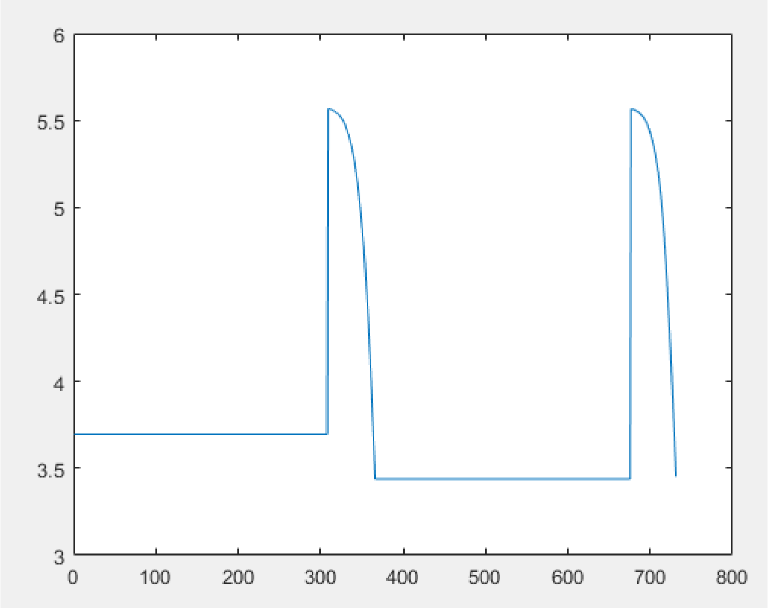
Some examples:

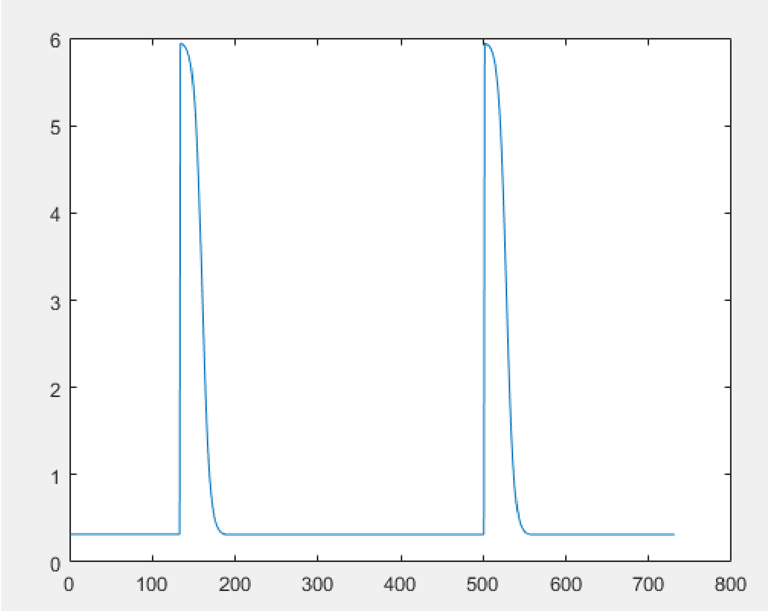


→ 10.000 runs with random sampling of LAI parameters in adequate ranges
→ Not a single realistic plant growth series

→ Adjusting the weather generator data

→ Adjusting the weather generator data





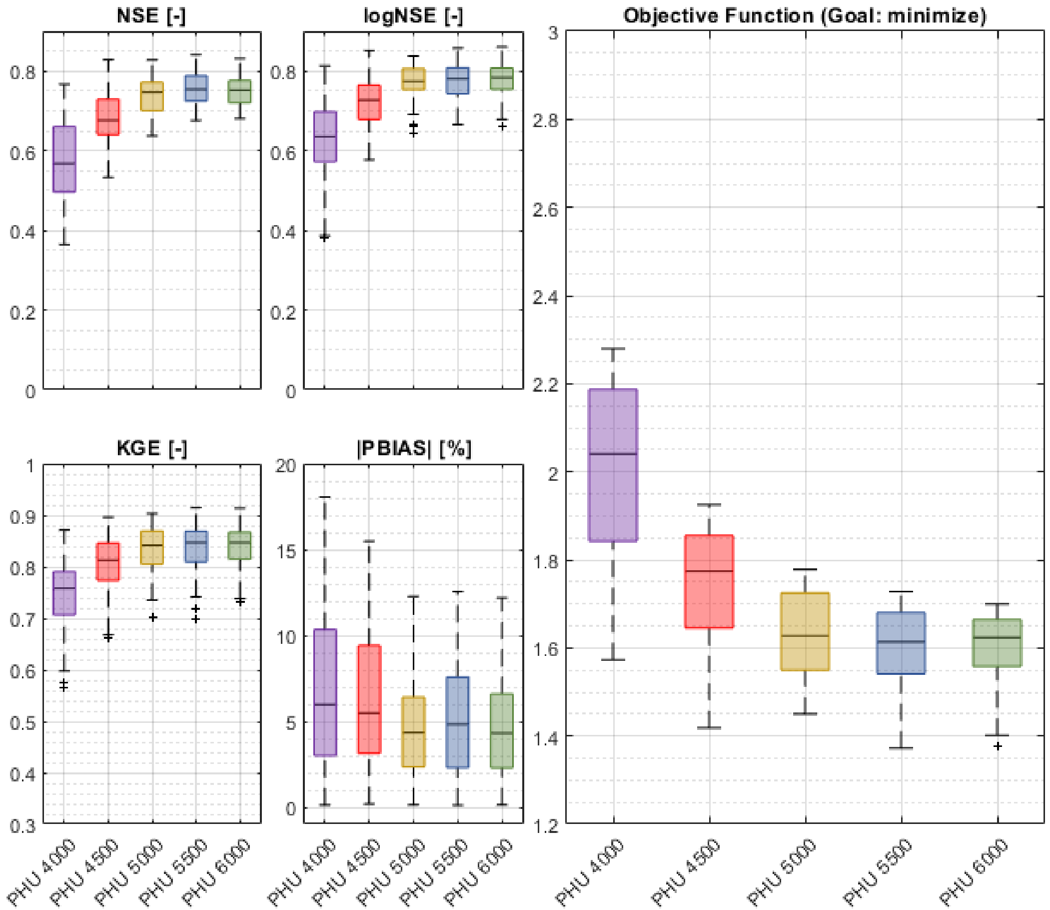
→ Exemplary run with validated meteorological input

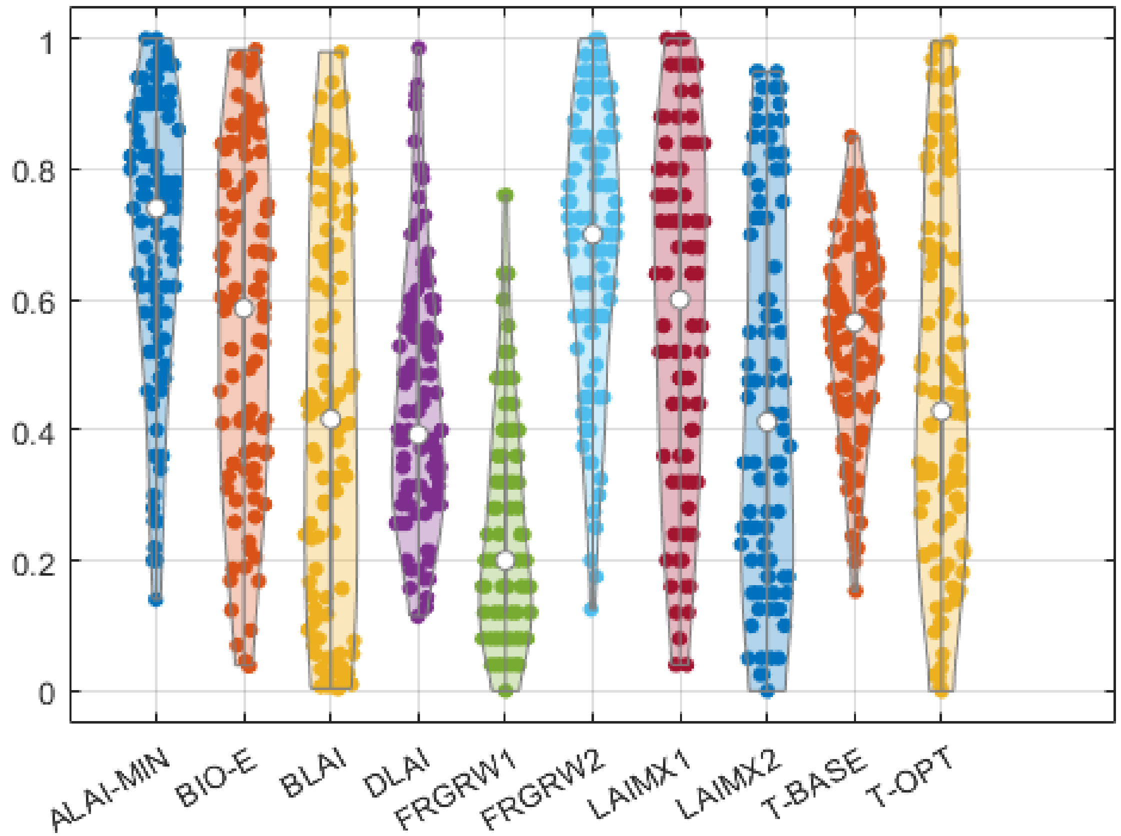
→ LAI series

→ “Cooler” wgen data (Tmin, Tmax reduced)

→ Same LAI parameters left

Plant-growth modelling – results (1 footprint model)





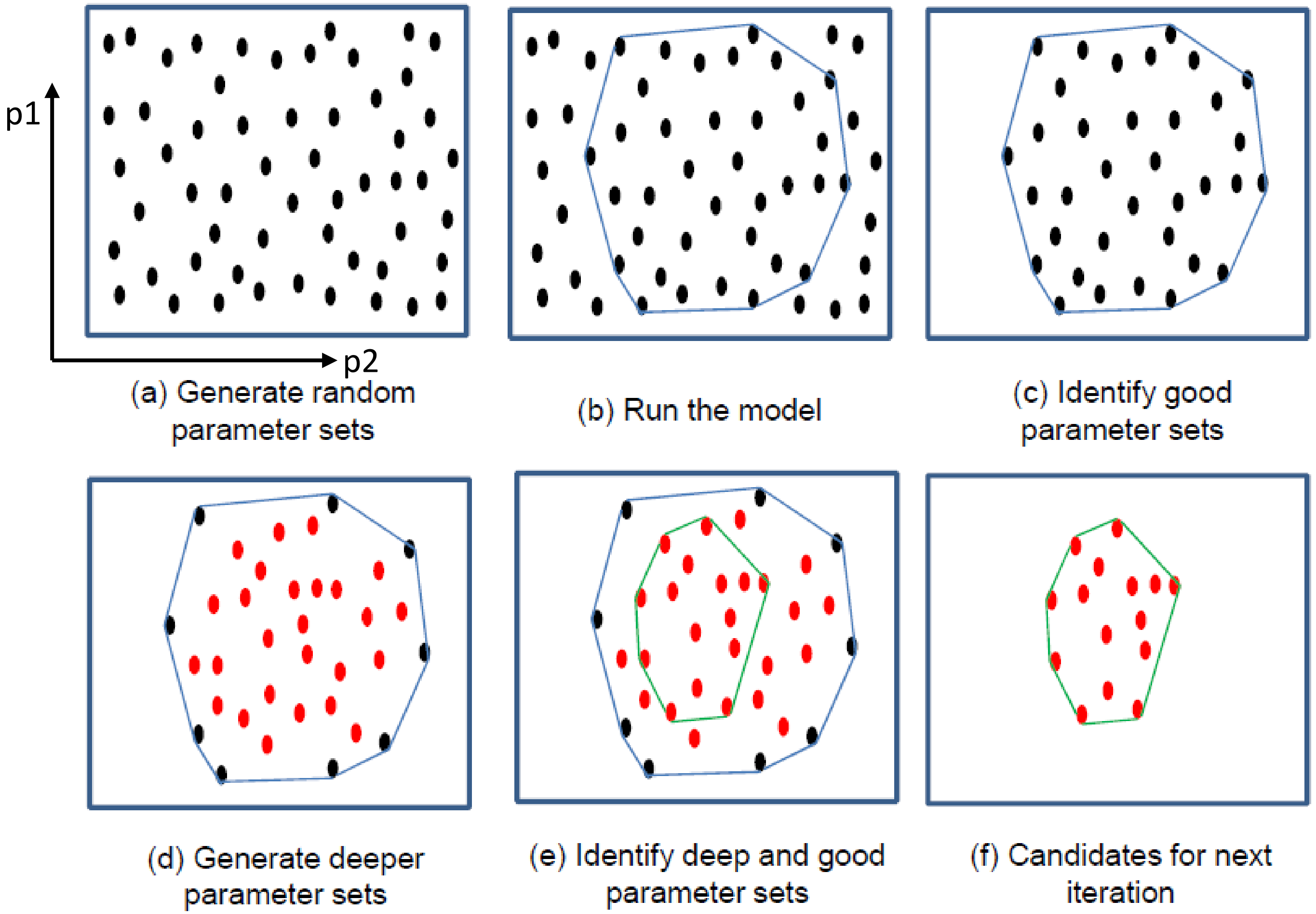
→ Performance for different PHU
→ Best 100 runs (1%)
→ No improvement > PHU=5000

→ Normalized parameters for PHU=6000
→ Best 100 runs (1%)
→ Decisive parameters (qualitative)

Robust Parameter Estimation (ROPE)

- Automatic parameter estimation by Bárdossy & Singh (2008)
- Iterative approach that combines:
  - Randomly sampled parameter sets
  - Selection of good sets according to objective function
  - Re-sampling according to depth function

According to objective function, e.g., KGE



Singh (2008)

According to depth function

Parameters for ET estimation

- ESCO
- EPCO
- GWGMN
- GW_delay
- Alpha_Bh
- GW_revap
- CH_k2
- CN_2
- SOL_AWC
- SOL_K
- SOL_BD