Potsdam Institute for Climate Impact Research

How to Tailor my Process-based Hydrological Model? Dynamic Identifiability Analysis of Flexible Model Structures

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How to tailor my model?

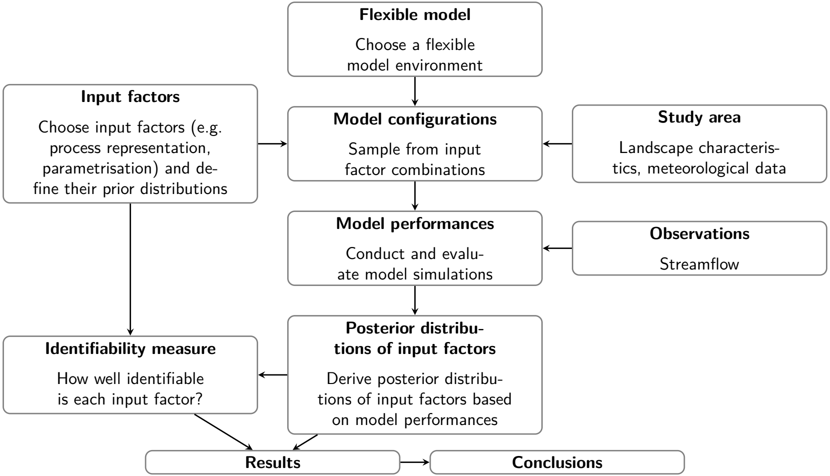
To tailor a model we can choose from alternative

- process representations
- solvers for the integration of the Ordinary Differential Equations (ODE) in time
- parametrisations

But how do we know

1. what is the optimal model configuration?
2. does the optimal configuration change over time?
3. how does it change in space?

Proposed framework *(based on the DYNIA framework by Wagener et al., 2003)*



NOTE: This is an interactive presentation. Click on the boxes to learn more. Please view in presentation mode.

Study area and data: Isábena catchment, NE Spain

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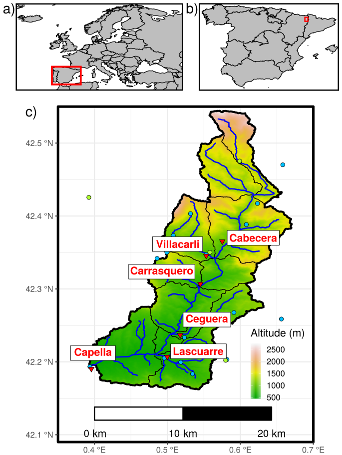
- Area: $425\,\text{km}^2$
- Mountainous topography: 500 m to 2700 m
- Rainfall spatially heterogeneous (annual sum 450 mm in lowlands, up to 1600 mm in mountains)
- Discharge at outlet $4.1\,\text{m}^3/\text{s}$ ($<1\,\text{m}^3/\text{s}$ to $370\,\text{m}^3/\text{s}$)
- Hydrological regime determined by natural factors
- Land cover: deciduous woodland, agriculture, pasture, and bushes in the valley bottoms with evergreen oaks and pines
- Many research projects, including intensive hydro-sedimentological monitoring
- Datasets: $15\,\text{m} \times 15\,\text{m}$ ASTER DEM, soil type and land-use maps, meteorological data, discharge data

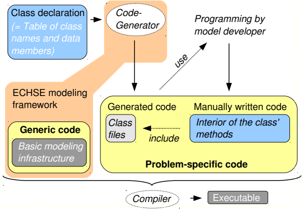
(Bronstert et al., 2014; Francke et al., 2018a; García-Ruiz et al., 2001)



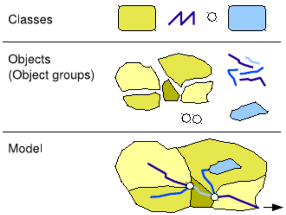
Thin black lines outline subbasins, red triangles mark the position of discharge gauges, blue and green points show gauges of rainfall and other meteorological variables, respectively.

- Free and open source: https://github.com/echse
- Two component framework
  - generic part
  - model engine (user code)
- Object-oriented programming concept (C++)
- User-friendly model implementation
- Pool of processes: simple exchange and extension of implementations
- Set of numerical integration schemes (ODE solvers)
- Arbitrary model conception (lumped vs. distributed, conceptual vs. process-oriented)

(Kneis, 2015)



ECHSE framework.



Model engine implementation.

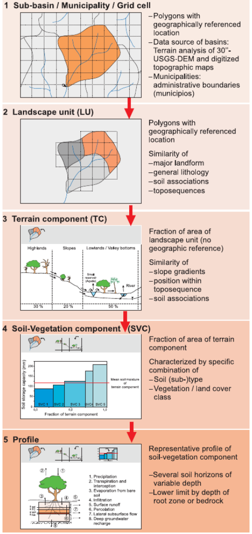
Conception of implemented engine based on the WASA-SED model

- Process-oriented hydrological model
- Complex hierarchical spatial discretisation scheme
  - Efficient simulation of hillslope-scale processes
- Adapted to semi-arid environments
  - Lateral runoff redistribution
  - Hortonian runoff
  - Ex- and re-infiltration

→ Particularly suited for environments with heterogeneous vegetation cover and considerable amounts of bare soil

→ Successfully applied in the Isábena and similar catchments

(Bronstert et al., 2014; Francke et al., 2018b; Güntner and Bronstert, 2004; Mueller et al., 2009, 2010)



Source: *Güntner (2002)*

Input factors and realisations

Input factors are adjustable elements of a model set-up. *(Pianosi et al., 2016)*
Specific values of the, in this case, discrete-valued input factors are denoted as *realisations*.

Input factor definitions for this case-study

Ia Evapotranspiration processes (32 realisations)

- Penman-Monteith, Shuttleworth & Wallace, alternatives for sub-processes (e.g. stomatal resistance)

Ib Soil water processes (8 realisations)

- Alternatives for infiltration, percolation, soil water retention

Ic Runoff concentration processes (2 realisations)

II ODE solvers (8 realisations)

III Parametrisations (1000 realisations)

- 7 parameters; realisations obtained by sampling from parameter distributions

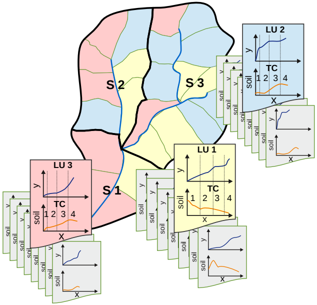
⇒ The realisations define the **prior distribution** for each input factor (equal weight for each realisation, i.e. uniform distribution assumed)

Model configurations

- $32 \times 8 \times 2 \times 8 \times 1000 = 4096000$ possible configurations from input factor combinations $\Rightarrow$ computationally not feasible
- 12 000 samples were randomly drawn

Model set-up for the case study (independent of specific configuration)

- Delineation of model units (subbasins, LUs, TCs, SVCs) using the lumpR software *(Pilz et al., 2017)*
- Derivation of soil and vegetation parameters from databases and pedotransfer functions
- Preprocessing of meteorological data (gap filling, spatial interpolation) with ECHSE tools *(Kneis, 2012)*



Model simulation and performance evaluation

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Simulation settings

- Three years from 1 January 2013 to 31 December 2015
- Daily resolution
- Up to 20 iterations of warm-up years to bring model states into equilibrium

Performance evaluation

- Case-specific choice of performance metric: root mean square error (RMSE)
- For dynamic analysis computed over moving window ($w = 15$ resulting 31 days) for each simulation day d: $RMSE(d) = \sqrt{\frac{1}{2w+1} \sum_{i=d-w}^{d+w} \left(q_s(i) - q_o(i)\right)^2}$ with q_s simulated and q_o observed discharge

Determination of posterior distributions

Bayesian approach: $\text{Posterior} \propto \text{Prior} \times \text{Likelihood}$

- Prior is defined by the realisations (and their weights) of each input factor
- Likelihood is derived by taking additional data into account $\Rightarrow$ many approaches exist

In this study employs an informal approach

- Oriented at the GLUE approach *(Beven and Binley, 1992)*
- Separate model configurations into behavioural and non-behavioural groups based on their performances
- Here: 10 % best performing configurations considered as behavioural

$\Rightarrow$ 1200 posterior model configurations

$\Rightarrow$ Remaining realisations and their frequencies define the posterior distribution of each input factor

Identifiability measure

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For each input factor

- n_{prior} is the number of realisations in the prior distribution
- n_{post} is the remaining number of realisations in the posterior distribution
- $IM = 1 - \frac{n_{post} - 1}{n_{prior} - 1}$ with $n_{prior}, n_{post} \in \mathbb{N}$

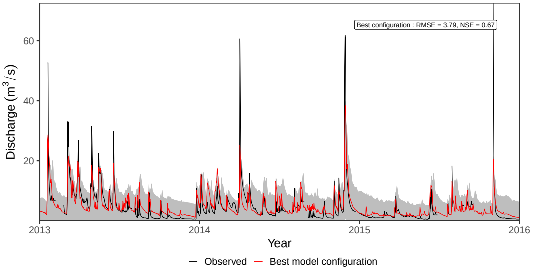
That means

- $IM = 0$ is obtained when $n_{post} = n_{prior}$
  - $\rightarrow$ all realisations of an input factor defined in its prior distribution are still present in the posterior distribution
  - $\rightarrow$ the input factor is not identifiable
- $IM = 1$ is obtained when $n_{post} = 1$
  - $\rightarrow$ only one realisation left in the posterior distribution
  - $\rightarrow$ the input factor is well identifiable

Results: discharge simulations

Next: static IM

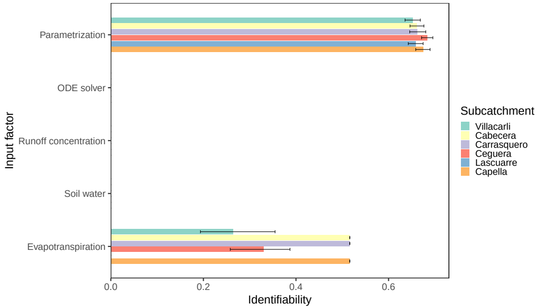
- Most observation values fall into 90 % probability range of model configurations
- Large peaks often underestimated
  - → Partly attributable to poorly detected heavy precipitation events
- Falling limbs of discharge events sometimes not well matched
  - → Measurement uncertainty?
  - → Missing calibration?
  - → Optimal model structure not yet included?



Gray area shows the 90 % probability range of all (prior, uncalibrated) model configurations.

Results: static identifiability measure

- Only Evapotranspiration and Parametrisation exhibit some degree of identifiability
- Consistently zero identifiability for ODE solver, Runoff concentration, and Soil water
  - → All implemented realisation can lead to acceptable model performance
- Relatively consistent results for different subcatchments (except Lascuarre)



Black errorbars represent the 95 % confidence interval estimated via bootstrapping.

Results: posterior distributions of input factors

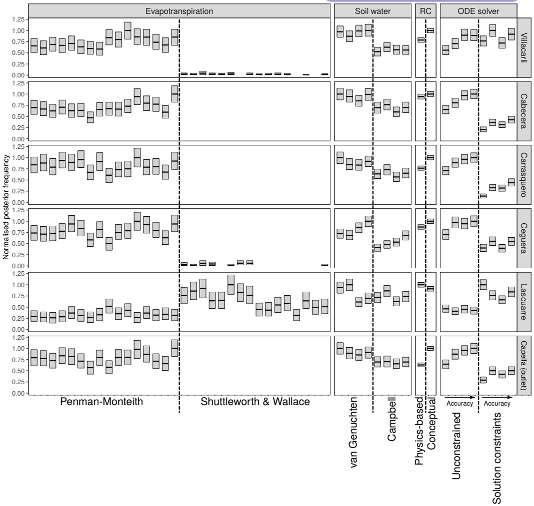
Next: posterior distributions II

Evapotranspiration

- Penman-Monteith clearly superior to Shuttleworth & Wallace except for Lascuarre
- For subprocesses no obvious pattern

Soil water

- Retention model of highest importance: van Genuchten (mostly) slightly superior to Campbell
- Realisations of other processes (infiltration and percolation approaches) equally plausible



Boxes represent the 95 % confidence interval and mean (black horizontal line) estimated via bootstrapping.

Results: posterior distributions of input factors

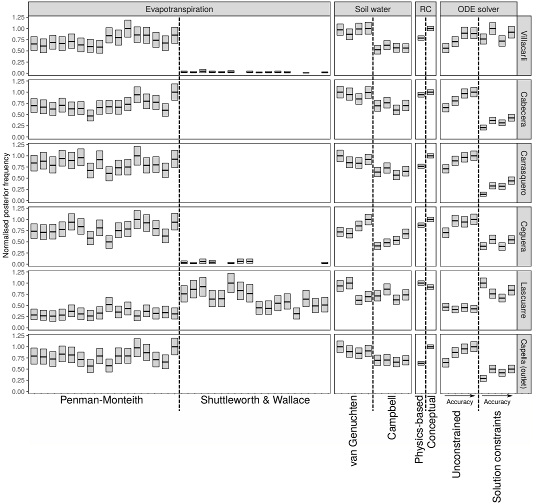
Next: dynamic posterior distributions

Runoff concentration (RC)

- Conceptual approach with delay factor (calibration parameter) superior (except Lascuarre)

ODE solver

- Unconstrained solvers mostly superior to solvers with solution constraints (physical limits)
  - → Model performance compensates for unrealistic model states?
- Solvers with higher accuracy (higher order) mostly achieve better performances
  - → Sometimes even simple Euler approach achieves high importance (Lascuarre)



Boxes represent the 95 % confidence interval and mean (black horizontal line) estimated via bootstrapping.

Results: dynamic posterior distributions

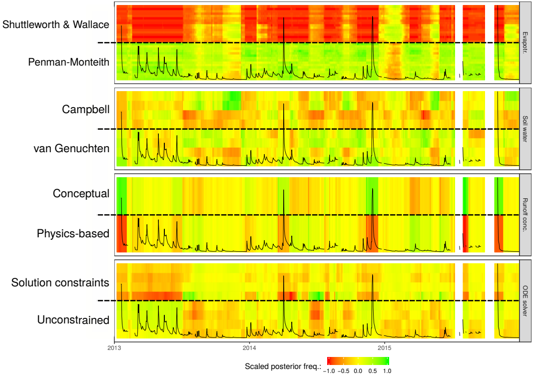
Next: dynamic posterior distributions II

Evapotranspiration

- Most of the time Penman-Monteith superior
- During dry periods Shuttleworth & Wallace gains importance

Soil water

- Highly diverse patterns → posterior distribution changes with flow / wetness conditions



Red: low posterior frequency, less plausible representations. Green: high posterior frequency, more plausible representations. Black lines: discharge hydrograph (gauge Capella = catchment outlet).

Results: dynamic posterior distributions

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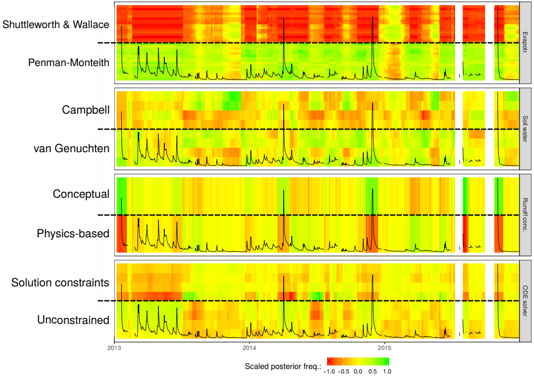
Runoff concentration

- During peak flows: conceptual approach favoured
- Most of the time no clear identifiability

ODE solver

- Highly diverse patterns $\rightarrow$ posterior distribution changes with flow / wetness conditions
- Unconstrained solvers slightly favoured during high flows / wet conditions



Red: low posterior frequency, less plausible representations. Green: high posterior frequency, more plausible representations. Black lines: discharge hydrograph (gauge Capella = catchment outlet).

Conclusions

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The proposed framework

- consists of coupling a flexible model environment with dynamic identifiability analysis
- can be used to identify most plausible model configuration(s)
- is generic and leaves many options to the user in terms of software, definition and implementation of input factors, model evaluation etc.
- can provide valuable information about process behaviour in a catchment
  - → Which process representations / underlying theory explains observed dynamics best?

The case study shows that

- parametrisation and evapotranspiration are the best identifiable input factors
- model structure identifiability varies over time
- identifiability is influenced by wetness conditions and landscape characteristics
- there are unexpected results possibly due to complex interactions and compensations effects between ODE solver, process representation and parametrisation
  - → Unconstrained ODE solvers lead to unrealistic model states but better model performance

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