Université Gustave Eiffel

UNIVERSITÉ Clermont Auvergne

INRAE la science pour la vie, l'humain, la terre
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Data assimilation: overview and constraints for agro-ecology modelling

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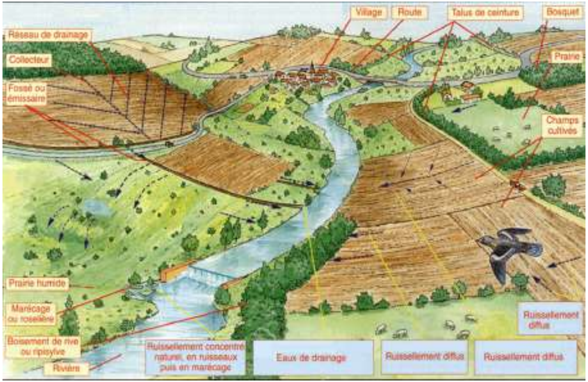
Plan

Context : How to improve the water quality ?

⇒ a better understanding of water and pesticide transfer in soil

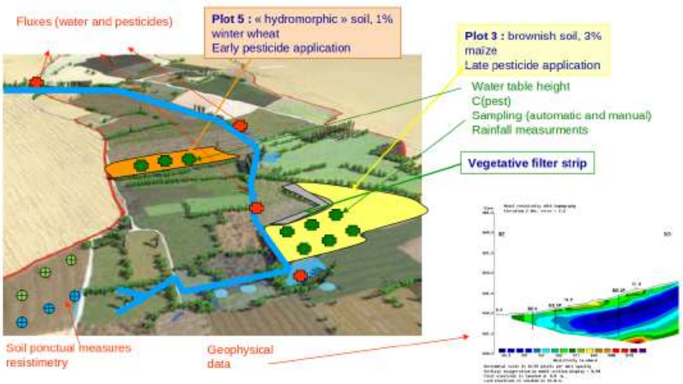
- Spatial heterogeneity of the soils, at all scales
- Soil and agricultural practices are more and more diverse
- Processes that drive the pesticide fate at the catchment scale are complex :
  - Hydrological transfer
  - adsorption
  - degradation



Spatially and temporally heterogeneous data. . .

Availability, quality, quantity of data are heterogeneous in space and time :

- remote sensing images
- field data (lysimeters in soil, water table and river measurments)
- geophysical data

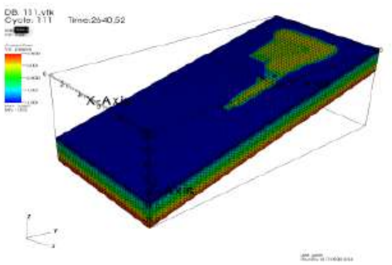


BUT without heavy experiments, this is very difficult to get the pesticides dynamics

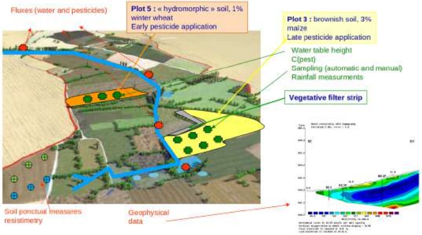
Spatially and temporally heterogeneous data...
...and pesticides modeling at several scales and several complexity degrees

- based on non linear equations and/or conceptual
- unknown boundary and initial conditions
- a large set of spatialized parameters that are difficult to measure/estimate
- many processes affecting pesticide transfer are not (well) represented (e.g., pref. flows)

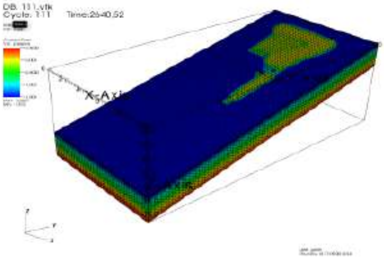
⇒ a high uncertainty (when we it is considered !)



Spatially heterogeneous data. . .



. . . and spatialized modeling

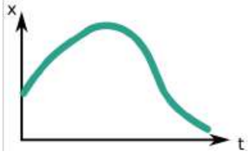


⇒ merging information from the available data and from the model
to get as close as possible to the "true" state

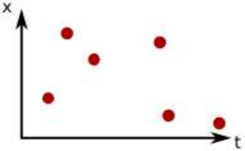
Data Assimilation techniques (or *model-data fusion*)

Plan

- the systematic use of data to constrain a numerical model
- first used in the 1960s in numerical weather forecasting models for short-term predictions of meteorological conditions
- in the 1970s, development in numerical ocean general circulation models (OGCMs)
- poorly developed in other domains (hydrology)



Model



Observations

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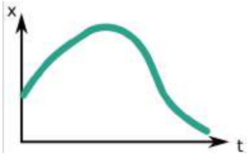

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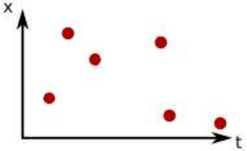
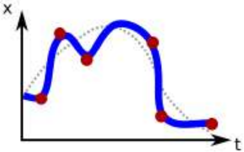


Observations



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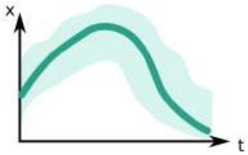

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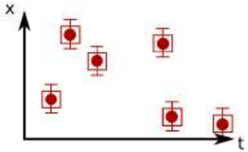

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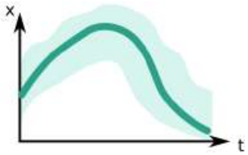

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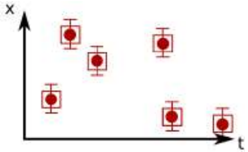

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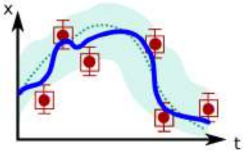

Data assimilation

The ingredients

$\mathbf{x} = (\mathbf{x_0},\mathbf{x_1},\ldots,\mathbf{x_N})^\mathbf{T}$ represents the state of system:
streamflow at the outlet, soil moisture, dissolved oxygen concentration in the river, etc.
We don't know it, but we do have information from :

- **the dynamical model** $x_k = M_{k-1\rightarrow k}[x_{k-1}, param] + \eta_k$

  η_k the model error of covariance matrix P_k

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Data assimilation

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- **the observation model** $y_k = H_k[x_k] + \varepsilon_k$

  y_k is the observation/data at time k
  ε_k the observation error, of covariance matrix R_k, e.g. instrumental error, representativeness
  $H : \mathcal{R}^m \to \mathcal{R}^d$ the observation operator that projects from model space to observational space

Data assimilation

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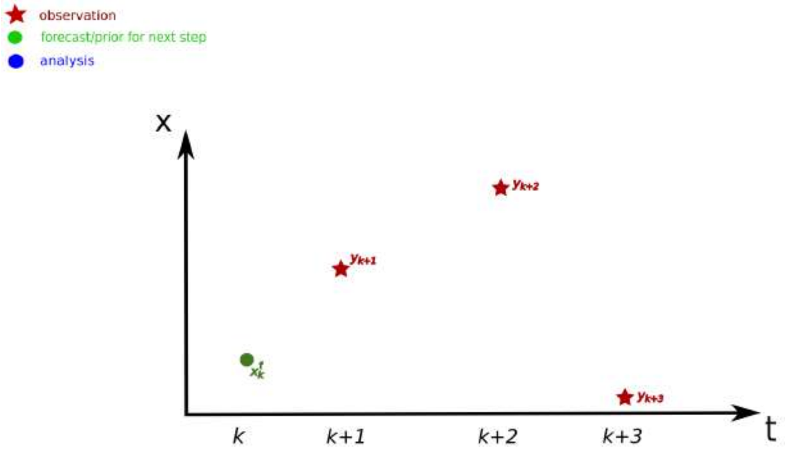
- **the dynamical model** $x_k = M_{k-1\to k}[x_{k-1}, param] + \eta_k$
- **the observation model** $y_k = H_k[x_k] + \varepsilon_k$
- We assume that model and obs. errors are random variables $\to$ described by pdf

$\Rightarrow$ Bayesian framework $\Rightarrow$ The Kalman Filter

The Kalman Filter (Kalman 1960) : estimate the optimal state at each observation time



0. At time k: $\mathbf{X}_k^f$

The Kalman Filter (Kalman 1960) : estimate the optimal state at each observation

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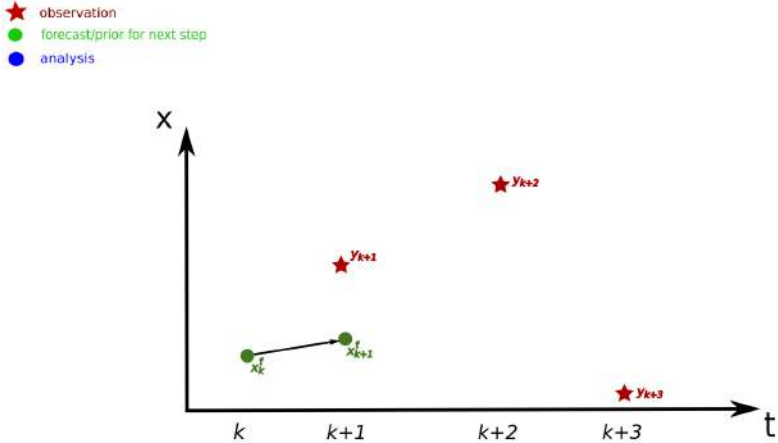

1. Forecast step: $\mathbf{X}_{k+1}^f = \mathbf{M}\mathbf{X}_k^f$

The Kalman Filter (Kalman 1960) : estimate the optimal state at each observation

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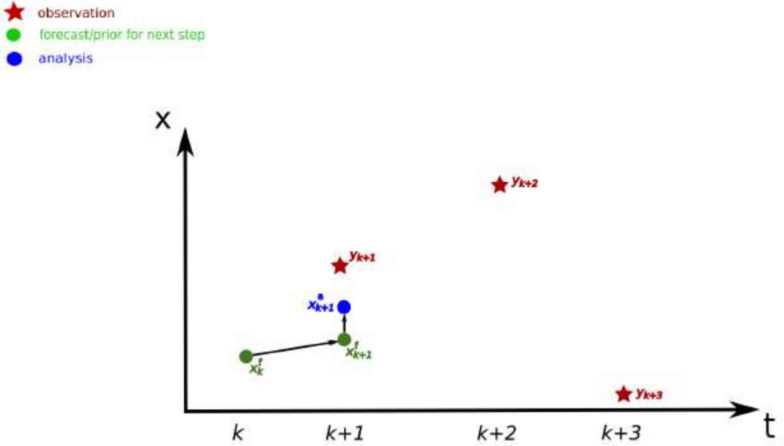

2. Analysis step: $\mathbf{X}^a_{k+1} = \mathbf{X}^f_{k+1} + \mathrm{K}_{k+1}(\mathbf{Y}_{k+1} - \mathbf{H}_{k+1}\mathbf{X}^f_{k+1})$

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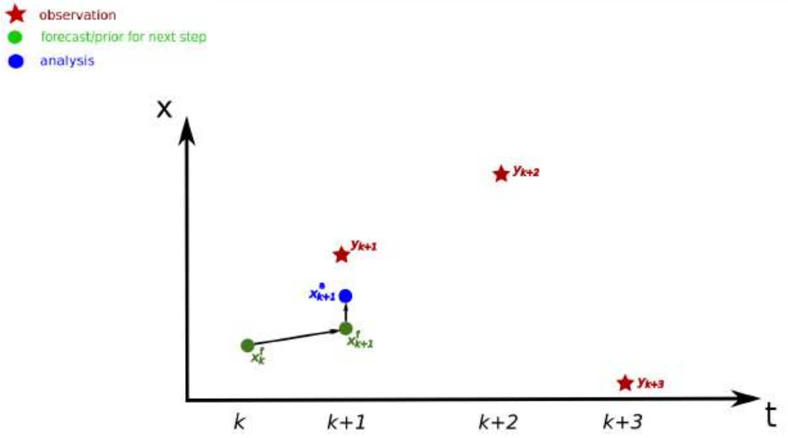

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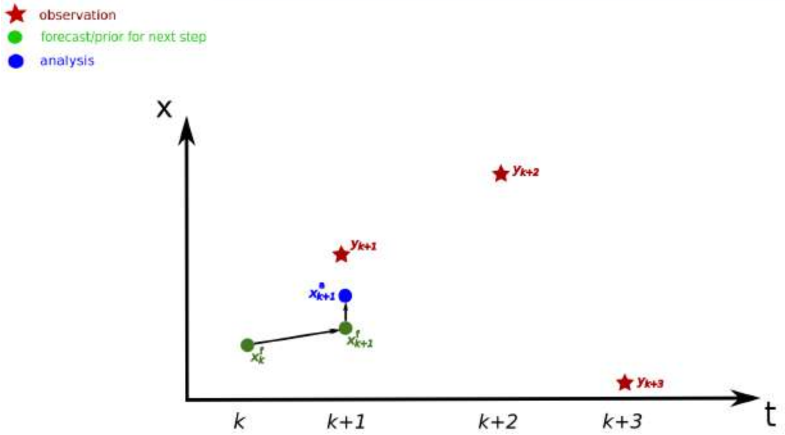
with $\mathrm{K}_{k+1} = \mathbf{P}^f_{k+1}\mathbf{H}^T_{k+1}[\mathbf{H}_{k+1}\mathbf{P}^f_{k+1}\mathbf{H}^T_{k+1} + \mathbf{R}_{k+1}]^{-1}$

The Kalman Filter (Kalman 1960) : estimate the optimal state at each observation time



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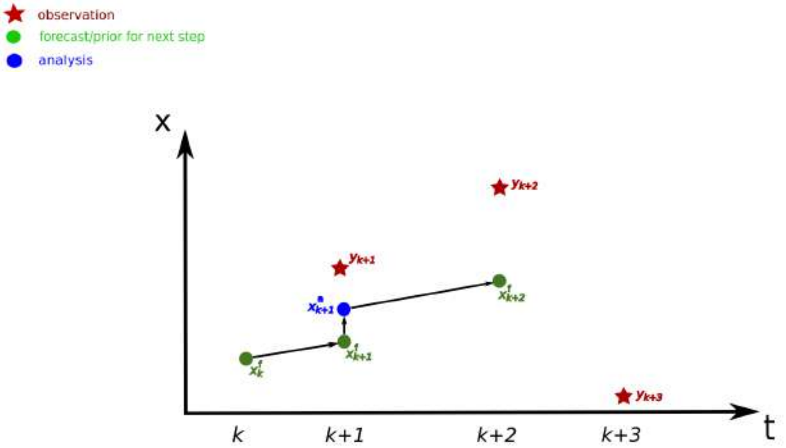
$$\mathbf{P}^a_{k+1} = \mathbf{P}^f_{k+1} - \mathbf{K}_{k+1}\mathbf{H}_{k+1}\mathbf{P}^f_{k+1}$$

The Kalman Filter (Kalman 1960) : estimate the optimal state at each observation time



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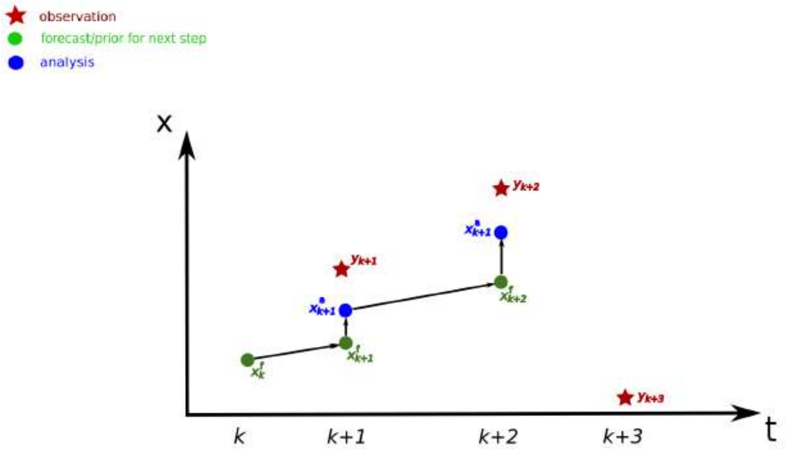


The Kalman Filter (Kalman 1960) : estimate the optimal state at each observation

time 

The KF assumes that:

- ✓ **all sources of errors are gaussian**
- ✓ **both the observational and dynamical models are linear**

→ not realistic in most cases !

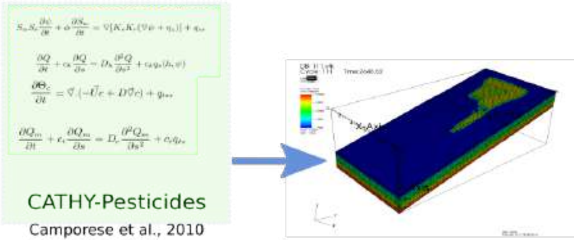
Data assimilation

The method for data assimilation should be suited to spatialized models

- models are physically-based but:
- highly nonlinear equations (Richards, . . .)
- some are more/less conceptual => discontinuities, thresholds

→ **definitely not gaussian !**

→ **Ensemble filter approaches**



Camporese et al., 2010
Gatel et al., 2019

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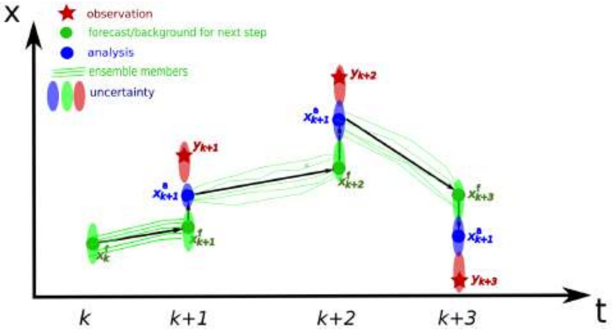
Data assimilation

Ensemble-based methods (Evensen 2003)

- a version of the Kalman filter for nonlinear problems at large dimension
- the state variable distribution is represented by an ensemble of state vectors x_k
- the error covariance matrices are represented by the ensemble covariance

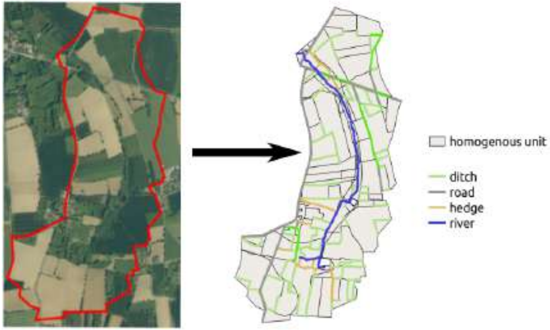


Plan

The PESHMELBA model (Rouzies et al. 2019)

PESticides et Hydrologie: Modélisation à l'EcheLle du BAssin versant

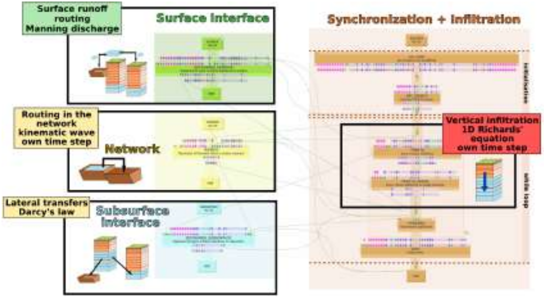
- ✓ Simulation of heterogenous landscapes composed of plots, vegetative filter zones, hedges, ditches and rivers
- ✓ Water transfers on surface and subsurface
- ✓ Solute advection, adsorption and degradation



The PESHMELBA model (Rouzies et al. 2019)

PESticides et Hydrologie: Modélisation à l'EcheLle du BAssin versant

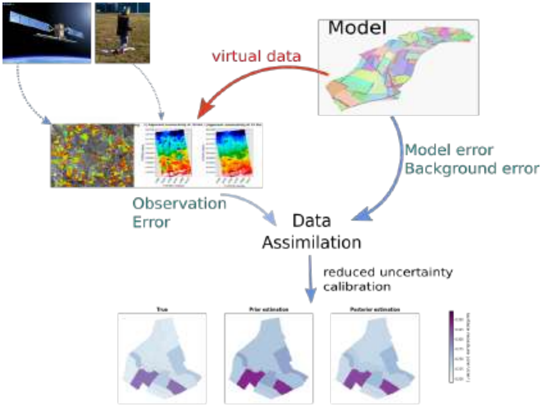
- ✓ Simulation of heterogenous landscapes composed of plots, vegetative filter zones, hedges, ditches and rivers
- ✓ Water transfers on surface and subsurface
- ✓ Solute advection, adsorption and degradation
- ✓ One module ≡ one process or ensemble of processes on a landscape element
- ✓ Coupling of modules within the OpenPALM coupler (Fouilloux and Piacentini 1999) turning the structure flexible



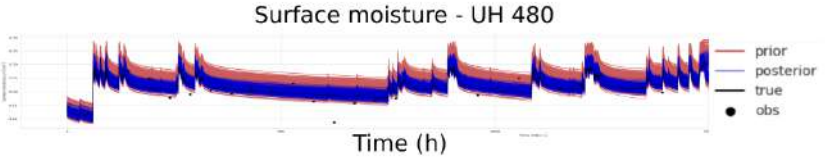
Twin experiments

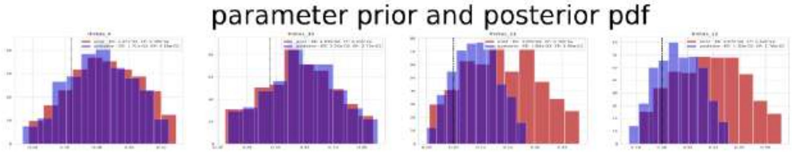
A virtual experiment where we know the true state : an output of the model

- obs $y = x^{true} + error$
- "data" = images of surface soil moisture => virtual data
- model = PESHMELBA
- errors are gaussian



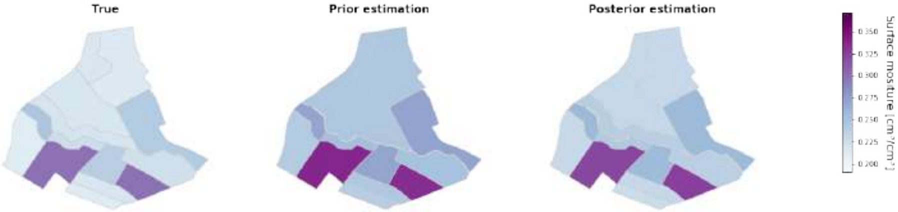
Twin experiments with PESHMELBA





reduction of the uncertainty
some parameters are well estimated

Twin experiments with PESHMELBA



Conclusion

- the twin experiment show the feasibility of DA in pesticide transfer modeling
- assimilate other images than at surface
- define the spatial (and temporal?) correlation in obs. error (E. Rouzies PhD)
- test with real images => scale the model to the data (observation operator)
- combine images with in situ data to improve the water quality predictions
- development on the CATHY model, purely physics-based (less discontinuities?)

⇒ data assimilation = an optimal way to merge information

Thank you!
Any questions ?

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