

# An adaptive regularization strategy for efficiently solving the Richards equation

François Févotte<sup>1</sup> Ari Rappaport<sup>4</sup> Martin Vohralík<sup>2,3</sup>

<sup>1</sup>Triscale Innov, 7 rue de la Croix Martre, 91120 Palaiseau, France

<sup>2</sup>Inria, 48 rue Barrault, Paris 75647, France

<sup>3</sup>Université Paris-Est, CERMICS (ENPC), 77455 Marne-la-Vallée, France

<sup>4</sup>ENSTA Paris, 828, Boulevard des Maréchaux, 91762 Palaiseau Cedex

Journée Inria/IFPEN, December 9, 2024



INSTITUT  
POLYTECHNIQUE  
DE PARIS

# Outline

- 1 Introduction
- 2 Regularization and adaptive algorithm
- 3 Numerical results
- 4 Conclusions and perspectives

# Richards equation: flow in unsaturated porous media

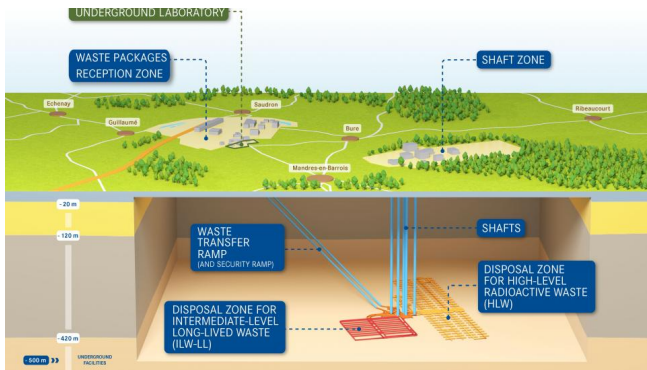


Figure: CIGÉO facility<sup>1</sup>

- ▶ Porous medium is a material containing **pores** (small regular voids)
- ▶ Safety certification of nuclear waste storage (flow of contaminants)

**Motivation:** PDE models are **highly nonlinear** and **nonsmooth**  $\implies$  difficult to solve numerically

<sup>1</sup>Image courtesy of [andra.fr](http://andra.fr)

# Richards equation: derivation and data

## Conservation of Mass (water)

$$\phi \partial_t s + \nabla \cdot \mathbf{q} = f(\mathbf{x}, t)$$

- ▶ Water saturation  $s$
- ▶  $\phi$  porosity,  $f$  external source
- ▶  $\mathbf{q}$  so-called Darcy flux

## Darcy's Law for Flow

$$\mathbf{q} = -\mathbf{K} \kappa(s) (\nabla p + \mathbf{g})$$

- ▶ Fluid pressure  $p$
- ▶  $\mathbf{K}$  absolute permeability tensor,  $\kappa$  relative permeability,  $\mathbf{g}$  gravity

# Putting it all together

Find a pressure  $p$  and saturation  $s$  such that

$$\phi \partial_t s - \nabla \cdot [\mathbf{K} \kappa(s) (\nabla p + \mathbf{g})] = f(\mathbf{x}, t), \quad (\mathbf{x}, t) \in \Omega \times (0, T)$$

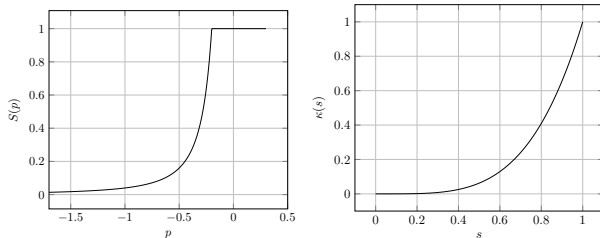


Figure: Brooks–Corey constitutive laws

- ▶ Capillary pressure relation:  $s = S(p)$
- ▶ Choose “pressure formulation”  $p$ : always defined

# Putting it all together

Find a pressure  $p$  and saturation  $s$  such that

$$\phi \partial_t S(p) - \nabla \cdot [\mathbf{K} \kappa(S(p)) (\nabla p + \mathbf{g})] = f(\mathbf{x}, t), \quad (\mathbf{x}, t) \in \Omega \times (0, T)$$

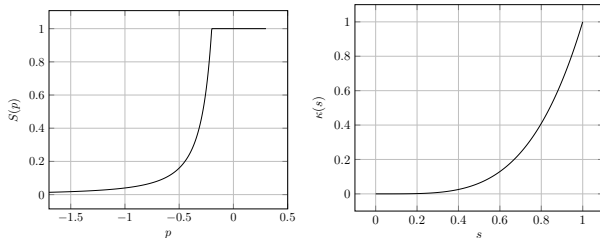


Figure: Brooks–Corey constitutive laws

- ▶ Capillary pressure relation:  $s = S(p)$
- ▶ Choose “pressure formulation”  $p$ : always defined

# Degeneracies and low differentiability

$$\phi \partial_t s - \nabla \cdot [\mathbf{K} \kappa(s) (\nabla p + \mathbf{g})] = f(\mathbf{x}, t), \quad (\mathbf{x}, t) \in \Omega \times (0, T)$$

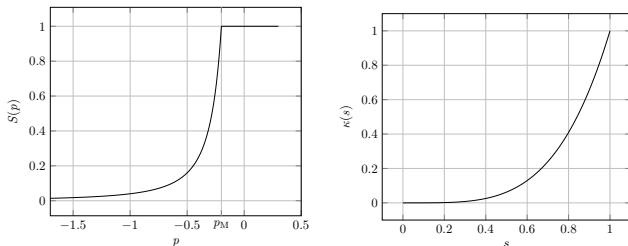


Figure: Brooks–Corey constitutive laws

- ▶ Elliptic:  $\partial_t s = 0$
- ▶ Hyperbolic (ODE):  $\kappa(s) = 0$
- ▶ Kink at  $p = p_M$  for Brooks–Corey constitutive law

# Degeneracies and low differentiability

$$\phi \partial_t s - \nabla \cdot [\mathbf{K} \kappa(s) (\nabla p + \mathbf{g})] = f(\mathbf{x}, t), \quad (\mathbf{x}, t) \in \Omega \times (0, T)$$

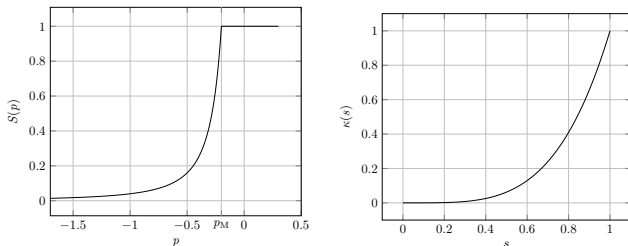


Figure: Brooks–Corey constitutive laws

- ▶ Elliptic:  $\partial_t s = 0$
- ▶ Hyperbolic (ODE):  $\kappa(s) = 0$
- ▶ Kink at  $p = p_M$  for Brooks–Corey constitutive law



# Degeneracies and low differentiability

$$\phi \partial_t s - \nabla \cdot [\mathbf{K} \kappa(s) (\nabla p + \mathbf{g})] = f(\mathbf{x}, t), \quad (\mathbf{x}, t) \in \Omega \times (0, T)$$

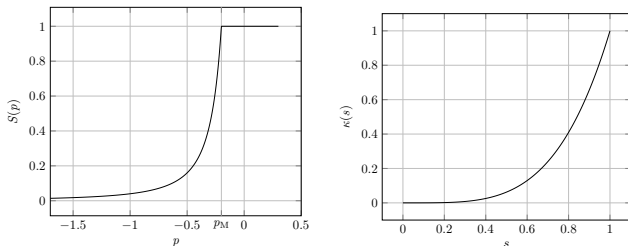


Figure: Brooks–Corey constitutive laws

- ▶ Elliptic:  $\partial_t s = 0$
- ▶ Hyperbolic (ODE):  $\kappa(s) = 0$
- ▶ Kink at  $p = p_M$  for Brooks–Corey constitutive law

# Degeneracies and low differentiability

$$\phi \partial_t s - \nabla \cdot [\mathbf{K} \kappa(s) (\nabla p + \mathbf{g})] = f(\mathbf{x}, t), \quad (\mathbf{x}, t) \in \Omega \times (0, T)$$

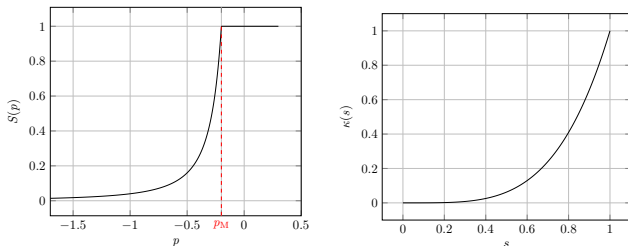


Figure: Brooks–Corey constitutive laws

- ▶ Elliptic:  $\partial_t s = 0$
- ▶ Hyperbolic (ODE):  $\kappa(s) = 0$
- ▶ Kink at  $p = p_M$  for Brooks–Corey constitutive law

# State of the art

## Variable switching



Forsyth, P. A., Y. S. Wu, and K. Pruess (1995). "Robust Numerical Methods for Saturated-Unsaturated Flow with Dry Initial Conditions in Heterogeneous Media". In: *Adv. Water Resour.* 18.1, pp. 25–38.



Diersch, H. J. G. and P. Perrochet (1999). "On the Primary Variable Switching Technique for Simulating Unsaturated-Saturated Flows". In: *Adv. Water Res.* 23.3, pp. 271–301.



Brenner, K. and C. Cancès (2017). "Improving Newton's method performance by parametrization: the case of the Richards equation". In: *SIAM J. Numer. Anal.* 55.4, pp. 1760–1785.



Bassetto, S., C. Cancès, G. Enchéry, and Q. H. Tran (2020). "Robust Newton Solver Based on Variable Switch for a Finite Volume Discretization of Richards Equation". In: *Finite Volumes for Complex Applications IX—Methods, Theoretical Aspects, Examples—FVCA 9, Bergen, Norway, June 2020*. Vol. 323. Springer Proc. Math. Stat. Springer, Cham, pp. 385–393.

## Subquadratic schemes



Celia, M. A., E. T. Bouloutas, and R. L. Zarba (1990). "A General Mass-Conservative Numerical Solution for the Unsaturated Flow Equation". In: *Water Resour. Res.* 26.7, pp. 1483–1496.



Pop, I. S., F. Radu, and P. Knabner (2004). "Mixed Finite Elements for the Richards' Equation: Linearization Procedure". In: *J. Comput. Appl. Math.* 168.1-2, pp. 365–373.



Mitra, K. and I. S. Pop (2019). "A Modified L-scheme to Solve Nonlinear Diffusion Problems". In: *Comp. & Math. Appl.* 7th International Conference on Advanced Computational Methods in Engineering (ACOMEN 2017) 77.6, pp. 1722–1738.



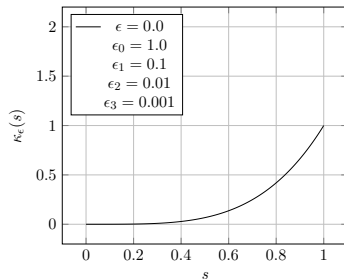
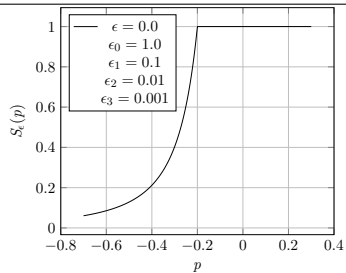
Stokke, J. S., K. Mitra, E. Storvik, J. W. Both, and F. A. Radu (2023). "An adaptive solution strategy for Richards' equation". In: *Comput. Math. Appl.* 152, pp. 155–167.

# Outline

- 1 Introduction
- 2 Regularization and adaptive algorithm
- 3 Numerical results
- 4 Conclusions and perspectives

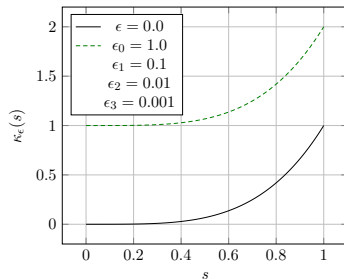
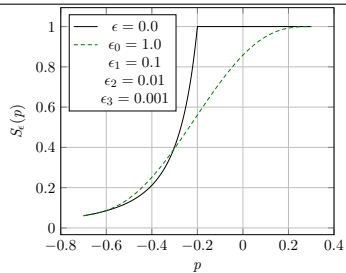
# Regularized sequence

Use solution with  $\epsilon_j$  as initial guess for solving  $\epsilon_{j+1}$



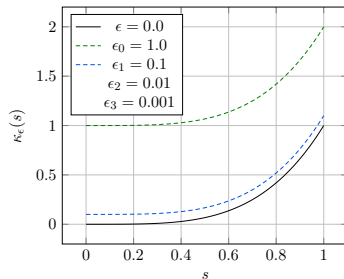
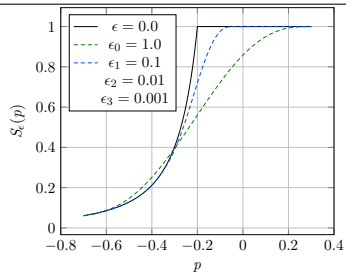
# Regularized sequence

Use solution with  $\epsilon_j$  as initial guess for solving  $\epsilon_{j+1}$



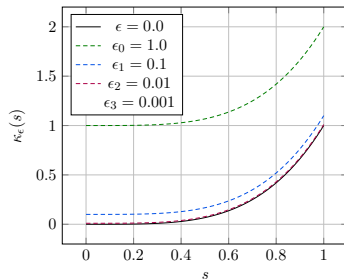
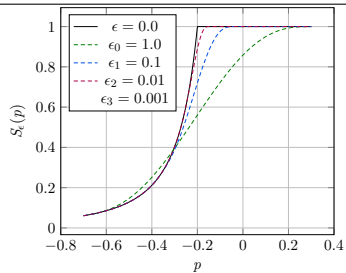
# Regularized sequence

Use solution with  $\epsilon_j$  as initial guess for solving  $\epsilon_{j+1}$



# Regularized sequence

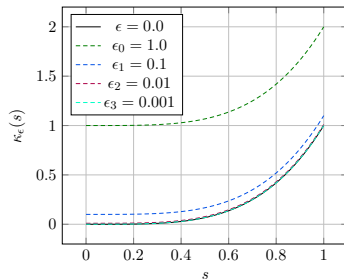
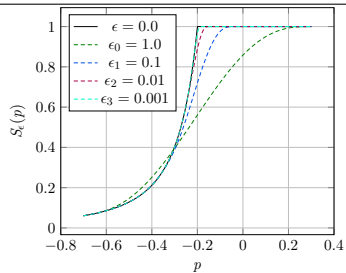
Use solution with  $\epsilon_j$  as initial guess for solving  $\epsilon_{j+1}$





# Regularized sequence

Use solution with  $\epsilon_j$  as initial guess for solving  $\epsilon_{j+1}$



# Discretization

## Method of lines

- ▶ Mesh  $\mathcal{T}_h$  of  $\Omega$ , fixed conforming  $\mathcal{P}^1$ -FEM in space

$$V_h := \{u_h \in H_0^1(\Omega), u_h|_K \in \mathcal{P}_1(K) \quad \forall K \in \mathcal{T}_h\}$$

- ▶ backward Euler in time: uniform time step  $\tau = 1/NT$ , for each  $n \in \{1, \dots, N\}$  and a given  $p_{n-1,h} \in V_h$ ,  $p_{n,h} \in V_h$  satisfying

$$\begin{aligned} \frac{1}{\tau}(\phi(S(p_{n,h}) - S(p_{n-1,h})), \varphi_h) + (\mathbf{F}(p_{n,h}), \nabla \varphi_h) \\ = (f(\cdot, t_n), \varphi_h) + (q_N, \varphi_h)_{\Gamma_N} \quad \forall \varphi_h \in V_h \end{aligned}$$

The *flux function* is defined as

$$\mathbf{F}(q) := \mathbf{K} \kappa(S(q)) [\nabla q + \mathbf{g}].$$

## Regularized and linearized problems

### Regularized problem (index $j$ )

$$\begin{aligned} \frac{1}{\tau} (S_{\epsilon_j}(p_{n,h}^j) - S_{\epsilon_j}(\bar{p}_{n-1,h}^j), \varphi_h) + (\mathbf{F}_{\epsilon_j}(p_{n,h}^j), \nabla \varphi_h) \\ = (f(\cdot, t_n), \varphi_h) + (q_N, \varphi_h)_{\Gamma_N} \quad \forall \varphi_h \in V_h, \end{aligned}$$

►  $\mathbf{F}_{\epsilon_j}(q) := \mathbf{K} \kappa_{\epsilon_j}(S_{\epsilon_j}(q))[\nabla q + \mathbf{g}]$ .

### Regularized/linearized problem (index $k$ )

$$\begin{aligned} \frac{1}{\tau} (\phi S_{\epsilon_j}(p_{n,h}^{j,k-1}) - S_{\epsilon_j}(\bar{p}_{n-1,h}^{j,\bar{k}}), \varphi_h) + \frac{1}{\tau} (\phi \mathbf{L}(p_{n,h}^{j,k} - p_{n,h}^{j,k-1}), \varphi_h) \\ + (\mathbf{F}_{\epsilon_j}^k, \nabla \varphi_h) + (q_N, \varphi_h)_{\Gamma_N} \\ = (f(\cdot, t_n), \varphi_h) \quad \forall \varphi_h \in V_h, \end{aligned}$$

►  $\mathbf{F}_{\epsilon_j}^k := \mathbf{K} \kappa_{\epsilon_j}(S_{\epsilon_j}(p_{n,h}^{j,k-1}))[\nabla p_{n,h}^{j,k} + \mathbf{g}] + \boldsymbol{\xi}(p_{n,h}^{j,k} - p_{n,h}^{j,k-1})$

►  $(\mathbf{L}, \boldsymbol{\xi}) \in \mathbf{L}^\infty(\Omega; \mathbb{R}^{d+1})$  depend on the specific linearization used.

# A posteriori error estimators

## Averaging in $\mathbf{H}(\text{div}, \Omega)$

- ▶ Lowest order Raviart-Thomas space  
 $\mathbf{RT}_0(\mathcal{T}_h) := \{\mathbf{v}_h \in [L^2(\Omega)]^d : \mathbf{v}_h|_K \in [\mathcal{P}(K)]^d + \mathbf{x}\mathcal{P}_0(K), \forall K \in \mathcal{T}_h\}$
- ▶ Reconstruction  $\sigma_{n,h}^{j,k} \in \mathbf{RT}_0(\mathcal{T}_h) \cap \mathbf{H}(\text{div}, \Omega)$  of  $-\mathbf{F}_{\epsilon_j}^k$  based on averaging with connection to *equilibrated* flux [Vlasák 2020; Ern, Nicaise, and Vohralík 2007]

## Component estimators

For an approximate solution  $p_{n,h}^{j,k}$ ,

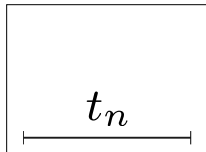
$$\eta_{\text{dis}}^{\ell,j,k} := \|\mathbf{F}_{\epsilon_j}^k + \sigma_{n,h}^{j,k}\| \quad (\text{discretization})$$

$$\eta_{\text{lin}}^{\ell,j,k} := \|\mathbf{F}_{\epsilon_j}(p_{n,h}^{j,k}) - \mathbf{F}_{\epsilon_j}^k\| \quad (\text{linearization})$$

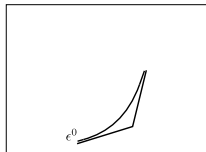
$$\eta_{\text{reg}}^{\ell,j,k} := \|\mathbf{F}(p_{n,h}^{j,k}) - \mathbf{F}_{\epsilon_j}(p_{n,h}^{j,k})\| \quad (\text{regularization})$$

# Adaptive algorithm for Richards based on a posteriori error estimators

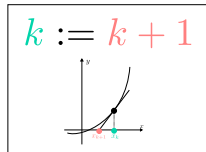
Timestepping



Regularization

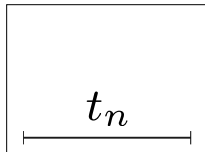


Linearization

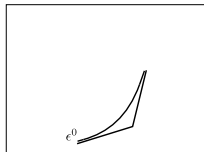


# Adaptive algorithm for Richards based on a posteriori error estimators

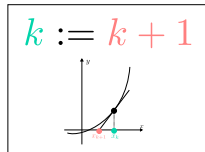
Timestepping



Regularization



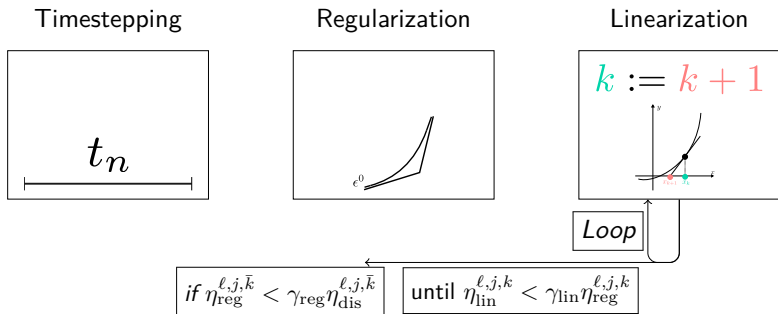
Linearization



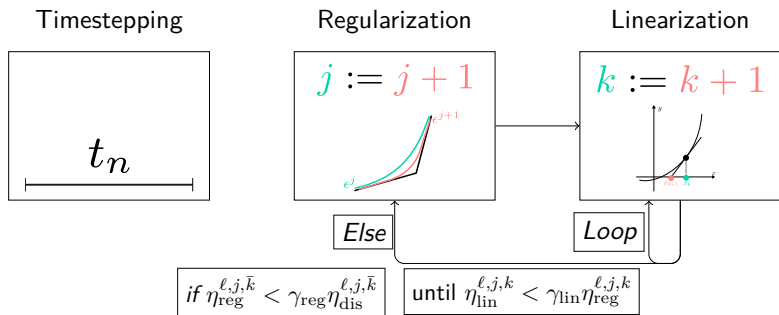
Loop

until  $\eta_{\text{lin}}^{\ell,j,k} < \gamma_{\text{lin}} \eta_{\text{reg}}^{\ell,j,k}$

# Adaptive algorithm for Richards based on a posteriori error estimators

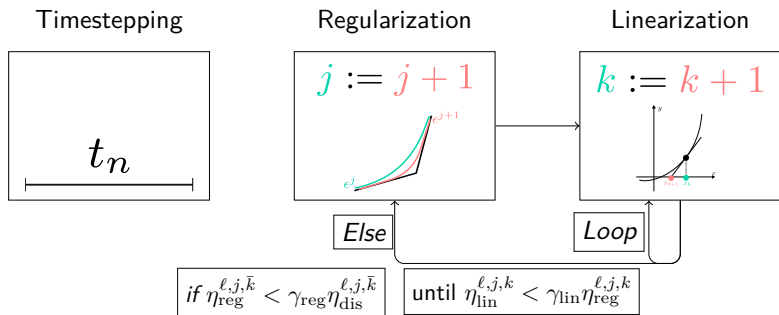


# Adaptive algorithm for Richards based on a posteriori error estimators

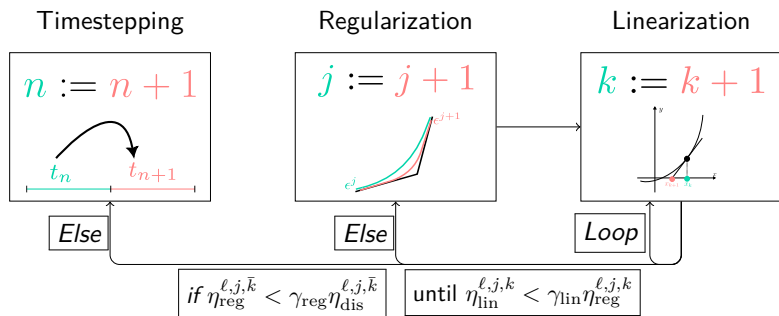




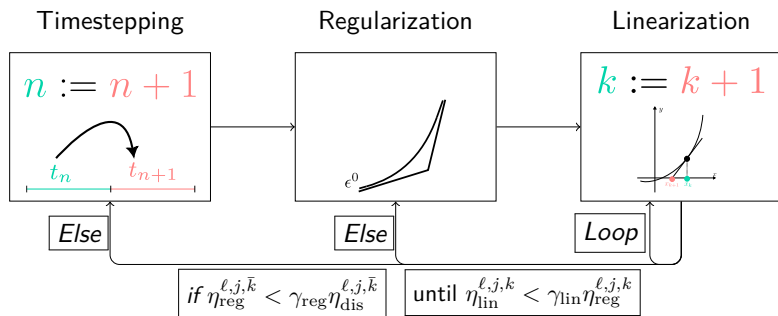
# Adaptive algorithm for Richards based on a posteriori error estimators



# Adaptive algorithm for Richards based on a posteriori error estimators



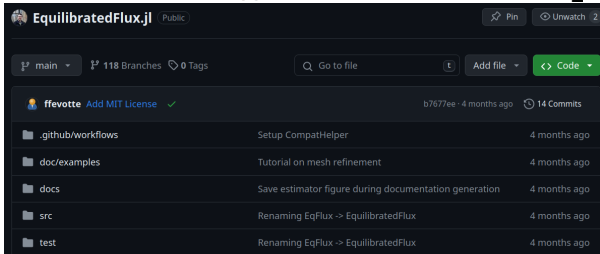
# Adaptive algorithm for Richards based on a posteriori error estimators



# Outline

- 1 Introduction
- 2 Regularization and adaptive algorithm
- 3 Numerical results**
- 4 Conclusions and perspectives

# Free and open source library



```

$$\mathbf{F} = \mathbf{K} \cdot ((\kappa \theta \circ S_n \theta) * \nabla(p_n^{k-1}) + (\kappa \theta \circ S_n \theta) * \mathbf{g})$$

$$\mathbf{F}_j = \mathbf{K} \cdot ((\kappa \circ S_n) * \nabla(p_n^{k-1}) + (\kappa \circ S_n) * \mathbf{g})$$

$$(\xi, \_) = \text{get\_L\_and\_}\xi(\text{linearization}, \text{data})$$

$$\mathbf{F}_j^{k-1} = \mathbf{K} \cdot ((\kappa \circ S_n) * \nabla(p_n^k) + (\kappa \circ S_n) * \mathbf{g}) + \xi * (p_n^k - p_n^{k-1})$$

$$\sigma_n = \text{EquilibratedFlux.build\_averaged\_flux}(-\mathbf{F}_j^{k-1}, \text{model})$$

```

# Methods tested for comparison

## Linearizations

- ▶ Newton's method:

$$L := S'_{\epsilon_j}(p_{n,h}^{j,k-1}), \quad \xi := \mathbf{K}(\kappa_{\epsilon_j} \circ S_{\epsilon_j})'(p_{n,h}^{j,k-1})[\nabla p_{n,h}^{j,k-1} + \mathbf{g}]$$

- ▶ modified Picard [Celia, Bouloutas, and Zarba 1990]:

$$L := S'_{\epsilon_j}(p_{n,h}^{j,k-1}), \quad \xi := \mathbf{0}$$

## Timestepping/regularization

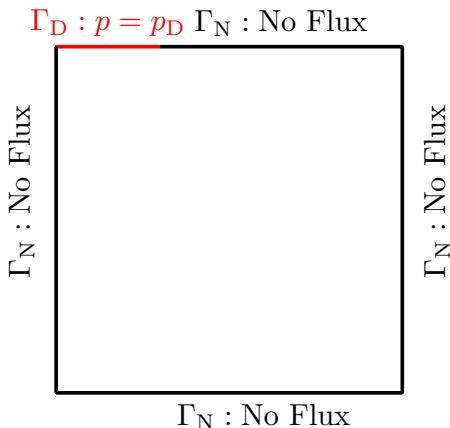
For Newton's method we consider

- ▶ No regularization and simple timestep cutting algorithm
- ▶ No regularization and uniform timestepping
- ▶ With regularization and uniform timestepping

For modified Picard only uniform timestepping and no regularization

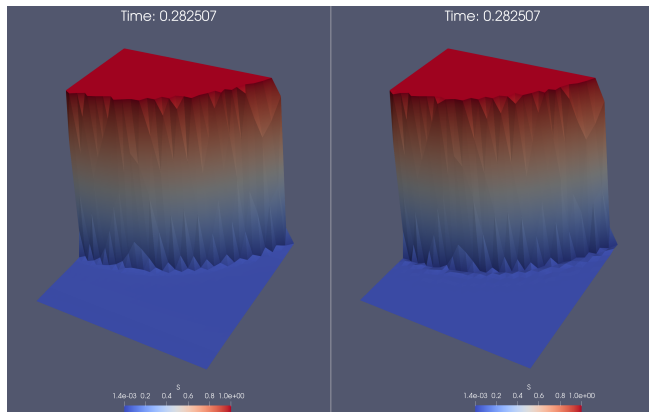
## Injection test: setup

- ▶  $\Omega = (0, 1)^2$
- ▶  $T = 1.0$
- ▶  $\tau = 2.82 \cdot 10^{-2}$
- ▶ Quasi uniform mesh with  $h = 2.82 \cdot 10^{-2}$
- ▶  $\Gamma_D = \{(x_1, x_2) | x_1 \in (0, 0.3), x_2 = 1\}$
- ▶  $\Gamma_N = \partial\Omega \setminus \Gamma_D$
- ▶  $\mathbf{g} = (0, -1)^T$
- ▶  $f = 0$
- ▶  $p_0 = -1, \quad s_0 = S(p_0)$
- ▶  $p_D = 1$



Inspired by test case in [Brenner and Cancès 2017]

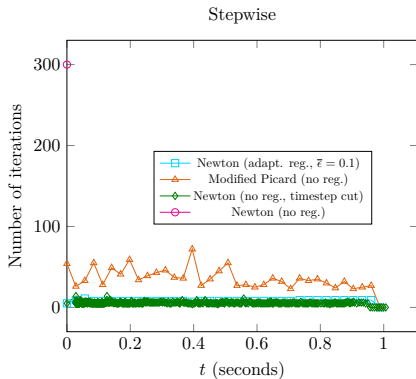
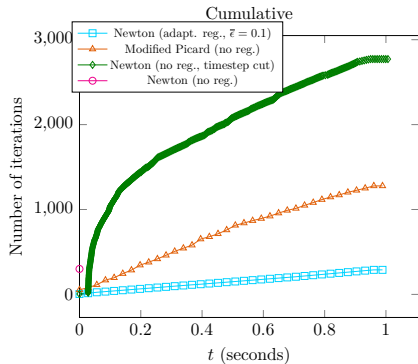
## Injection test: saturation comparison



- ▶ With (left) and without (right) regularization

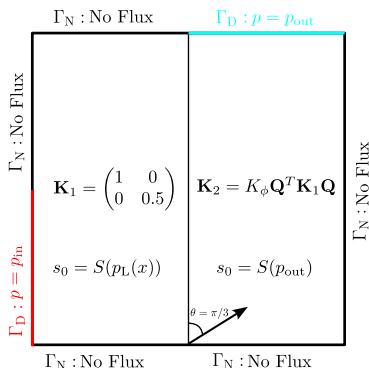


# Injection test: performance



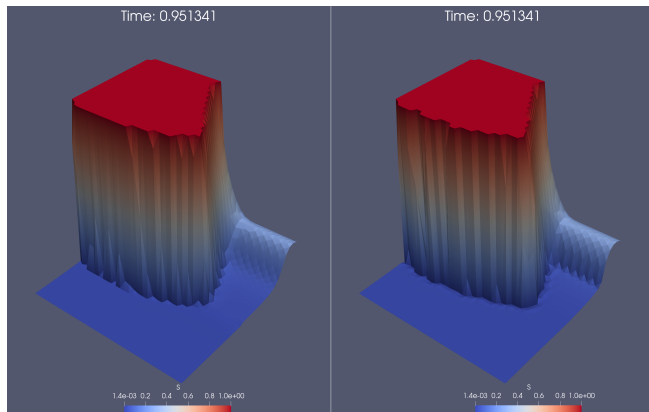
## Realistic test: setup

- ▶  $\Omega = (0, 1)^2$
- ▶ quasi uniform mesh with  $h = 2.02 \cdot 10^{-2}$
- ▶  $T = 1$
- ▶  $\tau_0 = 2.02 \cdot 10^{-2}$
- ▶  $\mathbf{g} = (-1, 0)^T$
- ▶  $\mathbf{Q} = \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix}$
- ▶  $K_\phi = 0.1$
- ▶  $p_L(\mathbf{x}) = \left( \frac{p_{\text{out}} - p_{\text{in}}}{0.5} \right) \mathbf{x}$
- ▶  $p_{\text{out}} = -2.0$
- ▶  $p_{\text{in}} = -0.2$
- ▶  $\phi = 1$



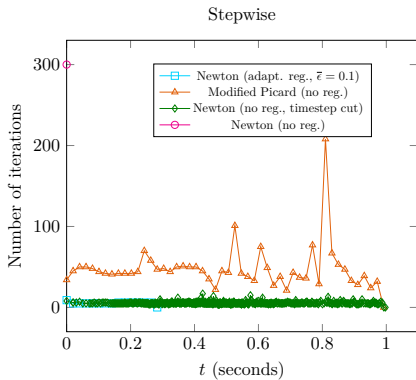
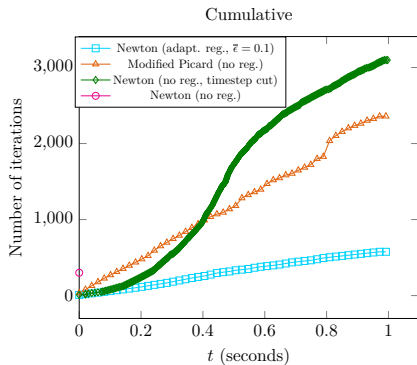
Inspired by test case in [Mitra and Vohralík 2024]

## Realistic test: saturation comparison

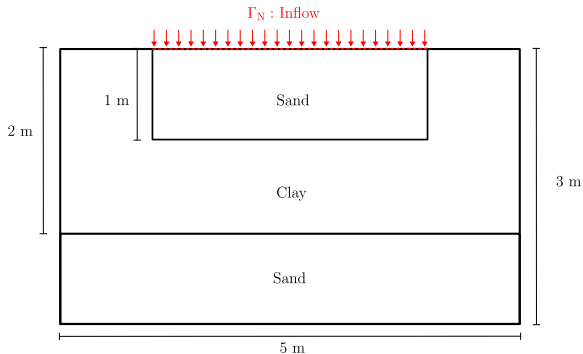


- ▶ With (left) and without (right) regularization

# Realistic test: performance



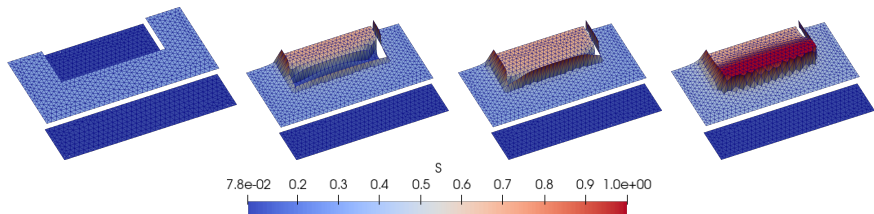
# Perched water table: setup



Material	$\kappa_c$	$\phi$	$S_R$	$S_V$	$\lambda_2$	$\alpha$
Sand	$6.262 \times 10^{-5}$	0.368	0.07818	1	0.553	2.8
Clay	$1.516 \times 10^{-6}$	0.4686	0.2262	1	0.2835	1.04

- ▶ Adapted from [Kirkland, Hills, and Wierenga 1992]

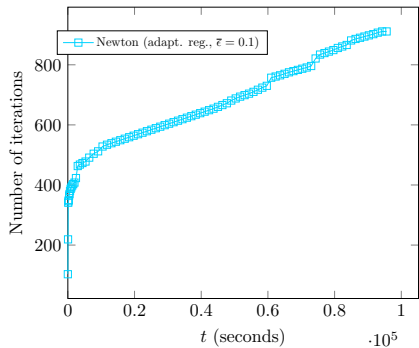
## Perched water table: saturation profile



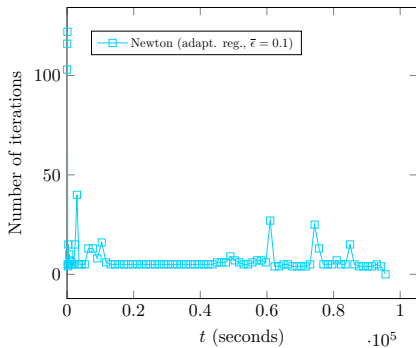
- ▶ Evolution of the saturation at time  $t \in \{0 \text{ s}, 21 \cdot 10^3 \text{ s}, 41 \cdot 10^3 \text{ s}, 86.1 \cdot 10^3 \text{ s} = 1 \text{ day}\}$ .

# Perched water table: performance

Cumulative



Stepwise



# Outline

- 1 Introduction
- 2 Regularization and adaptive algorithm
- 3 Numerical results
- 4 Conclusions and perspectives



## Summary

- ▶ Introduce regularization of common constitutive laws for Richards equation
- ▶ Error estimation based on flux reconstruction
- ▶ Adaptive algorithm based on balancing error components
- ▶ Tested on benchmark problems from the literature

Févotte, F., Rappaport, A., and Vohralík, M. *Adaptive regularization for the Richards equation*. *Comput. Geosci.* (2024).

## Perspectives

- ▶ Combine with existing techniques like variable switching
- ▶ Extension to two phase flow (variational inequalities)

Thank you for your attention!

## Summary

- ▶ Introduce regularization of common constitutive laws for Richards equation
- ▶ Error estimation based on flux reconstruction
- ▶ Adaptive algorithm based on balancing error components
- ▶ Tested on benchmark problems from the literature

Févotte, F., Rappaport, A., and Vohralík, M. *Adaptive regularization for the Richards equation*. Comput. Geosci. (2024).

## Perspectives

- ▶ Combine with existing techniques like variable switching
- ▶ Extension to two phase flow (variational inequalities)

Thank you for your attention!

## Summary

- ▶ Introduce regularization of common constitutive laws for Richards equation
- ▶ Error estimation based on flux reconstruction
- ▶ Adaptive algorithm based on balancing error components
- ▶ Tested on benchmark problems from the literature

Févotte, F., Rappaport, A., and Vohralík, M. *Adaptive regularization for the Richards equation*. Comput. Geosci. (2024).

## Perspectives

- ▶ Combine with existing techniques like variable switching
- ▶ Extension to two phase flow (variational inequalities)

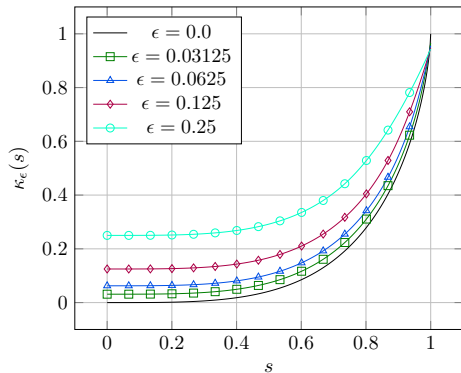
Thank you for your attention!

# Regularization of the relative permeability for Van-Genuchten

Follow the approach in [Bassetto, Cancès, Enchéry, and Tran 2020] where the relative permeability  $\kappa$  is replaced by a second degree polynomial near the critical point  $s = 1$ :

$$\kappa_\epsilon(s) = \begin{cases} \kappa(s) + \epsilon, & \text{if } s \leq 1 - \epsilon, \\ \tilde{\kappa}(s) + \epsilon, & \text{otherwise,} \end{cases}$$

$$\tilde{\kappa}(s) = \frac{\kappa''(1 - \epsilon)}{2}(s - (1 - \epsilon))^2 + \kappa'(1 - \epsilon)(s - (1 - \epsilon)) + \kappa(1 - \epsilon),$$



# Hermite interpolation for the Brooks–Corey Saturation

$$S_\epsilon(p_M - \epsilon) = S(p_M - \epsilon),$$

$$S_\epsilon(p_M + \epsilon) = S(p_M + \epsilon)$$

$$S'_\epsilon(p_M - \epsilon) = S'(p_M - \epsilon),$$

$$S'_\epsilon(p_M + \epsilon) = S'(p_M + \epsilon),$$

$$\vdots$$
$$\vdots$$

$$S_\epsilon^{(r)}(p_M - \epsilon) = S^{(r)}(p_M - \epsilon),$$

$$S_\epsilon^{(r)}(p_M + \epsilon) = S^{(r)}(p_M + \epsilon).$$

