Can you hear the size of a reservoir?

MOD510: Mandatory project #2

Deadline: 10. October 2021 (23:59)

Sep 27, 2021

Learning objectives. By completing this project, the student will:

- Develop numerical pressure solvers for the radial diffusivity equation, one for steady-state flow and one for transient flow.
- For the steady-state case, compare the model to analytical solutions.
- Compare the efficiency of sparse and dense matrix solvers.
- Use the time-dependent model to study pressure decline in a well, and estimate the size of a reservoir from well test data.

Read this before you start.

In this project we show that information coming from a *single point* in a reservoir can help determine the size of the reservoir, and its ability to transmit fluids. The project starts with theory to motivate and provide background for understanding the physics of fluid flow. However, the solution method we will employ is very similar to what you have already seen for the heat equation in [6]. Therefore, **you do not have to understand everything in order to solve the exercises**; for a quick start, jump to section 2.2 and continue from there. Note also that the Appendix contains **practical coding tips**, as well as some of the equations you will need for the project.

1 Introduction

Reservoirs are large pieces of porous rock that are buried underground. A sedimentary rock consists of many small grains, like sand on a beach. During geological time, the grains have become cemented together, but still there is

plenty of room for oil, water, and gas to occupy the pores in-between the grains. Usually 20-30 % of the total reservoir volume is filled with fluids, but sometimes it can be as high as 50 %. Reservoirs are most likely going to be very important in the future as carbon capture and storage (CCS) is viewed as one solution to the global warming challenge. Oil and gas is produced, and then the CO_2 can be re-injected in the reservoir as illustrated in figure 1, or CO_2 can be captured directly from the air as done in Iceland.

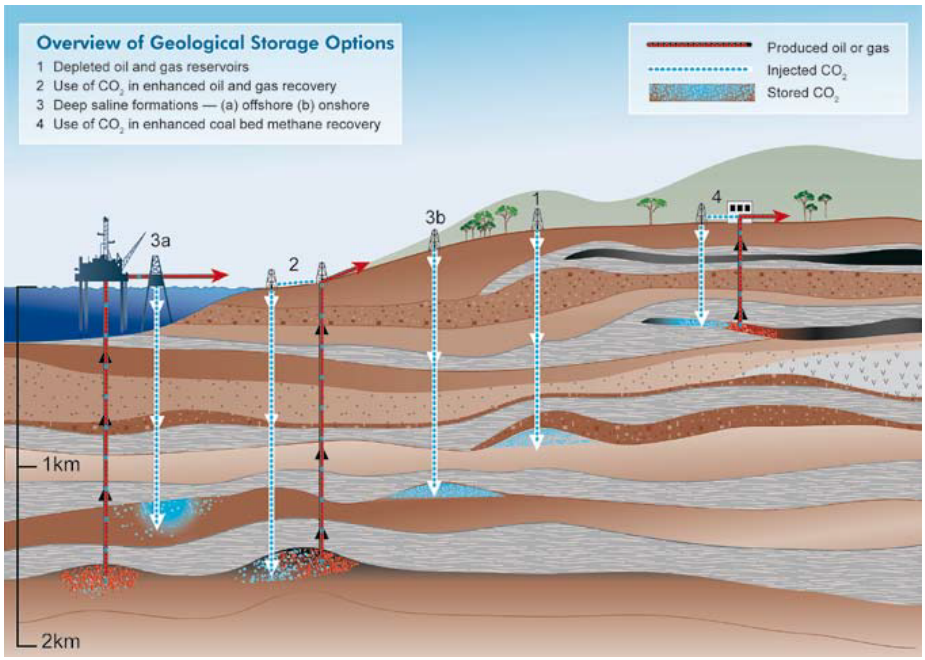

Figure 1: Different CO_2 storage options from [11].

Fluids can be extracted from a reservoir by drilling one or more production wells. Before opening up for production it is important to quantify the *absolute permeability*, which is a measure of how easily fluids flow through the rock. The absolute permeability plays the same role as does electric conductivity in electrodynamics [4]. For example, a high permeability means that fluids flow easily through the rock, just as a highly conductive (low resistance) material transmits electric current easily.

What actually drives fluid flow is the *pressure gradient*, ∇p. If we continue the analogy with electricity, ∇p plays the role of the voltage gradient inside a conductor. The magnitude of the pressure gradients depends on both the rock and fluid properties [1]. Initially, pressure differences are established by the natural energy of the reservoir itself. Additional pressure support may be achieved by injecting fluids, typically water and/or gas [5].

During production it is also useful to monitor whether the permeability changes with time. This is because injection or production of fluids may cause clogging of pores close to the wells, e.g, as a result of chemical reactions taking place. If this happens, the permeability will be reduced, which may cause excessive pressure build-up [8]. Another factor to consider is *reservoir compaction*. As fluids are produced, the pressure in the formation drops, which could lead to large increases in the effective stress in the reservoir, and to seabed subsidence. This happened at the Ekofisk, where platforms sank by several meters [13], see figure 2 Similar observations have been made in Venice, which is currently sinking. Part of the recorded subsidence of the city has been attributed to groundwater pumping operations [14].

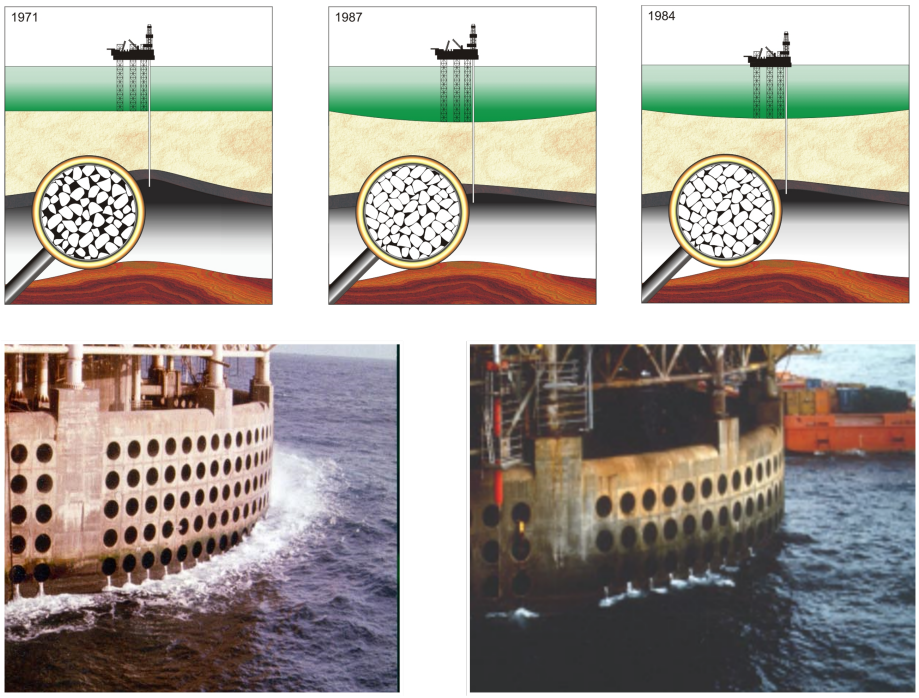

Figure 2: A brief history of the Ekofisk compaction from start of production in 1971, fluids were removed and as a consequence the grains were pushed closer together and the platform sank.

A key tool to avoid the above-mentioned problems is *well pressure testing* [9], which is the topic of this project. It turns out that by studying the time-dependence of well pressures during production, one can learn a lot about a reservoir. This information is clearly extremely relevant for an oil company, but it is of equal importance in geothermal applications, and during groundwater monitoring. Reservoirs are huge ($\sim$ km size), and the well is only about half a foot, but still the information coming from a single producing well can provide

valuable information, e.g., estimates for the size of the reservoir, and whether formation damage has likely occurred. If one finds that the reservoir has become clogged, one has to implement some kind of intervention, after which one can measure the effect of the intervention by repeating the well test.

2 Background theory

2.1 Derivation of the diffusivity equation

To derive an equation that describes fluid flow in a reservoir, the starting point is, as always, the *continuity equation*. The system we will consider is illustrated in figure 3. By applying a mass balance to the dotted volume shown in the figure, we can derive a one-dimensional version of the continuity equation [6]:

$$\frac{\partial q(x,t)}{\partial t} A(x) = -\frac{\partial (J(x,t)A(x))}{\partial x} + \dot{\sigma}(x,t)A(x)\,. \tag{1}$$

In the above expression, A is the cross-sectional area at position x, q denotes the mass of fluid per unit volume, J is the amount of mass flowing into the volume per unit time per unit area (i.e., the *flux*), and $\dot{\sigma}$ represents the amount of mass generated per unit volume per unit time.

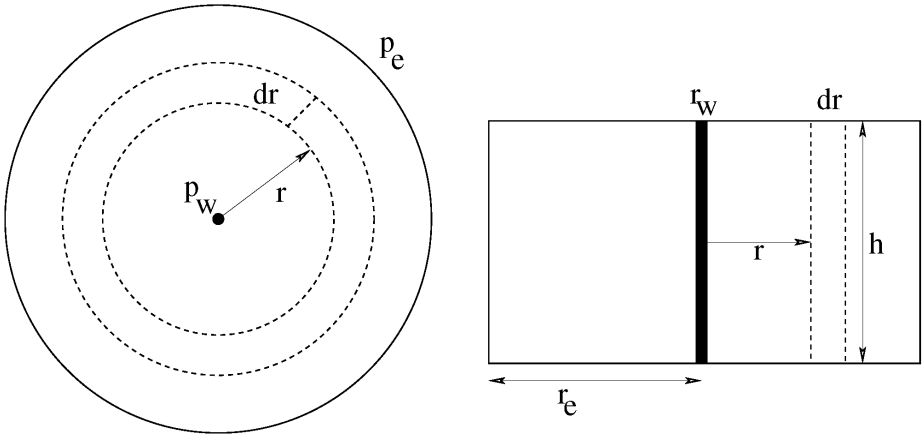

Figure 3: A vertical well placed in the middle of a cylindrical reservoir of constant thickness, h. The reservoir is the volume between the well radius at $r = r_w$ and the exterior radius at $r = r_e$. Left plot: Top view of the reservoir. Right plot: A view from the side.

For the situation depicted in figure 3, fluid flow is radially symmetric. Hence, we make the following identifications:

$$x \to r\,, \tag{2}$$

$$A(x) \to A(r) = 2\pi r h\,. \tag{3}$$

Since there are no wells inside the porous medium (only at the inner boundary, $r = r_w$), we get $\dot{\sigma} = 0$. Furthermore, since

$$\text{mass flux} = \frac{\text{mass}}{\text{area} \cdot \text{time}} = \frac{\text{mass} \cdot \text{length}}{\text{volume} \cdot \text{time}} = \text{density} \cdot \text{velocity}\,, \tag{4}$$

we see that $J(r) = \rho u_r$, where ρ is the fluid density, and u_r is the (radial) fluid velocity.

The mass term is $q = \phi\rho$, where ϕ is the porosity of the porous medium. We have to multiply density with porosity because fluids can only flow inside the void space in-between the grains of the rock. Typically, the porosity accounts for $\sim 20\%$ of the total volume.

By inserting all of the above, equation (1) can be reformulated into:

$$\begin{aligned} 2\pi r h \frac{\partial}{\partial t}\left(\phi\rho\right) &= -\frac{\partial}{\partial r}\left(2\pi r h \rho u_r\right)\,, \\ \frac{\partial}{\partial t}\left(\phi\rho\right) &= -\frac{1}{r}\frac{\partial}{\partial r}\left(r\rho u_r\right)\,. \end{aligned} \tag{5}$$

There are some important steps left:

1. We have to relate fluid velocity to pressure. Here, we will use an empirical law named after the French water engineer, Henry Darcy [2]. This equation is fundamental for everyone that studies groundwater flow.

2. The fluid density appears on both sides of equation (5), but we would like to relate fluid flow to *pressure* and not *density*. Fortunately we can express fluid density in terms of pressure by introducing a *fluid compressibility*-factor, c_f. If pressure increases, the density of the fluid increases.

3. On the left-hand side, the time derivative of the porosity enters. The porosity might also change when the fluid pressure changes (e.g., increasing pressure can lead to rock compaction). This can be accounted form by introducing a *rock compressibility*-factor, c_r.

For radially symmetric flow, Darcy's law [7] takes the form

$$u_r = -\frac{k}{\mu}\frac{\partial p}{\partial r}\,, \tag{6}$$

where k is the absolute permeability of the rock, p is fluid pressure, and μ is fluid viscosity. We will not show the full derivation of how to account for compressibility. However, by assuming that the fluid compressibility is low (this is the case for water [3]), and introducing the *total compressibility* $c_t = c_f + c_r$, it is possible to derive the *diffusivity equation*:

$$\frac{\partial p}{\partial t} = \eta\frac{1}{r}\frac{\partial}{\partial r}(r\frac{\partial p}{\partial r})\,, \tag{7}$$

where the *hydraulic diffusivity* is:

$$\eta = \frac{k}{\mu\phi c_t}\,. \tag{8}$$

Interpretation of the diffusivity equation.

The diffusivity equation describes how pressure waves travel in a porous rock: The factor η can be thought of as a diffusion constant, in analogy with molecular diffusion. Whenever you have a diffusion equation, you can use the relation

$$\text{diffusion constant} \approx \frac{\text{length}^2}{4 \cdot \text{time}} .$$

to give a rough estimate of the speed of "diffusion".

For example, if $\eta = 2.5\ \text{m}^2/\text{s}$ and the reservoir radius is 1 km, it will take approximately

$$\frac{(1000\ \text{m})^2}{4 \cdot 2.5\ \text{m}^2/\text{s}} \simeq 1.2\ \text{days}$$

for the pressure wave to reach the outer boundaries of the reservoir.

2.2 The radial flow equations including boundary conditions

Before attempting to find a solution to equation (7), we need boundary conditions. According to Darcy's law, the volumetric flow rate at the well bore is

$$Q = -\left(u \cdot A\right)\Big|_{r=r_w} = \frac{2\pi hkr}{\mu}\frac{\partial p}{\partial r}\Big|_{r=r_w} , \tag{9}$$

where we have adopted the sign convention that $Q > 0$ for production of fluids. In this project it will be assumed that Q is constant. At the exterior boundary, we require a constant fluid pressure,

$$p\left(r = r_e\right) = p_{\text{init}} , \tag{10}$$

where p_{init} is the initial fluid pressure in the reservoir. Before implementing the numerical solution, we perform a (clever) coordinate change $r \to y$, where y is

$$y = y(r) \equiv \ln \frac{r}{r_w} . \tag{11}$$

In the new y-coordinate, equations (7), (9), and (10) are transformed into

The equations you will need in the rest of the project.

$$\frac{\partial p}{\partial t} = \eta \frac{e^{-2y}}{r_w^2}\frac{\partial^2 p}{\partial y^2} , \tag{12}$$

$$\frac{\partial p}{\partial y}\left(y = y_w\right) = \frac{Q\mu}{2\pi hk} , \tag{13}$$

$$p\left(y = y_e\right) = p_{\text{init}} . \tag{14}$$

Note: In order to plot the pressure vs the *physical coordinate* r, you will have to invert equation (11)

$$r = r_w e^y \tag{15}$$

3 Exercise 1: Steady-state solution

The simplest situation is when there is no pressure-variation in time, i.e., steady-state flow. Then, we can replace the partial derivatives with ordinary derivatives, and equations (12), (13), and (14) become:

$$\frac{d^2p}{dy^2}(y) = 0 \text{ for all y}\,, \tag{16}$$

$$\frac{dp}{dy}\,(y = y_w) = \alpha \tag{17}$$

$$p(y = y_e) = p_{\text{init}}\,. \tag{18}$$

Notice.

In exercise 1 we want to focus on numerical implementation aspects. Therefore, we simply set $\alpha \equiv Q\mu/2\pi hk = 1$. Later in the project, you **will have to use physical input parameters** for Q, μ, h, and k in order to match data.

Part 1.

- Show that the analytical solution to equations (16), (17), and (18) is

$$p(y) = p_{\text{init}} + \alpha(y - y_e)\,. \tag{19}$$

Part 2. To obtain a numerical steady-state solution, we start by dividing the total flow domain into N equally-sized grid blocks in the y-coordinates, and we select the *midpoint* of each y-block as our grid points (see figure 4). Let p_i be a short-hand notation for the pressure solution at grid point number i, $i = 0, 1, \ldots, N-1$.

- Approximate the second derivative of pressure in equation (16) with an appropriate finite difference formulation (see Appendix A)
- For grid point number i, write down the resulting finite difference equation in terms of the variables p_i. Remember to include the truncation error term.

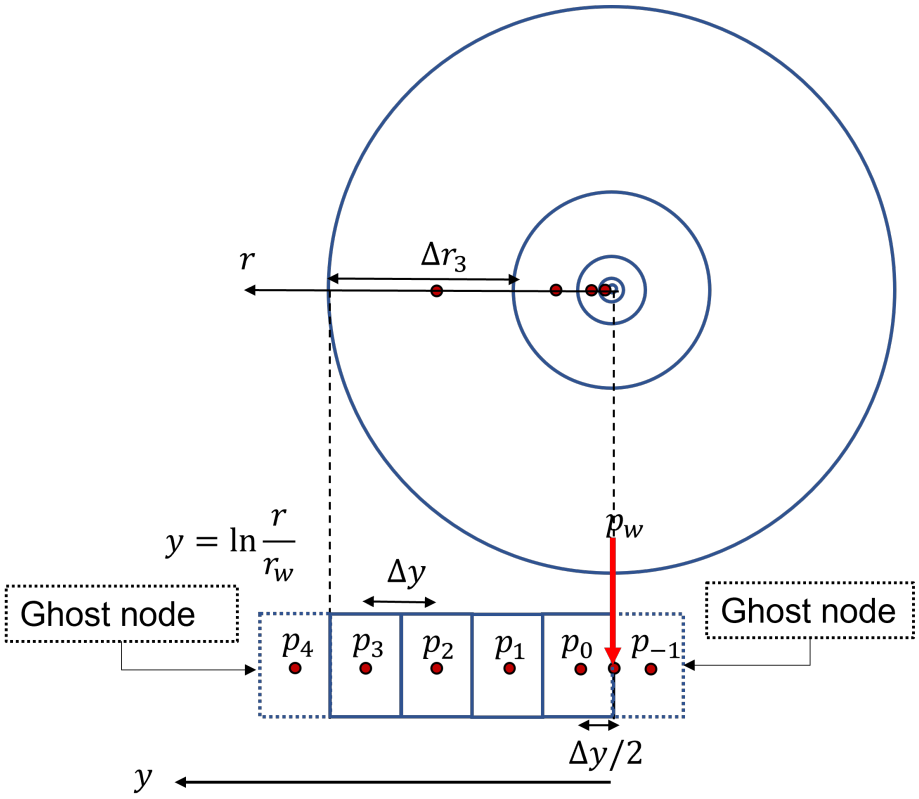

Figure 4: Sketch of the coordinate transformation $r \to y$. Note that the pressure is always evaluated at the center of the y-blocks.

Note that we cannot implement the numerical scheme in Python quite yet, because we have not accounted for boundary conditions. To account for the boundary condition at the well, we can apply a *central difference* approximation to express the pressure at the "ghost node" $i = -1$ in terms of p_0 (see figure 4). Similarly, we have to apply the boundary condition at $y = y_e$ to find a formula for the "fictive pressure" p_N in terms of known pressure values.

Part 3. If $p_e = p(y_e) = p_{\text{init}}$, the "lazy" option for the exterior reservoir boundary is to set

$$p_N = p_e \tag{20}$$

- Let $N = 4$. For the "lazy" implementation of the boundary condition at $y = y_e$, equation (20), show that the matrix equation we need to solve is

$$\begin{pmatrix} -1 & 1 & 0 & 0 \\ 1 & -2 & 1 & 0 \\ 0 & 1 & -2 & 1 \\ 0 & 0 & 1 & -2 \end{pmatrix} \begin{pmatrix} p_0 \\ p_1 \\ p_2 \\ p_3 \end{pmatrix} = \begin{pmatrix} \alpha \Delta y \\ 0 \\ 0 \\ -p_e \end{pmatrix}. \tag{21}$$

Part 4. We can investigate the error of the "lazy" approximation formally with Taylor's formula:

$$\begin{aligned} p_N &= p(y_e + \frac{\Delta y}{2}) \\ &= p(y_e) + p'(y_e)\frac{\Delta y}{2} + \frac{1}{2}\frac{d^2p}{dy^2}\left(\frac{\Delta y}{2}\right)^2 + \cdots . \end{aligned} \tag{22}$$

In the steady state limit we see from equation (16) that $d^2p/dy^2 = 0$, hence all higher-order terms are zero. Therefore, we get

$$p_N = p_e + p'(y_e)\frac{\Delta y}{2}. \tag{23}$$

A smarter solution for $i = N - 1$ is therefore to write

$$p'(y_e) = \frac{P_N - P_{N-1}}{\Delta y}, \tag{24}$$

and to use equation (23) to derive a "not-so-lazy" boundary condition

$$p_N = 2p_e - p_{N-1} \tag{25}$$

- Let $N = 4$. What is the matrix equation we need to solve when using equation (25) as boundary condition?

Part 5.

- For both implementations of the boundary condition at $y = y_e$, solve the matrix equation for $N = 4, 40, 400$, and 4000.
- Compare with the analytical expression, equation (19), *in a single point.*
- Does the numerical error scale as you expect in the two cases? Where do the errors originate from?

4 Exercise 2: Time-dependent solution

Read this before starting to code!

In the rest of the project you will use physical values for all model parameters, which means you have to keep track of a lot of variables and physical units. To stay organized, we **strongly recommend** that you code your time-dependent pressure solver into a single Python class. If you do not want to start from scratch, you may use the class in Appendix D as a starting point.

If you want, you could also include the steady-state solver from the first Exercise as a special case of the more general solver. If you do this, **only hand in a single version of the final class**. Regardless of whether you use classes or not, you should try to limit code duplication by breaking your simulation program(s) into several smaller functions. A single "top-level" function can be implemented to execute all the necessary steps in order. **Remember to give all functions and classes descriptive names**.

To capture how pressure changes in time, we go back to the original diffusivity equation. We apply the following *implicit time-discreization* (see Appendix A for notation and derivation):

Implicit scheme for grid point i.

$$\frac{p_i^{n+1} - p_i^n}{\Delta t} = \eta \cdot \frac{e^{-2y_i}}{r_w^2} \cdot \frac{p_{i+1}^{n+1} + p_{i-1}^{n+1} - 2p_i^{n+1}}{\Delta y^2} \tag{26}$$

Part 1.

- Show that for the special case $N = 4$, the matrix equation we need to solve each time step is:

$$\underbrace{\begin{pmatrix} 1+\xi_0 & -\xi_0 & 0 & 0 \\ -\xi_1 & 1+2\xi_1 & -\xi_1 & 0 \\ 0 & -\xi_2 & 1+2\xi_2 & -\xi_2 \\ 0 & 0 & -\xi_3 & 1+3\xi_3 \end{pmatrix}}_{\mathbf{A}} \underbrace{\begin{pmatrix} p_0^{n+1} \\ p_1^{n+1} \\ p_2^{n+1} \\ p_3^{n+1} \end{pmatrix}}_{\mathbf{p}^{n+1}} = \underbrace{\begin{pmatrix} p_0^n \\ p_1^n \\ p_2^n \\ p_3^n \end{pmatrix}}_{\mathbf{p}^n} + \underbrace{\begin{pmatrix} -\beta\xi_0 \\ 0 \\ 0 \\ 2p_i\xi_{N-1} \end{pmatrix}}_{\mathbf{d}}, \tag{27}$$

where we have defined

$$\xi_i \equiv \frac{\eta e^{-2y_i} \Delta t}{r_w^2 \Delta y^2},$$

and

$$\beta \equiv \frac{Q\mu\Delta y}{2\pi kh}.$$

Part 2. Again let $N = 4$. Assume default model input parameters (see Appendix C), and that $\Delta t = 0.01$ day.

- Show that the matrix is (in SI units):

$$\begin{pmatrix} 6.30844146e+03 & -6.30744146e+03 & 0.00000000e+00 & 0.00000000e+00 \\ -1.14232623e+02 & 2.29465247e+02 & -1.14232623e+02 & 0.00000000e+00 \\ 0.00000000e+00 & -2.06884080e+00 & 5.13768160e+00 & -2.06884080e+00 \\ 0.00000000e+00 & 0.00000000e+00 & -3.74683004e-02 & 1.11240490e+00 \end{pmatrix}$$

Part 3.

- Implement a simulator that solves the time-dependent problem for any choice of input parameters.

For tips on how to get started, see Appendix A.1 and Appendix D.

5 Exercise 3: Accuracy and performance

Part 1.

- Compare your numerical solution with the *line-source solution* given by equation (35). Do this for several values of N. To do the comparison you need to plot your solution in terms of the *physical coordinates* (i.e., $r(y) = r_w e^y$).

Note: The line-source solution is valid at intermediate times, when reservoir boundary effects are negligible.

Part 2. Next, we want to take advantage of the symmetry of the problem. At run-time, the simulator should be able to choose between three different matrix solvers (dense (`numpy.linalg.solve`), sparse using SciPy (`scipy.sparse.linalg.spsolve`), and sparse using the Thomas algorithm). An implementation of the Thomas algorithm can be found in appendix E.

- Use the `%timeit` option in Jupyter to evaluate the speed of each solver.
- How large must N be in order to see a difference?

Part 3.

- (**OPTIONAL**) The analytical solution to the time-dependent problem is extremely complex [10]. Assuming you do not have access to it, how could you investigate numerical errors of your implementation? (e.g., how error scales with step size)

6 Exercise 4: Match model to well test data

In the final exercise we are going to study data from a well test. During a well test, the production engineer starts to produce from the reservoir, while monitoring how well pressure changes in time.

Part 1. So far, we have calculated the pressure distribution *inside the reservoir*. The actual observable well pressure is missing from our calculations, but we can estimate it by discretizing equation (13).

- Use a first-order finite difference approximation to find a formula for the well pressure in terms of the well block pressure, p_0.

Hint: Use Taylor's formula with step-size $\Delta y/2$.

Part 2.

- Extend your simulator by adding a function that calculates the well pressure.

Part 3. Well test data are available in the text file `well_bhp.dat` (located in the `data` folder).

- Read the well test data into Python, and make a scatter plot of well pressure versus time.

Part 4. Towards the end of the test, we see that the well pressure stabilizes towards a constant value. This indicates that the pressure wave has reached the edge of the reservoir.

For this part you may assume default model input (Appendix C) for all parameters except the following three: k, p_i, and r_e.

- Fit your numerical model to the well test data by changing the values of k, p_i, and r_e.
- Make a plot in which you compare 1) the well test data, 2) your numerical well pressure solution, and 3) the corresponding line-source solution at $r = r_w$.

Hints:

- Use a logarithmic scale on the x-axis
- You may try to match the well test curve manually, but it might be easier to use automated curve-fitting.

Part 5.

- Based on the value you found for r_e, what is the total volume of water in the reservoir?

A Derivation of implicit finite difference scheme

We are going to use a fixed time step, Δt, for our simulations. Let $t_n = n \cdot \Delta t$ denote the time after taking n steps, and let y_i be a short-hand notation for grid point number i ($i = 0, 1, \ldots, N-1$). We also introduce the following notation:

$$p_i^n \equiv p(y_i, t_n) \tag{28}$$

$$p_i^{n+1} \equiv p(y_i, t_{n+1})\,. \tag{29}$$

To discretize the left-hand side of equation (12) for point with index i, we use a backward difference for the time variable:

$$\left.\frac{dp}{dt}\right|_i = \frac{p(y_i, t+\Delta t) - p(y_i, t)}{\Delta t} + \mathcal{O}(\Delta t) = \frac{p_i^{n+1} - p_i^n}{\Delta t} + \mathcal{O}(\Delta t). \tag{30}$$

For the right-hand side, we use a central difference scheme to approximate the spatial derivative. However, we also have to decide what value to use for the time-variable. If we select the time t_{n+1}, corresponding to the pressure solutions p_i^{n+1}, we say that we use an *implicit* scheme:

$$\left.\frac{d^2p}{dy^2}\right|_i \approx \frac{d^2p}{dy^2}(y_i, t = t_{n+1}) = \frac{p_{i+1}^{n+1} + p_{i-1}^{n+1} - 2p_i^{n+1}}{\Delta y^2} + \mathcal{O}(\Delta y^2) \tag{31}$$

By neglecting higher order terms, we get the finite difference scheme shown in the main text.

A.1 Implicit scheme: Sketch of implementation

Start by assuming that the pressure is the same everywhere at time zero:

$$\mathbf{p^0} = \begin{pmatrix} p_i \\ p_i \\ \ldots \\ p_i \\ p_i \end{pmatrix}. \tag{32}$$

After setting the initial condition, we have to implement a time loop to update the pressure distribution repeatedly for each time step. For the first time step, we have to solve the matrix equation:

$$\mathbf{A}\mathbf{p}^1 = \mathbf{p}^0 + \mathbf{d}\,,$$

where $\mathbf{p}^n$ is the vector holding all pressure values at time t_n. After updating the pressures, we can compute the second time step by solving

$$\mathbf{A}\mathbf{p}^2 = \mathbf{p}^1 + \mathbf{d}\,,$$

and so on. Note that since the time step is constant, and the boundary conditions stay fixed, we only have to calculate the matrix once. On the other hand, **the right-hand side vector must be updated every time step** (since it makes use of the most recent pressure solution).

B Line-source solution

There are several transient solutions to the diffusivity equation, but most of them are very difficult to derive and implement [10]. To simplify, it is common to use the *line-source solution*, which is based on slightly different boundary conditions than we have assumed in this project:

- It considers the well to be infinitely small (i.e. a line), thus neglecting the influence of the finite well radius.
- The reservoir is assumed to be infinite in extent.
- Instead of assuming a constant pressure at a fixed distance $r = r_e$, the line-source solution assumes a constant pressure at infinity.

In mathematical terms, the boundary conditions for the line-source solution are:

$$\lim_{r\to 0}\left(\frac{2\pi hk}{\mu} r\frac{\partial p}{\partial r}\right) = Q_{well}\,, \tag{33}$$

and

$$\lim_{r\to\infty} p(r,t) = p_i\,. \tag{34}$$

The solution to equations (7), (33), and (34) is [12]

$$p(r,t) = p_i + \frac{Q\mu}{4\pi kh}\cdot\mathcal{W}\left(-\frac{r^2}{4\eta t}\right)\,, \tag{35}$$

where $\mathcal{W}$ is the *exponential function*, defined in terms of an integral:

$$\mathcal{W}(x) = \int_{-\infty}^{x}\frac{e^u}{u}\,du\,. \tag{36}$$

In Python this function can easily be computed with the `sp.special.expi` function.

C Table of default model input parameters

name	symbol	default value	unit
Well radius	rw	0.328	ft
Outer reservoir boundary	re	1000	ft
Height of reservoir	h	8	ft
Porosity	phi	0.2	dimensionless
Fluid viscosity	mu	1.0	mPas (cP)
Total (rock+fluid) compressibility	ct	7.80E-06	1/psi
Constant flow rate at well	Q	1000	bbl/day
Absolute permeability	k	500	mD
Initial reservoir pressure	pi	3900	psi

D Example code to get you started

```
class RadialDiffusivityEquationSolver:
    """
    A finite difference solver for the radial diffusivity equation.
    We use the coordinate transformation y = ln(r/rw) to set up and
    solve the pressure equation.

    The solver uses SI units internally, while "practical field units"
    are required as input.

    Except for the number of grid points and the choice of time step,
    all class instance attributes are provided with default values.

    Input arguments:

        name                                symbol      unit
        ----------------------------------------------------------------
        Number of grid points                N          dimensionless
        Constant time step                   dt         days
        Well radius                          rw         ft
        Outer reservoir boundary             re         ft
        Height of reservoir                  h          ft
        Absolute permeability                k          mD
        Porosity                             phi        dimensionless
        Fluid viscosity                      mu         mPas (cP)
        Total (rock+fluid) compressibility   ct         1 / psi
        Constant flow rate at well           Q          bbl / day
        Initial reservoir pressure           pi         psi
        ----------------------------------------------------------------
    """

    def __init__(self,
                 N,
                 dt,
                 rw=0.328,
                 re=1000.0,
                 h=8.0,
                 phi=0.2,
                 mu=1.0,
                 ct=7.8e-6,
                 Q=1000.0,
                 k=500,
```

```
                  pi=3900.0):

        # Unit conversion factors (input units --> SI)
        self.ft_to_m_ = 0.3048
        self.psi_to_pa_ = 6894.75729
        self.day_to_sec_ = 24.*60.*60.
        self.bbl_to_m3_ = 0.1589873

        # Grid
        self.N_ = N
        self.rw_ = rw*self.ft_to_m_
        self.re_ = re*self.ft_to_m_
        self.h_ = h*self.ft_to_m_

        # Rock and fluid properties
        self.k_ = k*1e-15 / 1.01325
        self.phi_ = phi
        self.mu_ = mu*1e-3
        self.ct_ = ct / self.psi_to_pa_

        # Initial and boundary conditions
        self.Q_ = Q*self.bbl_to_m3_ / self.day_to_sec_
        self.pi_ = pi*self.psi_to_pa_

        # Time control for simulation
        self.dt_ = dt*self.day_to_sec_

        # TO DO: Add more stuff below here....
        # (grid coordinates, dy, eta, etc.)
```

E Thomas Algorithm

The Thomas algorithm can be implemented quite easily in python, its speed is greatly improved if you use Numba, below you can find a possible implementation.

```
import numba as nb
import numpy as np

@nb.jit(nopython=True)
def thomas_algorithm(l, d, u, r):
    """
    Solves a tridiagonal linear system of equations with the Thomas-algorithm.

    The code is based on pseudo-code from the following reference:

        Cheney, E. W., & Kincaid, D. R.
        Numerical mathematics and computing, 7th edition,
        Cengage Learning, 2013.

    IMPORTANT NOTES:
        - This function modifies the contents of the input matrix and rhs.
        - For Numba to work properly, we must input NumPy arrays, and not lists.

    :param l: A NumPy array containing the lower diagonal (l[0] is not used).
    :param d: A NumPy array containing the main diagonal.
    :param u: A NumPy array containing the upper diagonal (u[-1] is not used).
    :param r: A NumPy array containing the system right-hand side vector.
    :return: A NumPy array containing the solution vector.
    """
```

```
    # Allocate memory for solution
    solution = np.zeros_like(d)
    n = len(solution)

    # Forward elimination
    for k in range(1, n):
        xmult = l[k] / d[k-1]
        d[k] = d[k] - xmult*u[k-1]
        r[k] = r[k] - xmult*r[k-1]

    # Back-substitution
    solution[n-1] = r[n-1] / d[n-1]
    for k in range(n-2, -1, -1):
        solution[k] = (r[k]-u[k]*solution[k+1])/d[k]

    return solution


def solve_tdt(dense_matrix,rhs):
    """
    Tridiagonal solver using the Thomas algorithm
    Extracts the lower (l), main (d), and upper (u)
    diagonals from a dense matrix.

    :param: Input dense matrix (A) (2D NumPy array).
            rhs (b) right hand side of Ax=b
    :return: solution to the matrix equation Ax=b
    """

    d = np.diag(dense_matrix, k=0)
    u = np.zeros_like(d)
    l = np.zeros_like(d)
    u[:-1] = np.diag(dense_matrix, k=1)
    l[1:] = np.diag(dense_matrix, k=-1)
    return thomas_algorithm(l, d, u, rhs)
```

F Guidelines for project submission

You should bear the following points in mind when working on the project:

- Start your notebook by providing a short introduction in which you outline the nature of the problem(s) to be investigated.
- End your notebook with a brief summary of what you feel you learned from the project (if anything). Also, if you have any general comments or suggestions for what could be improved in future assignments, this is the place to do it.
- All code that you make use of should be present in the notebook, and it should ideally execute without any errors (especially run-time errors). If you are not able to fix everything before the deadline, you should give your best understanding of what is not working, and how you might go about fixing it.

- Avoid duplicating code! If you find yourself copying and pasting a lot of code, it is a strong indication that you should define reuseable functions and/or classes.
- If you use an algorithm that is not fully described in the assignment text, you should try to explain it in your own words. This also applies if the method is described elsewhere in the course material.
- In some cases it may suffice to explain your work via comments in the code itself, but other times you might want to include a more elaborate explanation in terms of, e.g., mathematics and/or pseudocode.
- In general, it is a good habit to comment your code (though it can be overdone).
- When working with approximate solutions to equations, it is very useful to check your results against known exact (analytical) solutions, should they be available.
- It is also a good test of a model implementation to study what happens at known 'edge cases'.
- Any figures you include should be easily understandable. You should label axes appropriately, and depending on the problem, include other legends etc. Also, you should discuss your figures in the main text.
- It is always good if you can reflect a little bit around *why* you see what you see.

References

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