

## Mathematical Modeling of the Earth System

9) Random Systems (Stochastic equations, Lattice Gases)

10) Cryosphere (Sea ice, ice sheets, and permafrost)

11) Earth system models including tracers and dynamical vegetation

**How well do we understand Earth?**



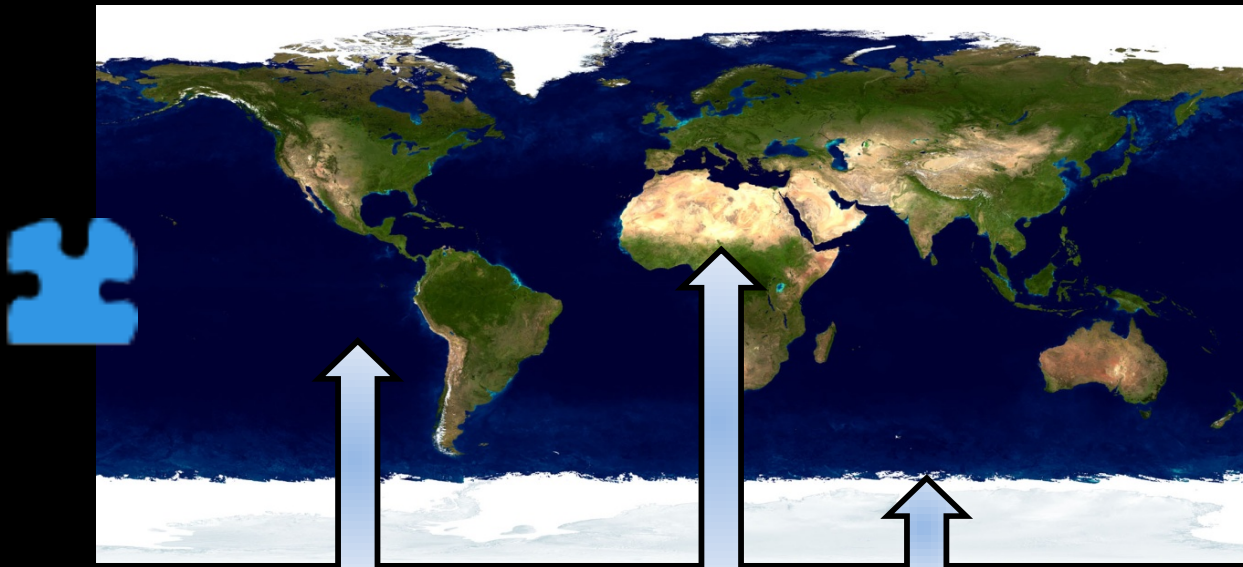




**Weather**



**Climate**

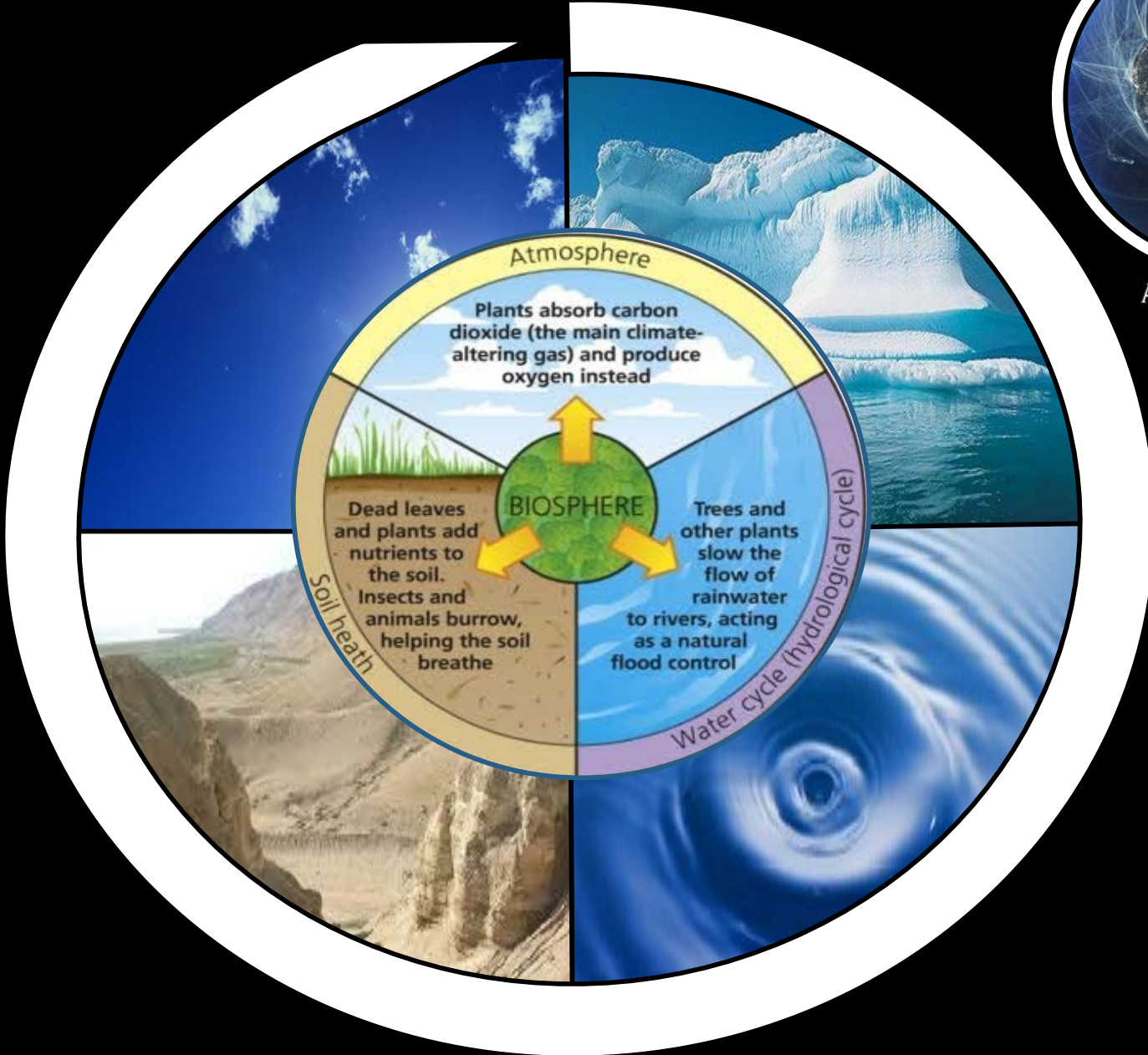


**Oceans, land, Ice**

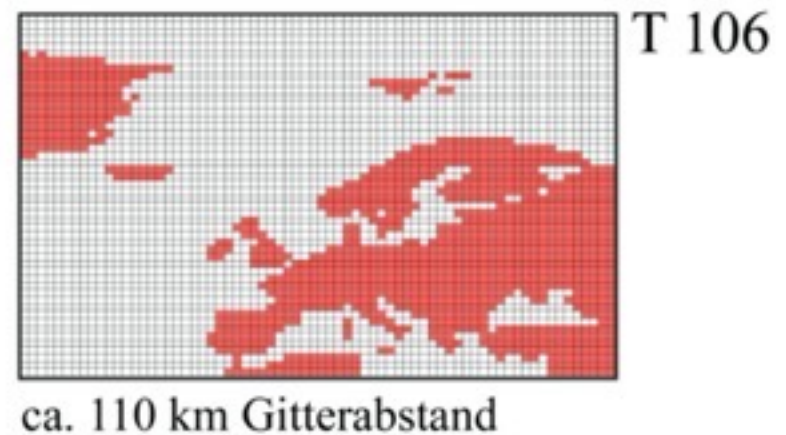
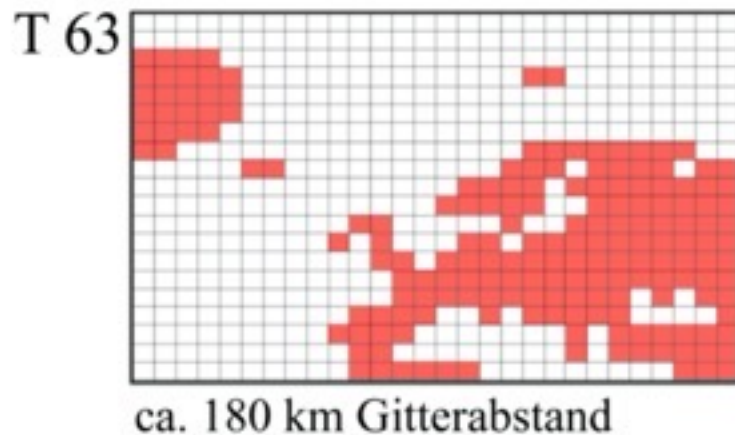
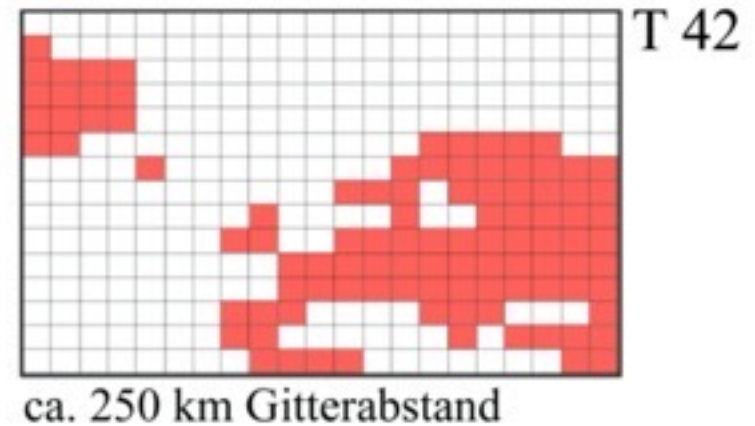
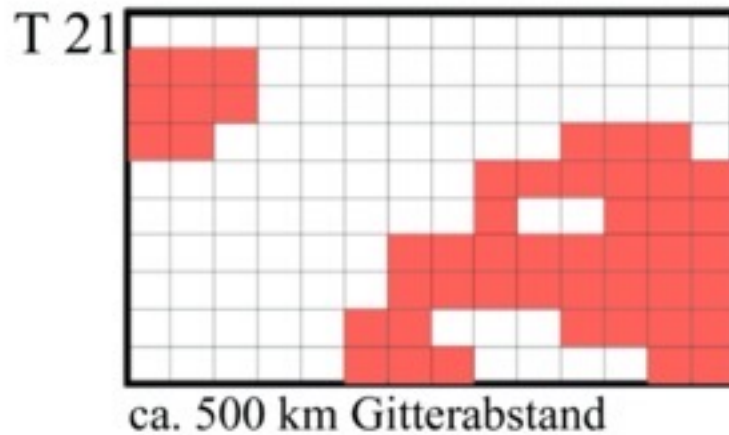
# Earth System



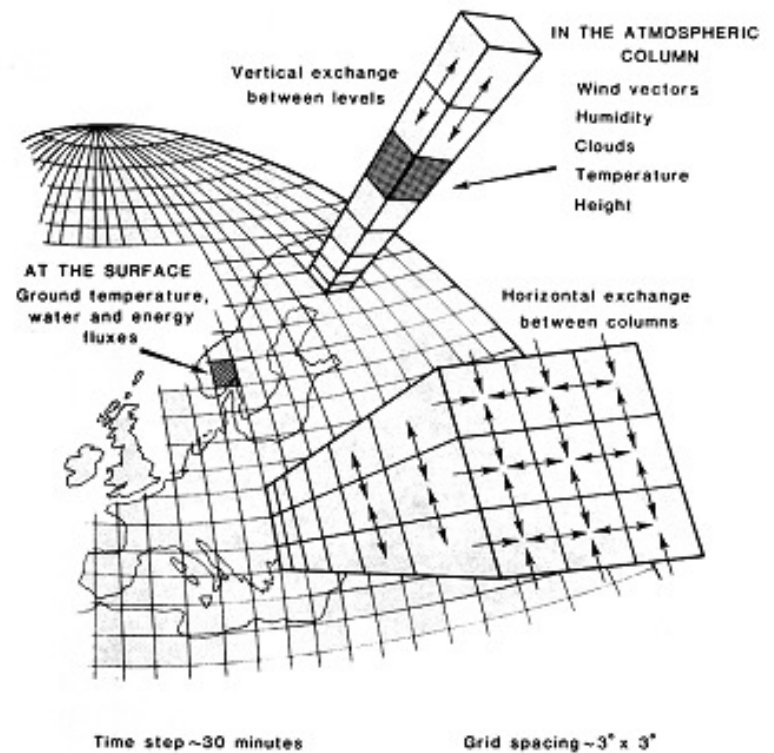
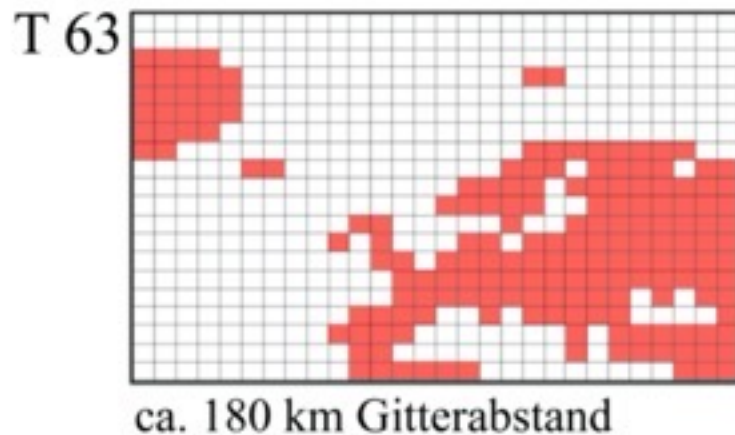
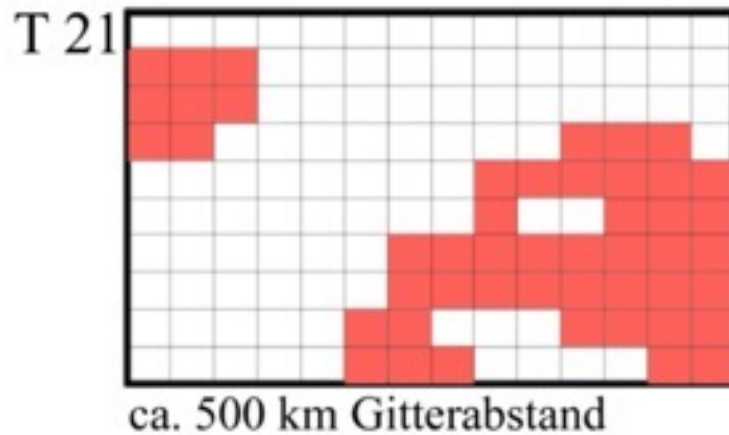
ANTHROPOSHERE

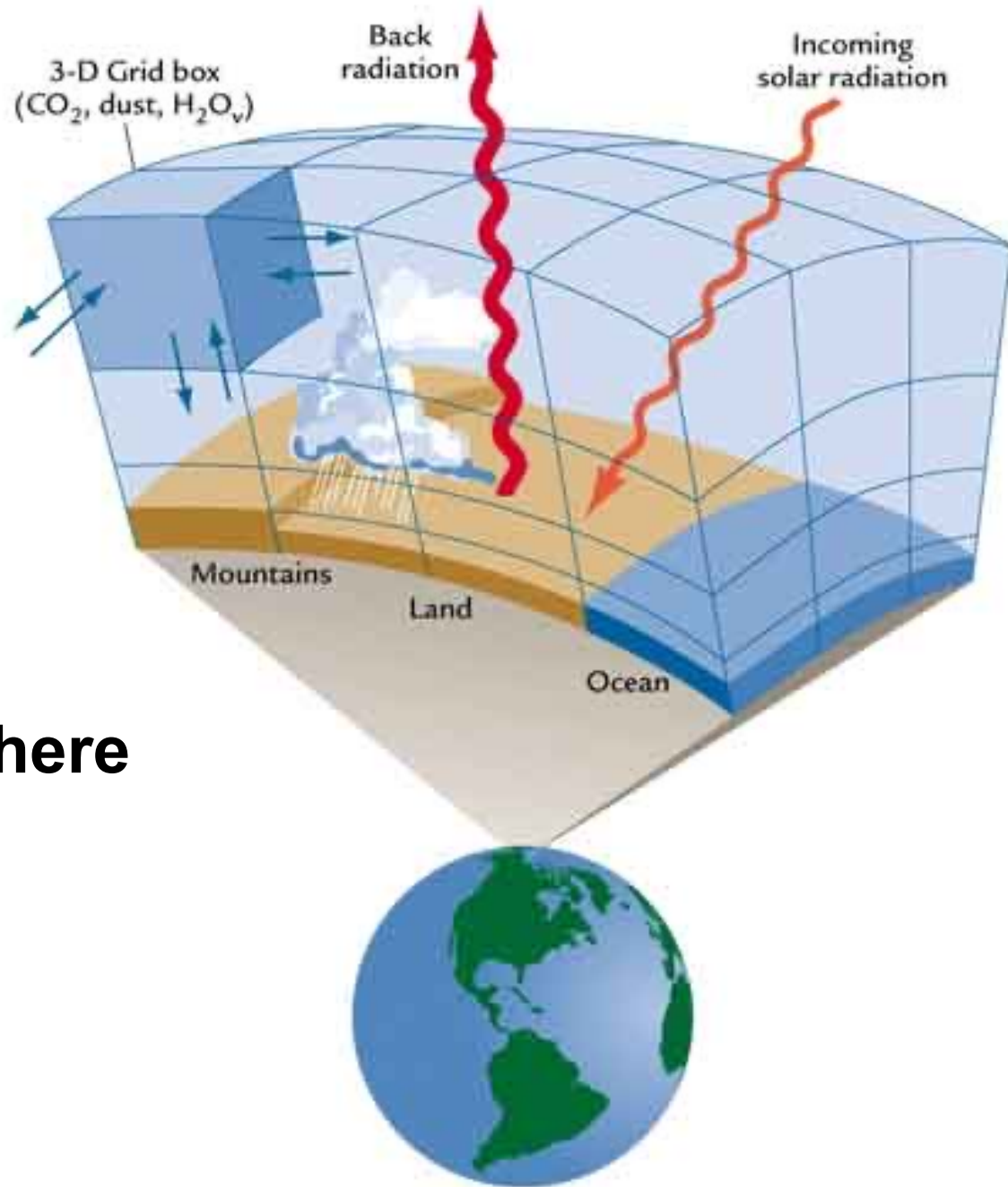


# Examples of Resolution (global spectral model, zoom onto Europe)



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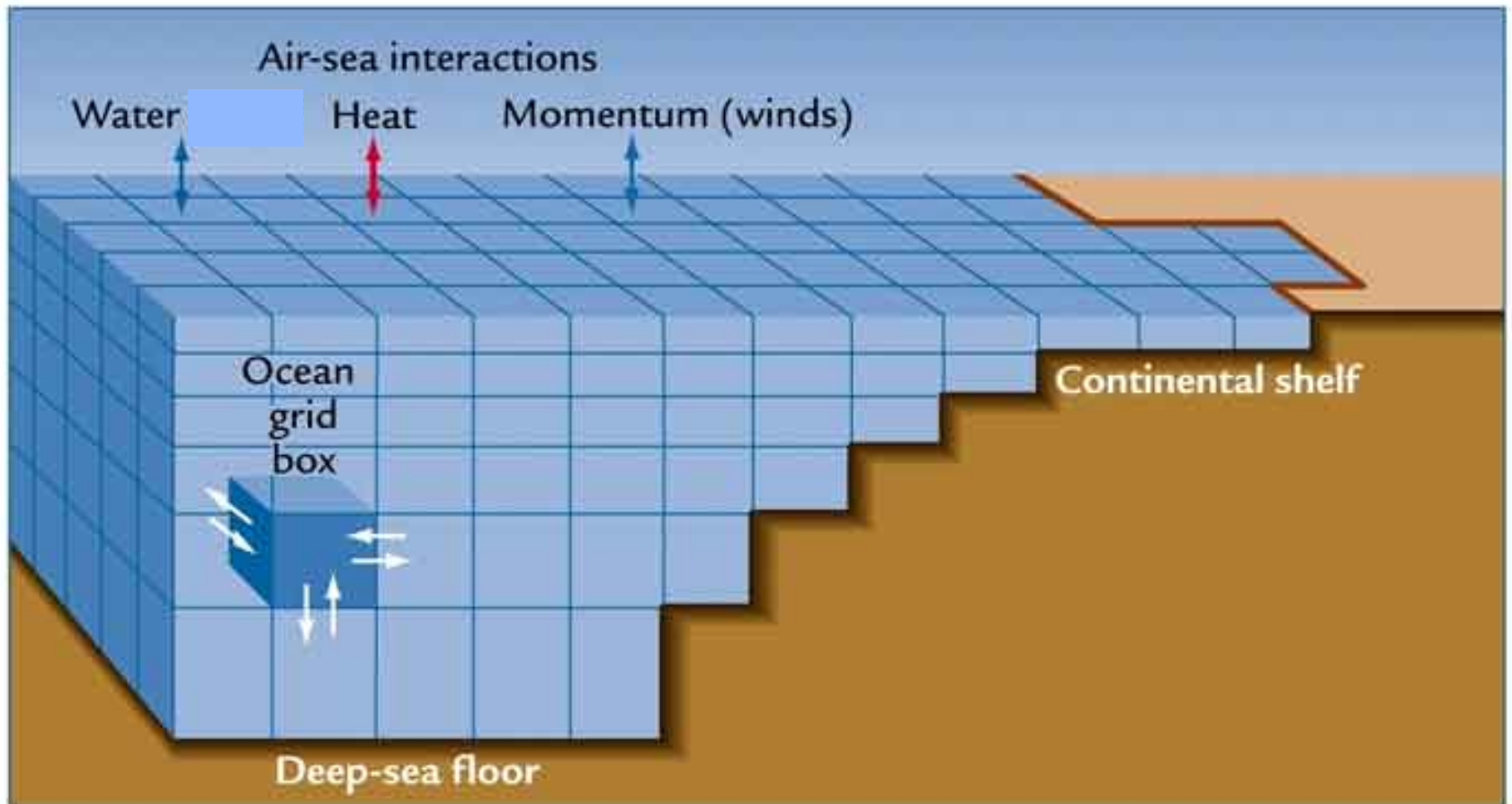


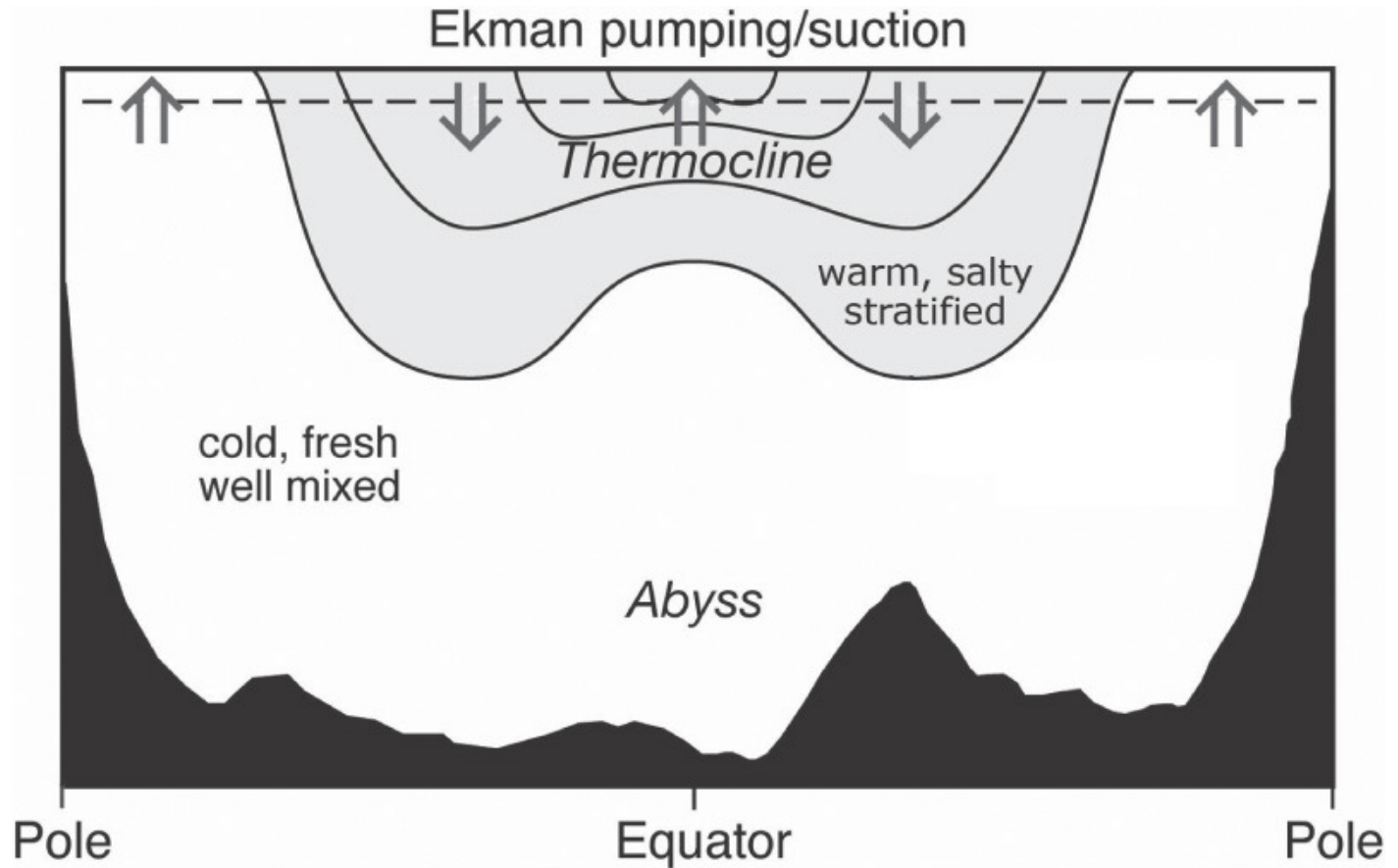


# Atmosphere Model



# Ocean circulation models and boundary conditions

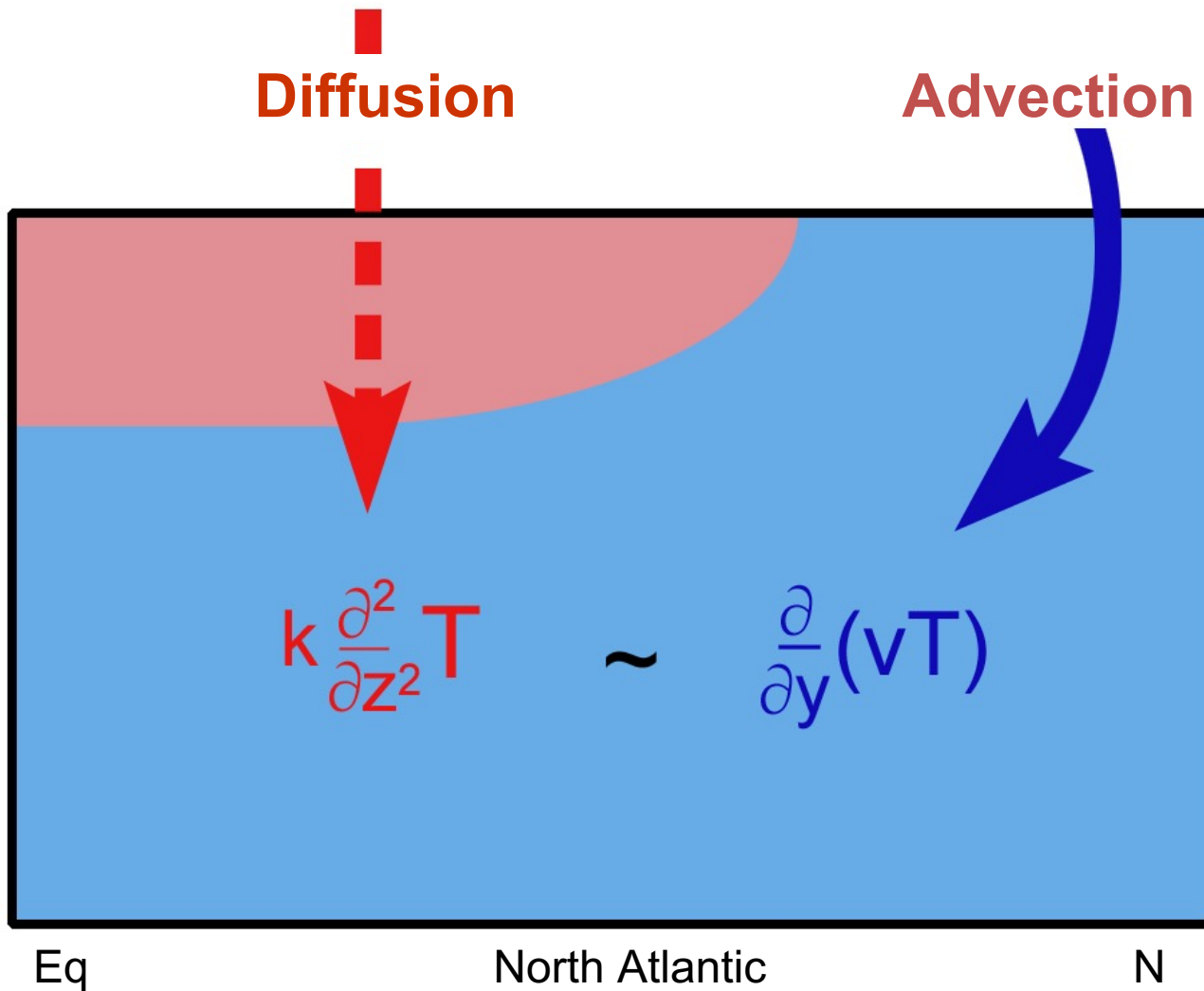




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Ekman: winds blowing on the sea surface produce a thin, horizontal boundary layer, ( $\sim 100\text{ m}$ )

# Ocean Dynamics: Temperature change



# Mathematical Modelling

## Classes of models

**Ordinary differential eq. (Box models)**

**Partial differential eq. (Diffusion & Advection)**

**Stochastic (different time & length scales)**

**Discrete dynamics (e.g., Population dynamics)**

# Finite differences: Diffusion-advection

$$\frac{\partial C(x,t)}{\partial t} + u \frac{\partial C(x,t)}{\partial x} = \kappa \frac{\partial^2 C(x,t)}{\partial x^2} \quad (1)$$

# Finite differences: Diffusion-advection

$$\frac{\partial C(x,t)}{\partial t} + u \frac{\partial C(x,t)}{\partial x} = \kappa \frac{\partial^2 C(x,t)}{\partial x^2} \quad (1)$$

Approximate the derivatives using the centered difference scheme:

$$\frac{\partial C_{i,j}}{\partial t} \approx \frac{C_{i,j+1} - C_{i,j-1}}{2\Delta t} \quad (2)$$

$$\frac{\partial C_{i,j}}{\partial x} \approx \frac{C_{i+1,j} - C_{i-1,j}}{2\Delta x} \quad (3)$$

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Inserting (2)-(4) into (1) gives

$$\frac{C_{i,j+1} - C_{i,j-1}}{2\Delta t} + u \frac{C_{i+1,j} - C_{i-1,j}}{2\Delta x} \approx \kappa \frac{C_{i+1,j-1} - 2C_{i,j-1} + C_{i-1,j-1}}{\Delta x^2} \quad (5)$$

(Note that we evaluate the diffusion term at time  $j-1$  instead of time  $j$  to avoid numerical instability.) Rephrasing

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## Leapfrog scheme

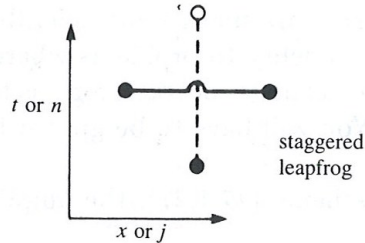
$$C_{i,j+1} \approx C_{i,j-1} - u \frac{\Delta t}{\Delta x} (C_{i+1,j} - C_{i-1,j}) + \kappa \frac{2\Delta t}{\Delta x^2} (C_{i+1,j-1} - 2C_{i,j-1} + C_{i-1,j-1}) \quad (6)$$



# Finite differences: Diffusion-advection

$$\frac{\partial C(x,t)}{\partial t} + u \frac{\partial C(x,t)}{\partial x} = \kappa \frac{\partial^2 C(x,t)}{\partial x^2}$$

## Leap-Frog Scheme (CTCS Scheme)



The leap-frog scheme is second order in time and space,

$$T_i^{n+1} = T_i^{n-1} - \frac{V\Delta t}{\Delta x} (T_{i+1}^n - T_{i-1}^n)$$

but it requires that the **two** last time levels are kept in memory.

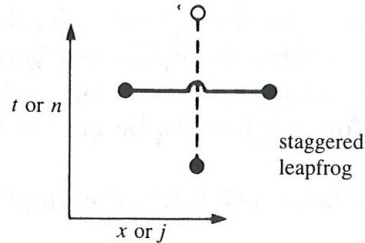
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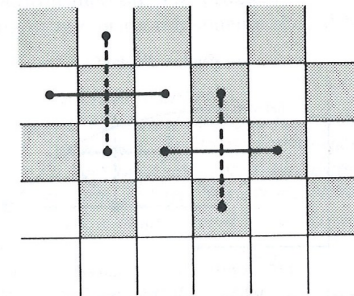


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## Chess Board for Leap-Frog



Leap-frog is stable, provided CFL-criterion is fulfilled, less diffusive than upwind, but leads to oscillations, especially at sharp gradients. There can be a decoupling of two solutions!

## Leapfrog scheme

$$C_{i,j+1} \approx C_{i,j-1} - u \frac{\Delta t}{\Delta x} (C_{i+1,j} - C_{i-1,j}) + \kappa \frac{2\Delta t}{\Delta x^2} (C_{i+1,j-1} - 2C_{i,j-1} + C_{i-1,j-1}) \quad (6)$$

# Shallow Water Model

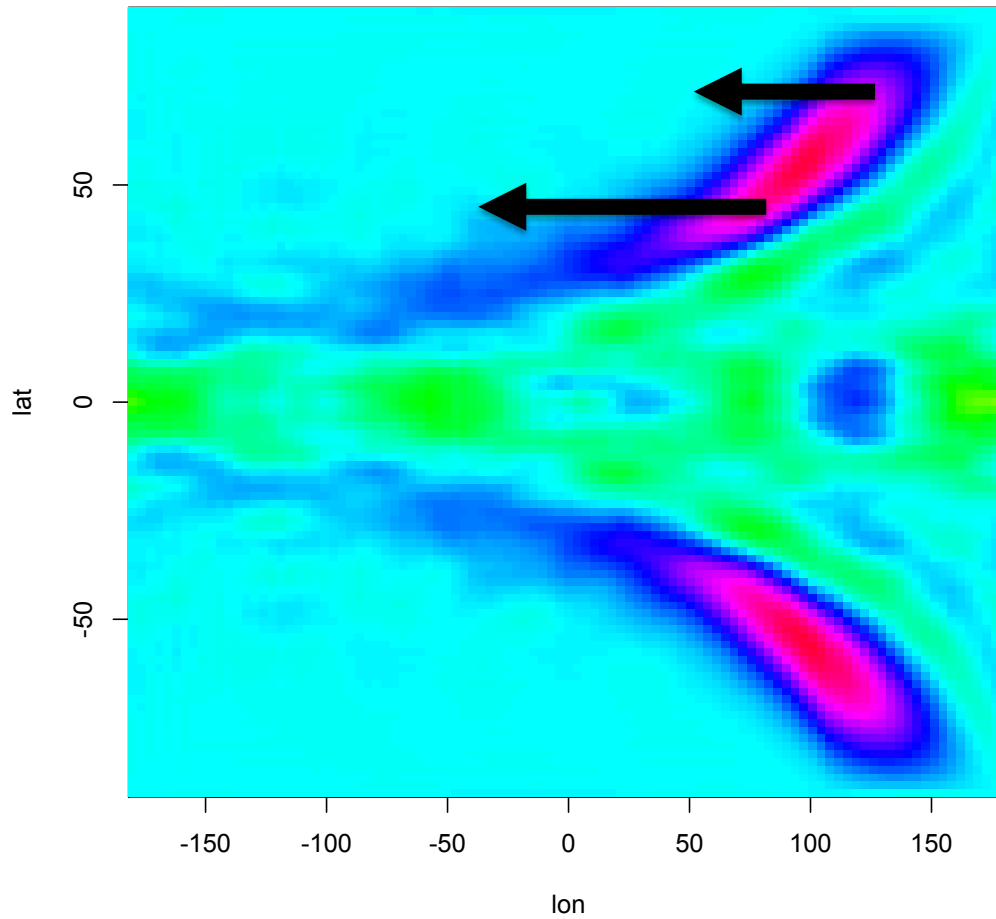
## Rossby and gravity waves

$$\partial_t u = f v - g \partial_x \eta$$

$$\partial_t v = -f u - g \partial_y \eta$$

$$\partial_t \eta = -\partial_x (H u) - \partial_y (H v)$$

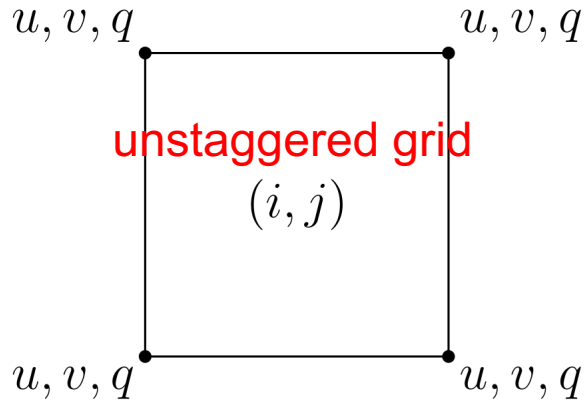
```
u.new[ia.0,ia.0]<-u.old[ia.0,ia.0]-g*dt/dx*(h[ia.p1,ia.0]-h[ia.m1,ia.0])+dt*f*v
v.new[ia.0,ia.0]<-v.old[ia.0,ia.0]-g*dt/dy*(h[ia.0,ia.p1]-h[ia.0,ia.m1])-dt*f*u
h.new[ia.0,ia.0]<-h.old[ia.0,ia.0]-H*dt*((u[ia.p1,ia.0]-u[ia.m1,ia.0])/dx + (v[ia.0,ia.p1]-
v[ia.0,ia.m1])/dy)
```



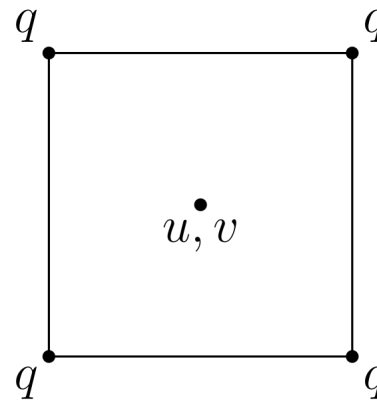
$$\omega(k, l) = -\frac{\beta k}{k^2 + l^2},$$

Figure 7.3: Global Rossby and Kelvin wave signatures in the exercise 49.

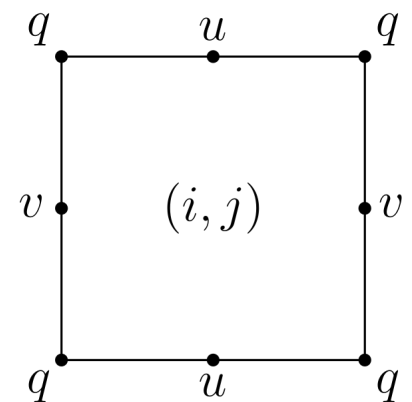
# 2D Staggered grids: Arakawa



(A)

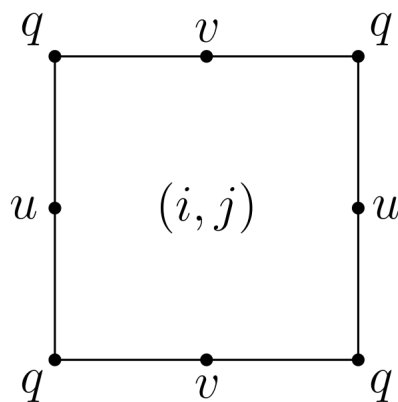


(B)



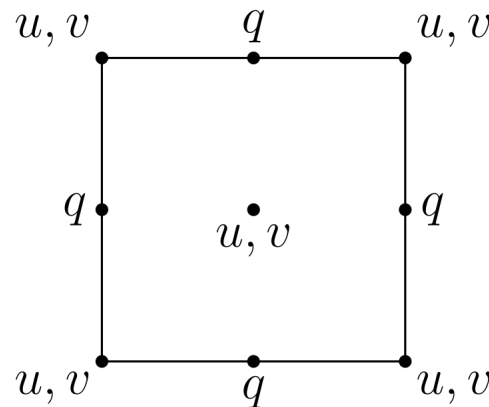
(C)

Advection of tracers



(D)

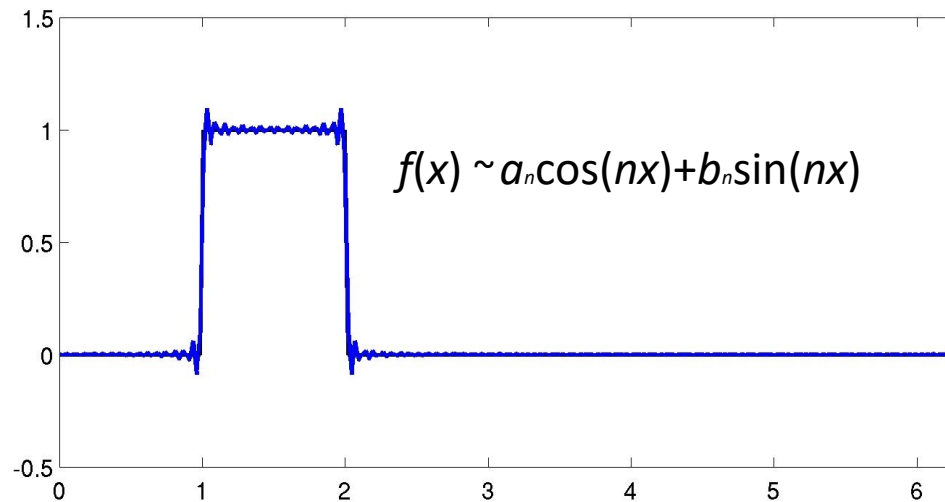
Rotated C



(E)

# Spectral methods

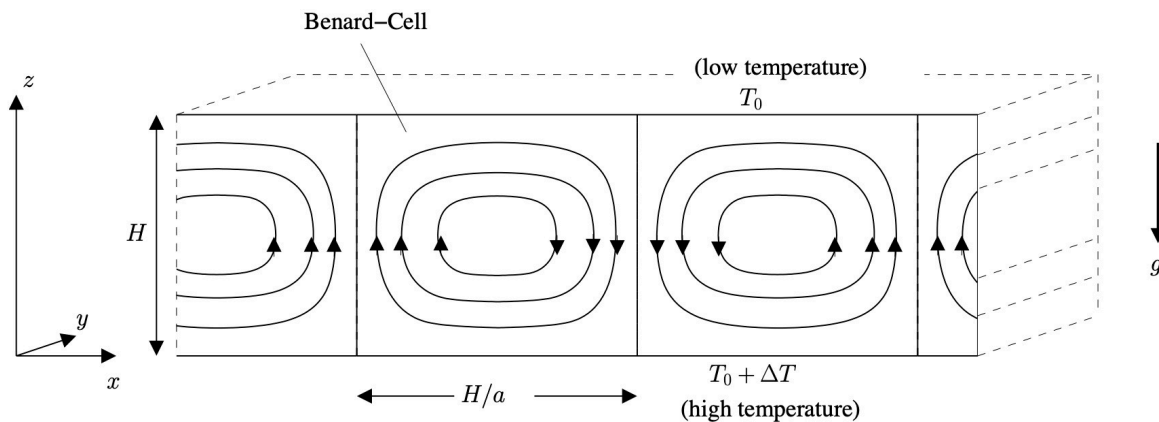
Rayleigh Bernard System  
in lecture Dynamics II



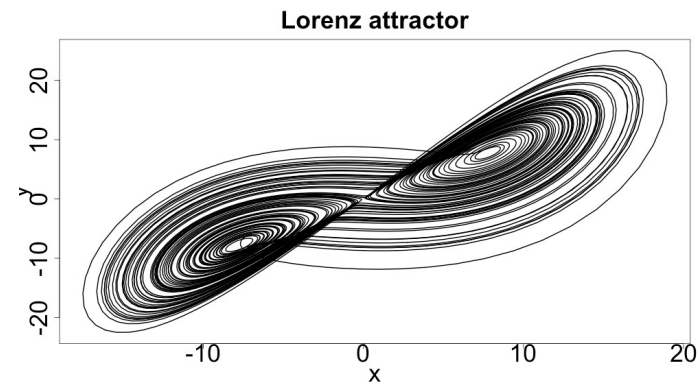
solve the diffusion equation  
 $\partial_t T = D \partial_x^2 T$

# Fourier–Galerkin method

used for the basis functions (the famous chaotic Lorenz set of differential equations were found as a Fourier- Galerkin approximation to atmospheric convection (Lorenz, 1963))



$$\Psi(x,z,t) = \sum_k \sum_l \Psi_{k,l}(t) \sin(k\pi a H x) \times \sin(l\pi H z)$$



# Finite differences and finite element methods

**finite differences:** approximate partial differential equations.  
Questions to analyze and improve the stability and accuracy

## Finite-difference Approximation of Derivatives

## A 2nd-order accurate Difference Quotient

There are **many ways** to replace differential quotients with difference quotients, e.g.:

$$\begin{aligned}\frac{\partial T}{\partial x} &\rightarrow \frac{T_j - T_{j-1}}{\Delta x} && \text{(backward)} \\ &\rightarrow \frac{T_{j+1} - T_j}{\Delta x} && \text{(forward)} \\ &\rightarrow \frac{T_{j+1} - T_{j-1}}{2\Delta x} && \text{(centered)}\end{aligned}$$

in the centered difference approximation, however, we obtain from Taylor's theorem

$$\frac{T(x + \Delta x) - T(x - \Delta x)}{2\Delta x} = \frac{\partial T}{\partial x} + \frac{1}{3!} \frac{\partial^3 T}{\partial x^3} (\Delta x)^2 + \dots$$

because the terms proportional to the second derivative cancel out. The error in the centered finite-difference approximation is **of the order  $(\Delta x)^2$** .

All these tend to  $\frac{\partial T}{\partial x}$  for  $\Delta x \rightarrow 0$



# Finite differences and **finite element methods**

As powerful as these ideas are, there are two important cases where they do not directly apply: problems that are

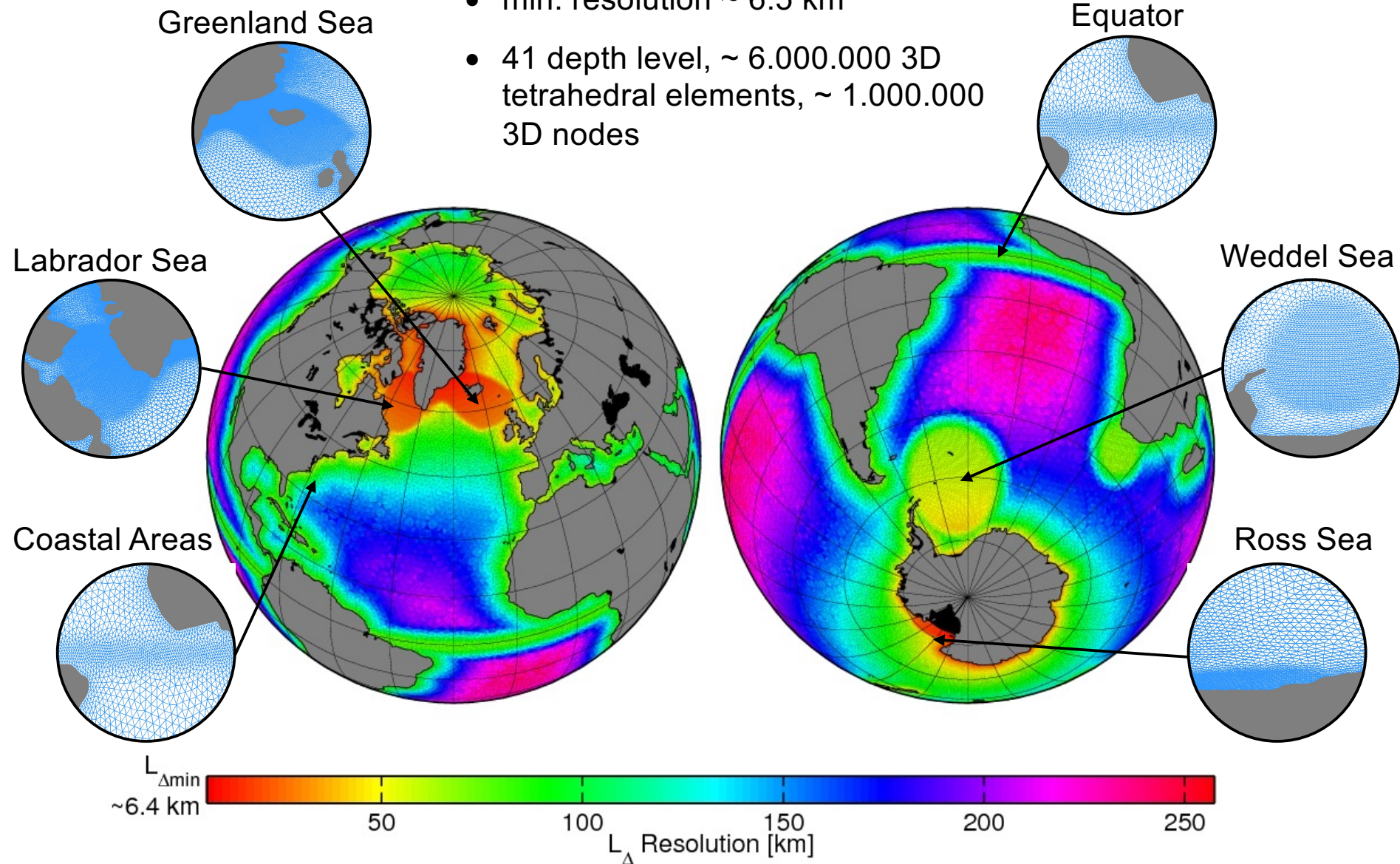
- described in terms of a **spatially inhomogeneous grid**,
- posed in **terms of a variational principle**.

For example, in studying the deformations, it can be most natural to describe it in terms of **finding the minimum energy configuration** instead of a partial differential equation, and for computational efficiency it is certainly important to match the location of the solution nodes to the shape of the body.

These limitations with finite differences can be solved by the use of **finite element methods**.

# Ocean Model Setup in finite elements

- mesh with high resolution at deep water mass formation areas
- min. resolution  $\sim 6.5$  km
- 41 depth level,  $\sim 6.000.000$  3D tetrahedral elements,  $\sim 1.000.000$  3D nodes



# Mathematical Modelling

## Classes of models

**Ordinary differential eq. (Box models)**

**Partial differential eq. (Diffusion & Advection)**

**Stochastic (different time & length scales)**

**Discrete dynamics (e.g., Population dynamics)**

# Euler integrator

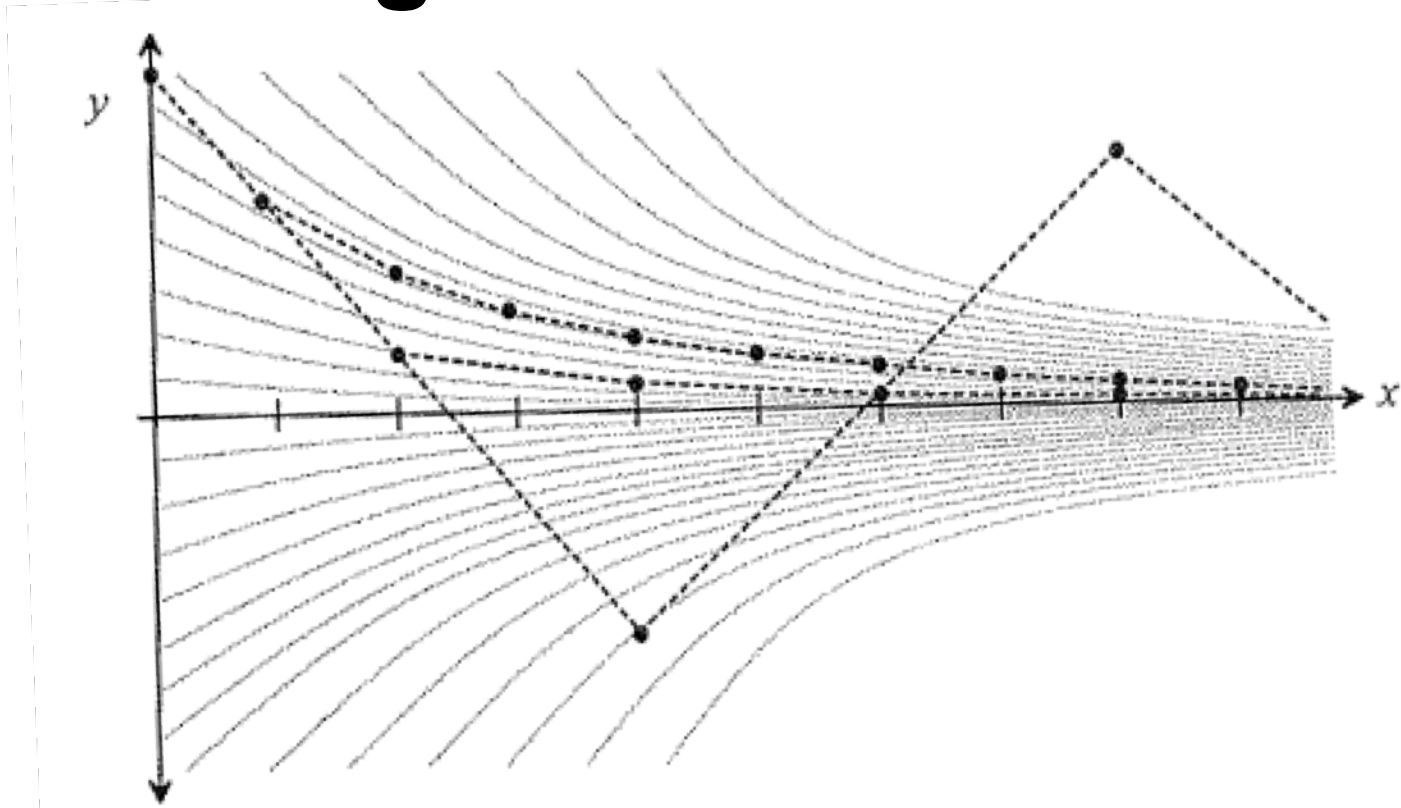


Figure 6.2. Origin of oscillation in the Euler method. The gray lines show the family of solutions of  $dy/dx = Ay$ , and the dotted lines show the numerical solution for various step sizes.

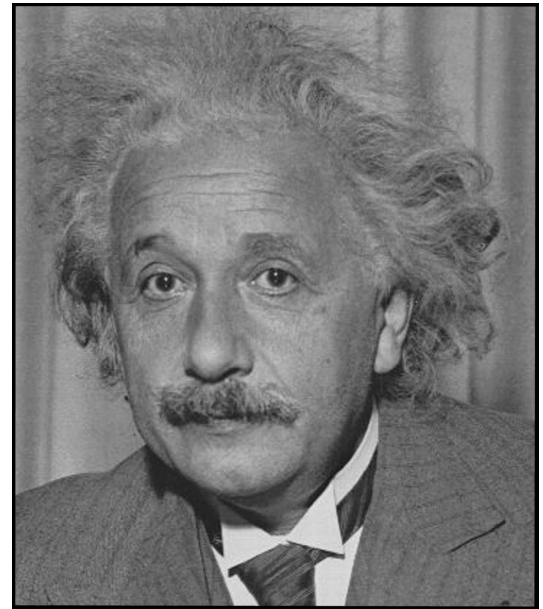
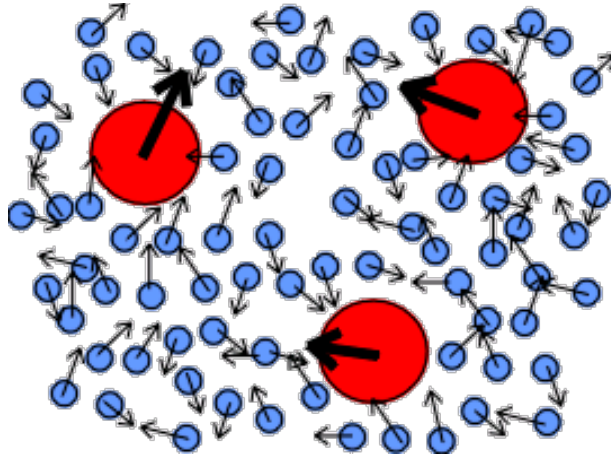
This algorithm approximates the point computation by this formula

$$p_{k+1} = p_k + hv(p_k)$$

where  $h$  specifies the *integration step*.

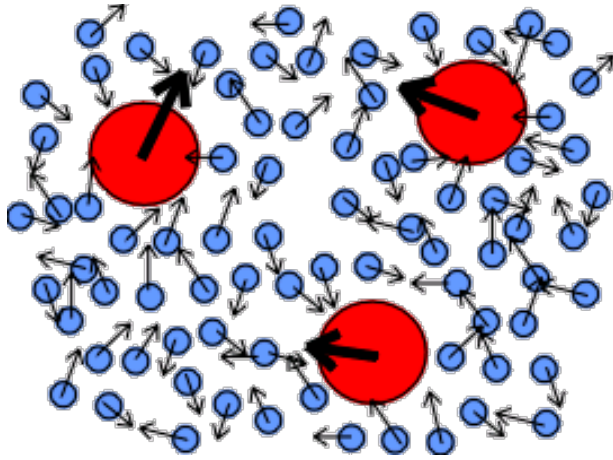
The streamline is then constructed by successive integration.

# Brownian Motion



Einstein, Orstein, Uhlenbeck, Wiener, Fokker, Planck et al.

$$dx/dt = f(x) + g(x) dw/dt$$

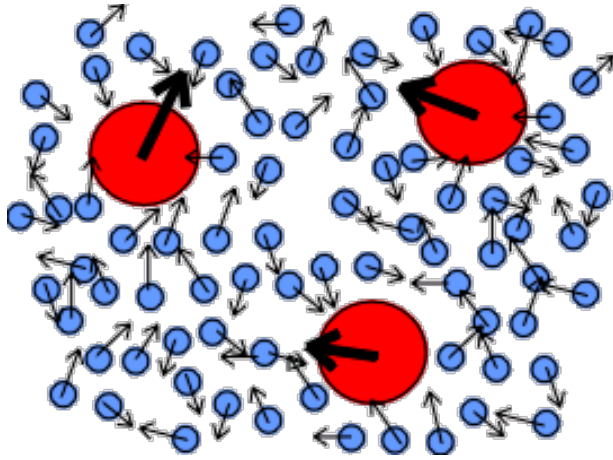


# Brownian motion

is the random movement of particles, caused by their bombardment on all sides by bigger molecules.

This motion can be seen in the behavior of pollen grains placed in a glass of water

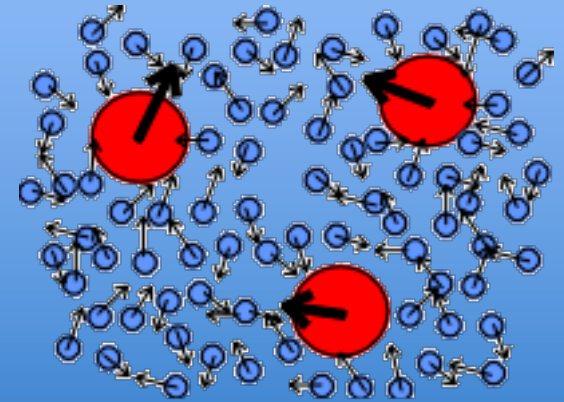
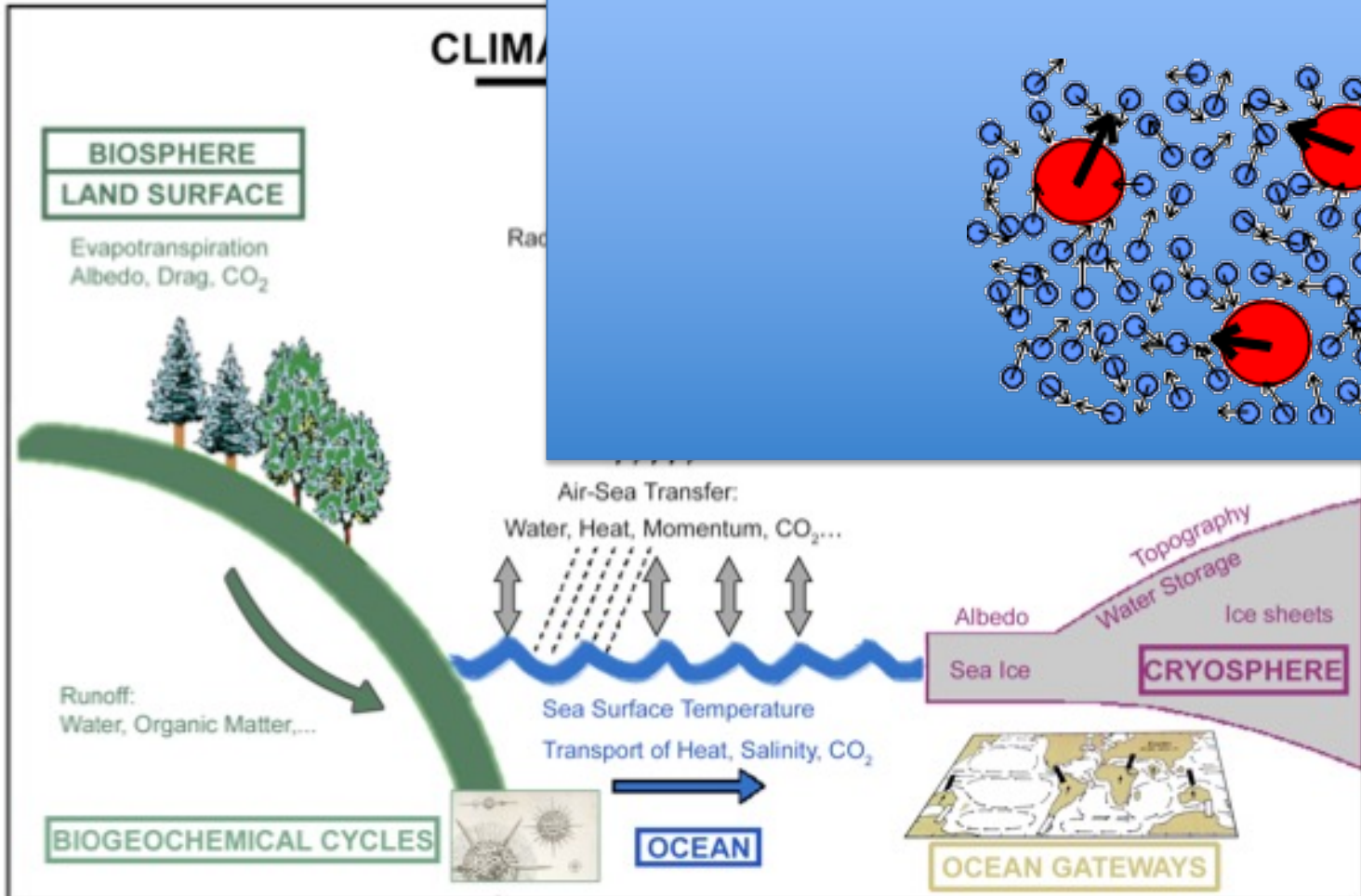
Because this motion often drives the interaction of time and spatial scales, it is important in several fields.



**Following an idea of Hasselmann one can divide the climate dynamics into two parts.** These two parts are the slowly changing climate part and rapidly changing weather part. **The** weather part can be modeled by a stochastic process such as white noise

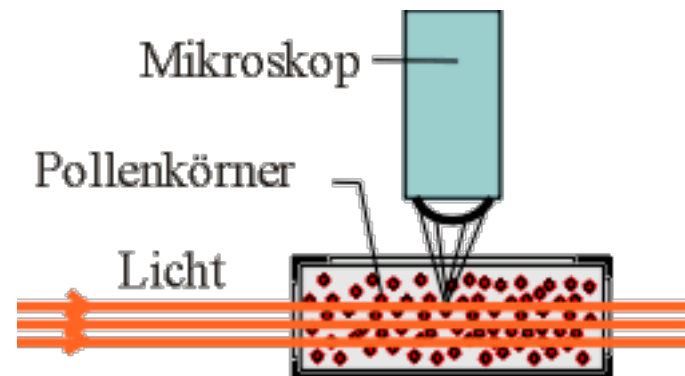
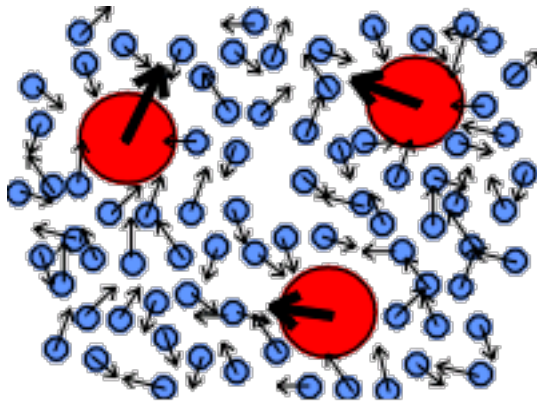
# Climate variability

- Brownian Particle: Climate
- Molecules: Weather





# Brownian Motion: visible under the Mikroskop: Motion of particles



pulses, irregular

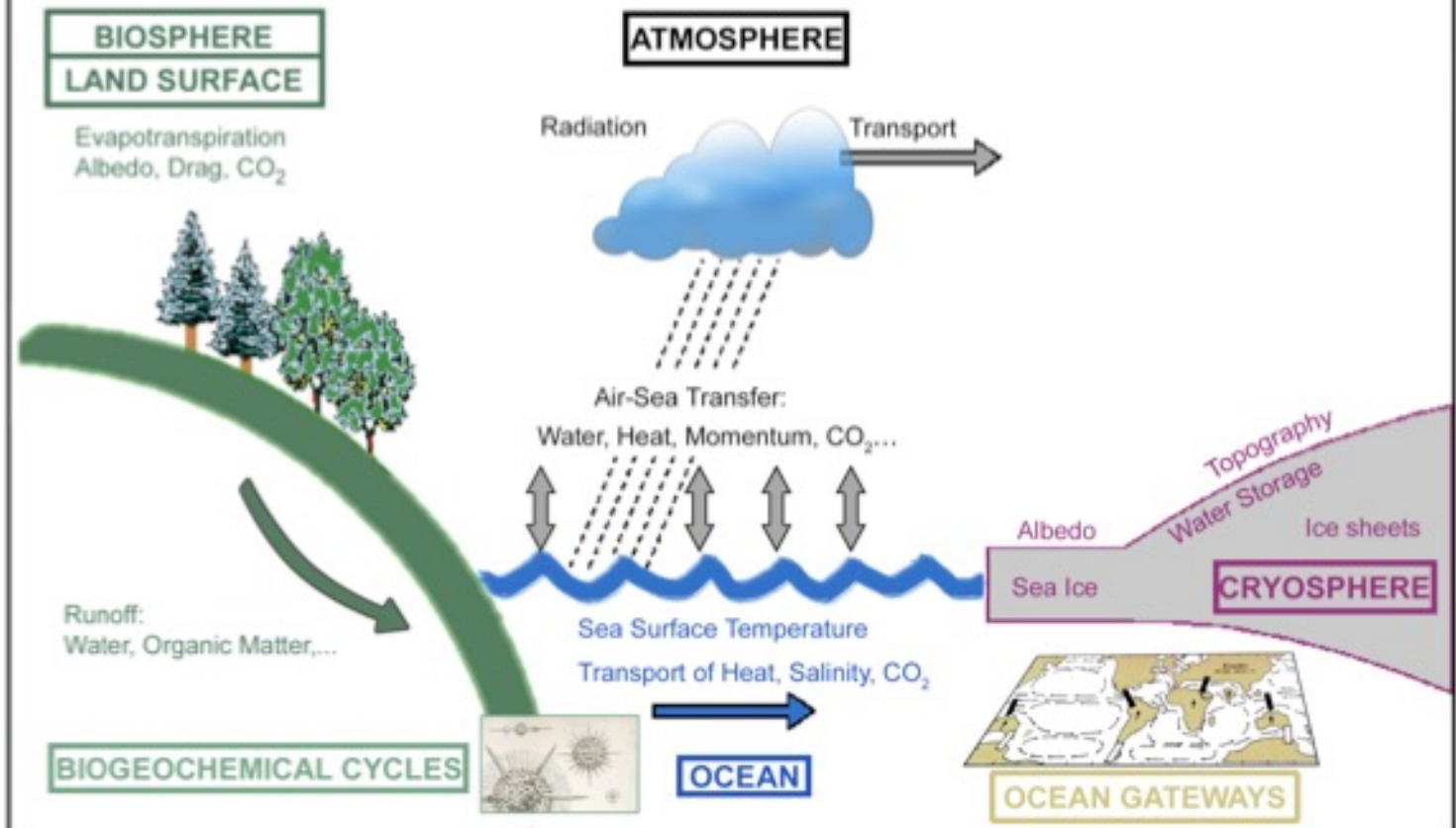
Living?

Pulses from all directions, random

# Physics of the 20<sup>th</sup> century

- The matter the world is made of
- views: Elementary particles, quantum mechanics, relativity theory
- Limit of divisibility (Democritus, Aristotle): Matter is not a continuous whole: "The world cannot be composed of infinitely small particles".

# CLIMATE SUB-SYSTEMS



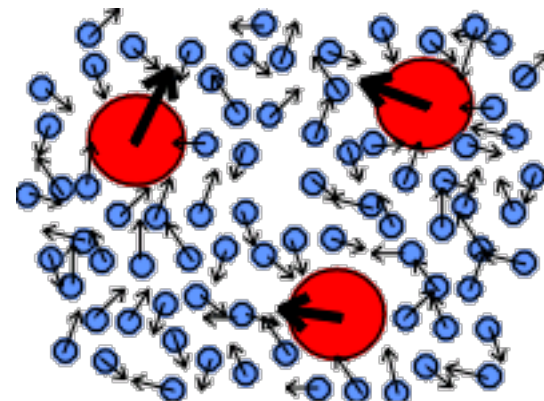
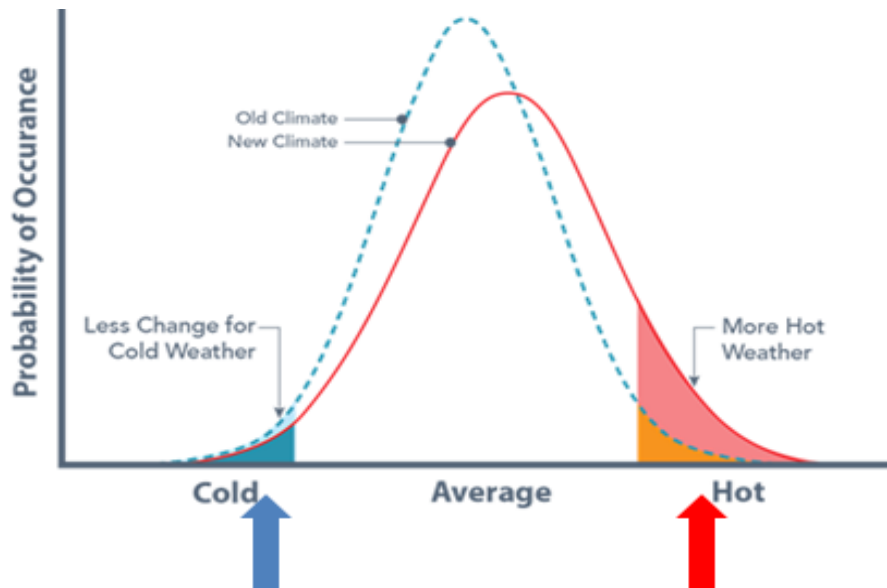
# Das Klimaproblem aus physikalischer Sicht

## Climate

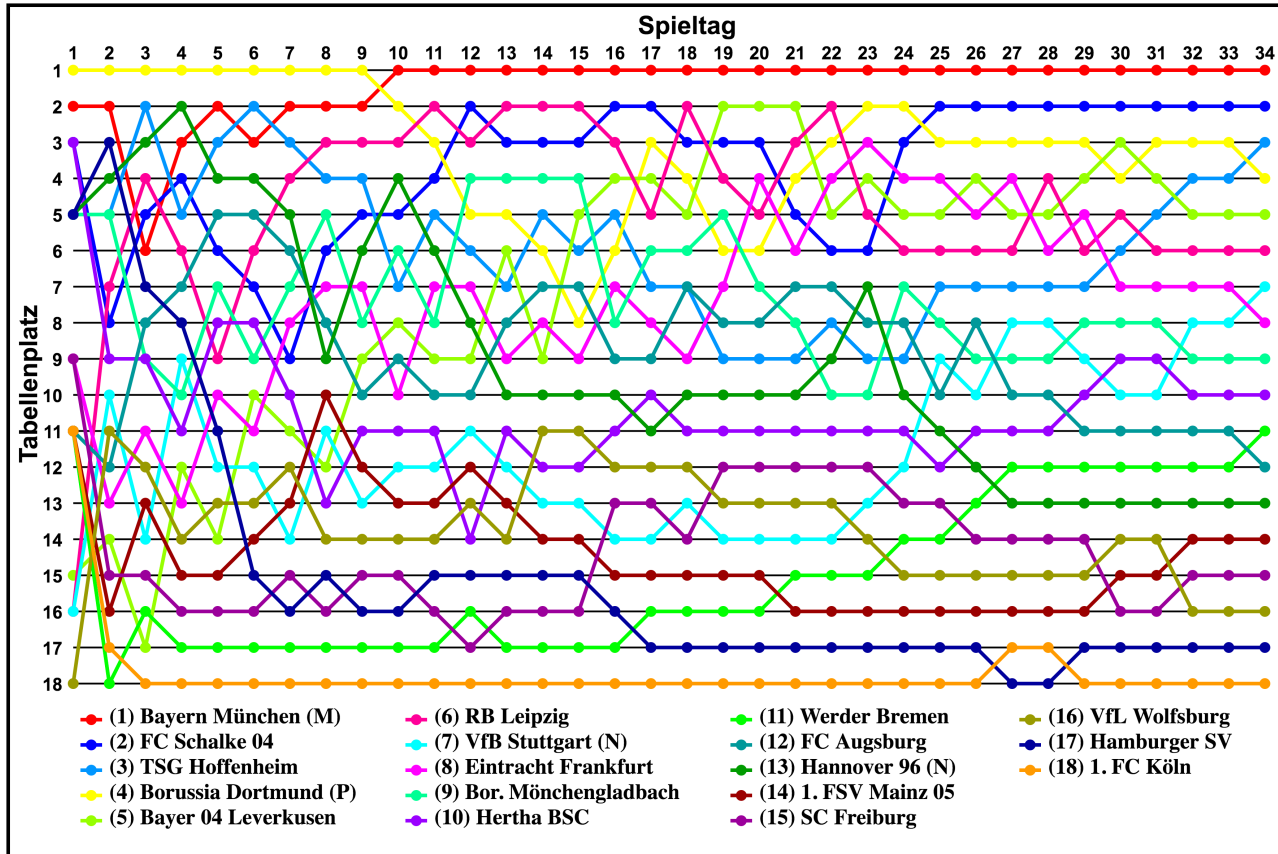
Brownsche Partikel: Klim

Moleküle: Wetter

## Probabilities



# Predictability



# Coarse graining -> Stochastic

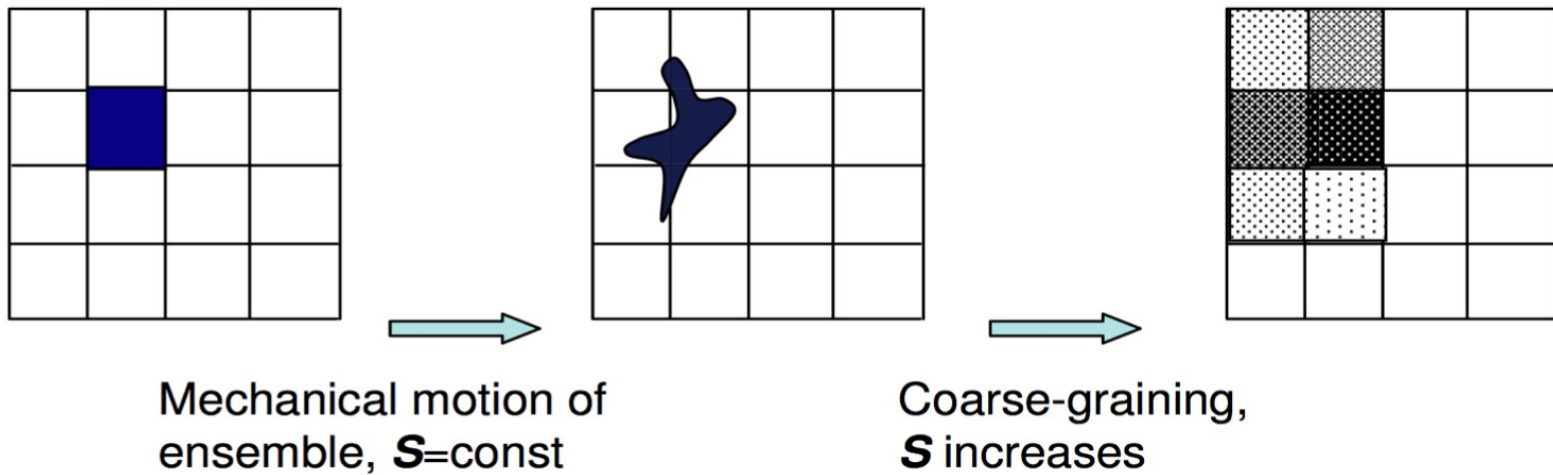


Figure 8.11: The Ehrenfests coarse-graining: two motion - coarse-graining cycles in 2D (values of probability density are presented by hatching density).