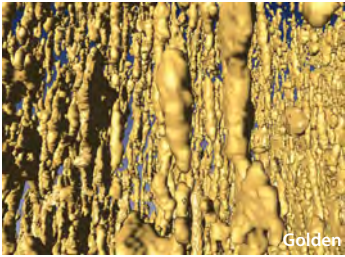
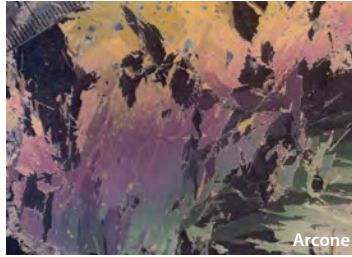


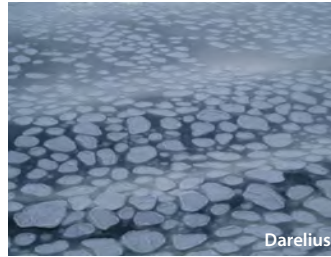
millimeters



centimeters



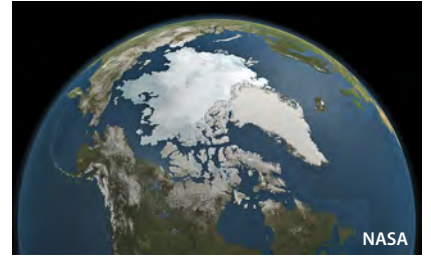
meters



kilometers

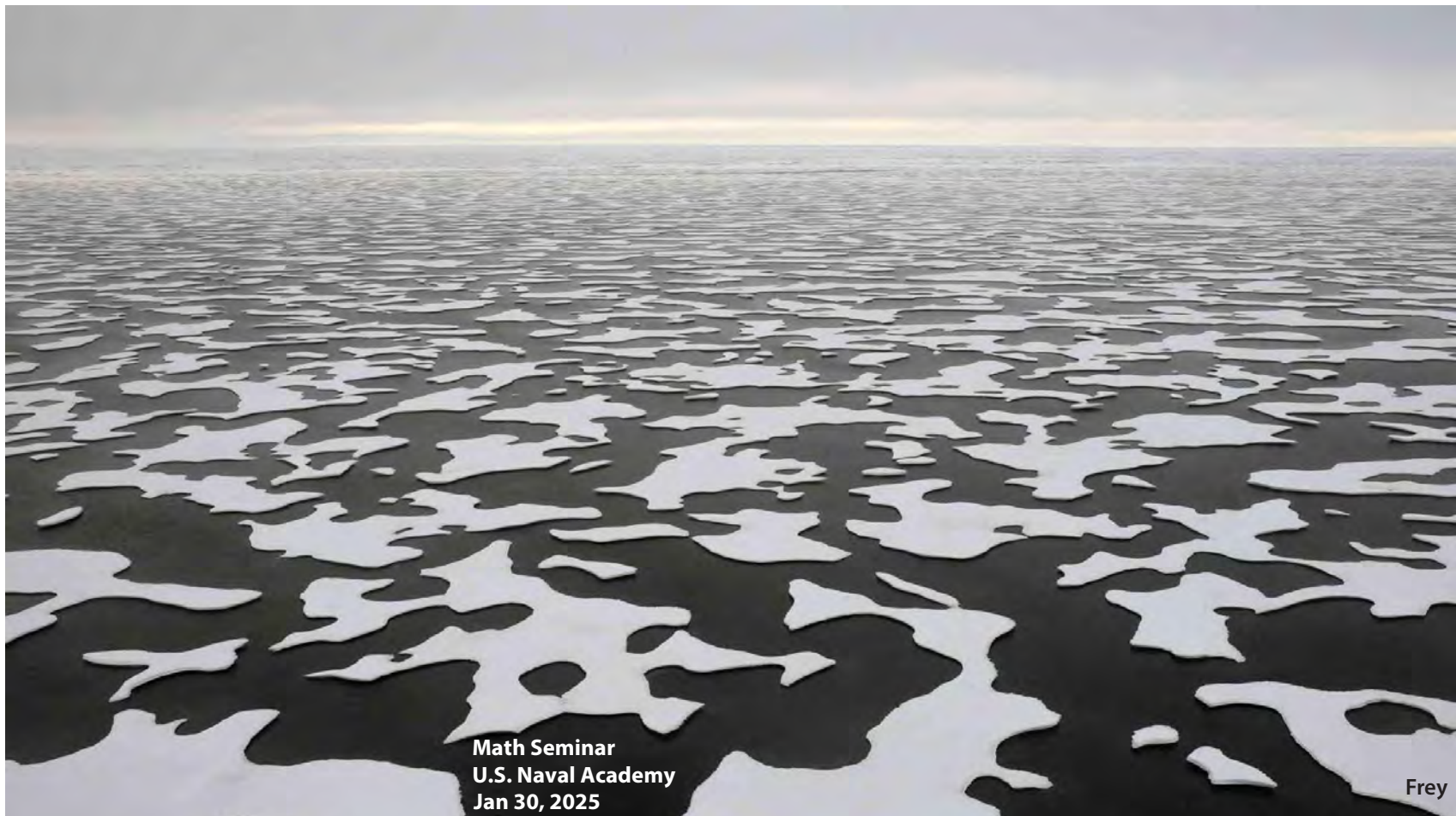


10^3 kilometers



From Micro to Macro in Modeling Sea Ice

Ken Golden, University of Utah



Math Seminar
U.S. Naval Academy
Jan 30, 2025

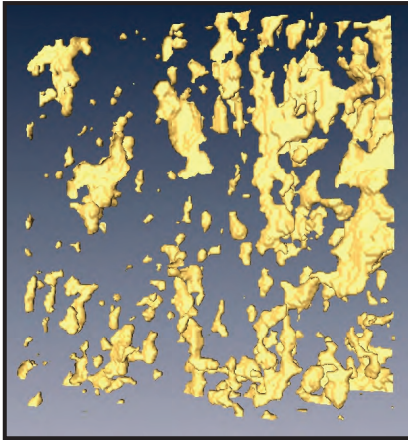
Sea Ice is a Multiscale Composite Material

microscale

brine inclusions

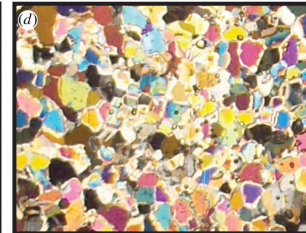
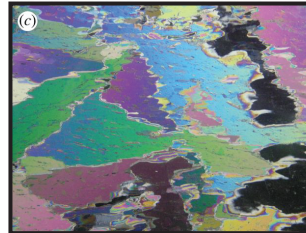
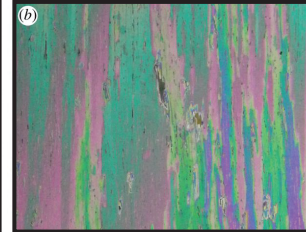


Weeks & Assur 1969



H. Eicken
Golden et al. GRL 2007

polycrystals

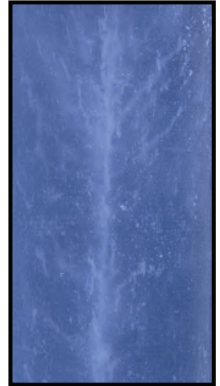


Gully et al. Proc. Roy. Soc. A 2015

brine channels



D. Cole



K. Golden

millimeters

centimeters

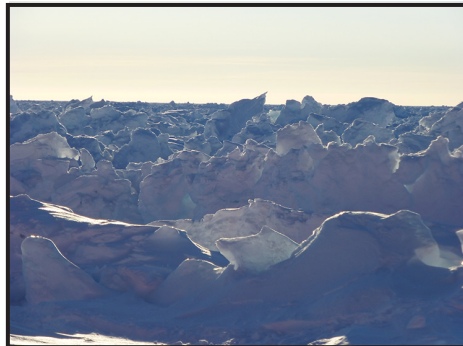
mesoscale

Arctic melt ponds



K. Frey

Antarctic pressure ridges



K. Golden

meters

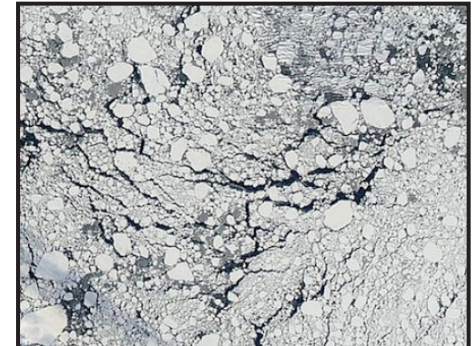
macroscale

sea ice floes



J. Weller

sea ice pack



NASA

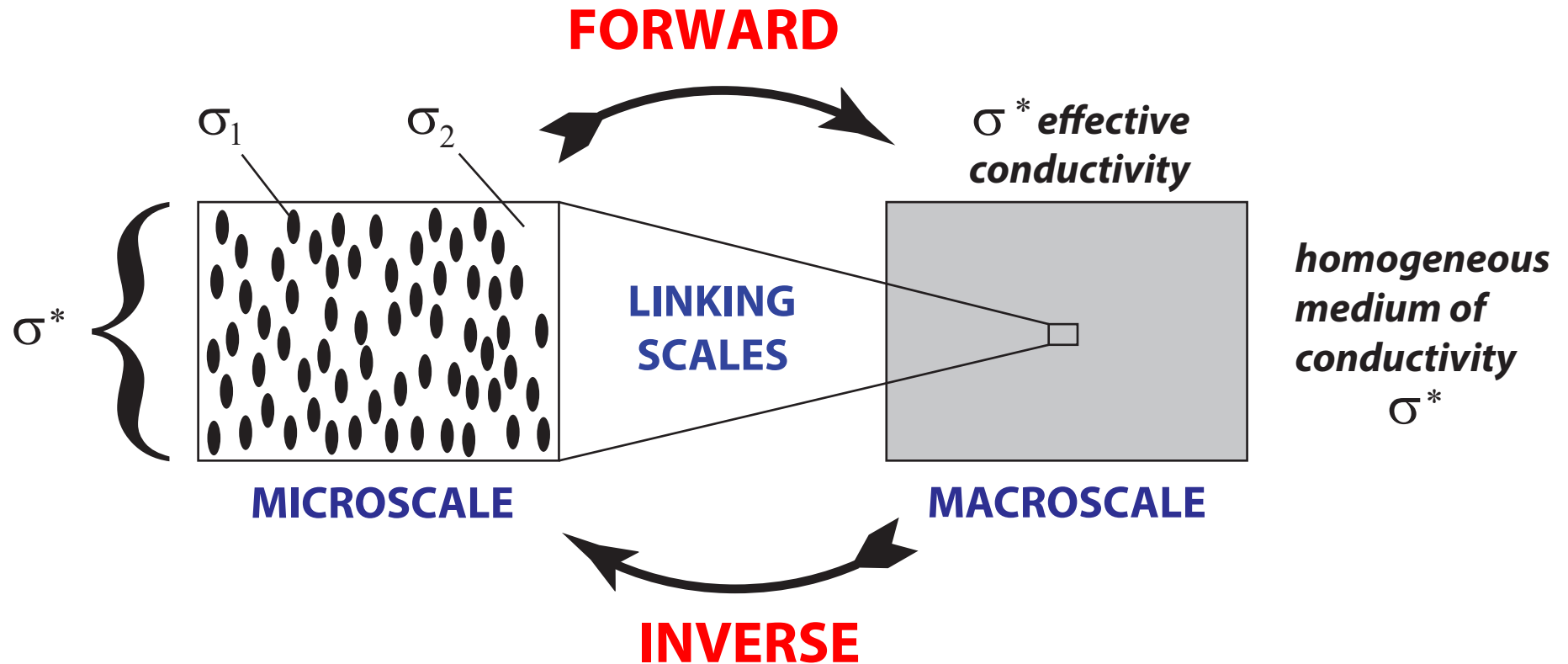
kilometers

Central theme:

How do we use “small scale” information to find effective behavior on larger scales relevant to climate and ecological models?

**OBJECTIVE: advance how sea ice is represented in climate models
improve projections of fate of SEA ICE and its ECOSYSTEMS**

HOMOGENIZATION for Composite Materials



Maxwell 1873, Einstein 1906

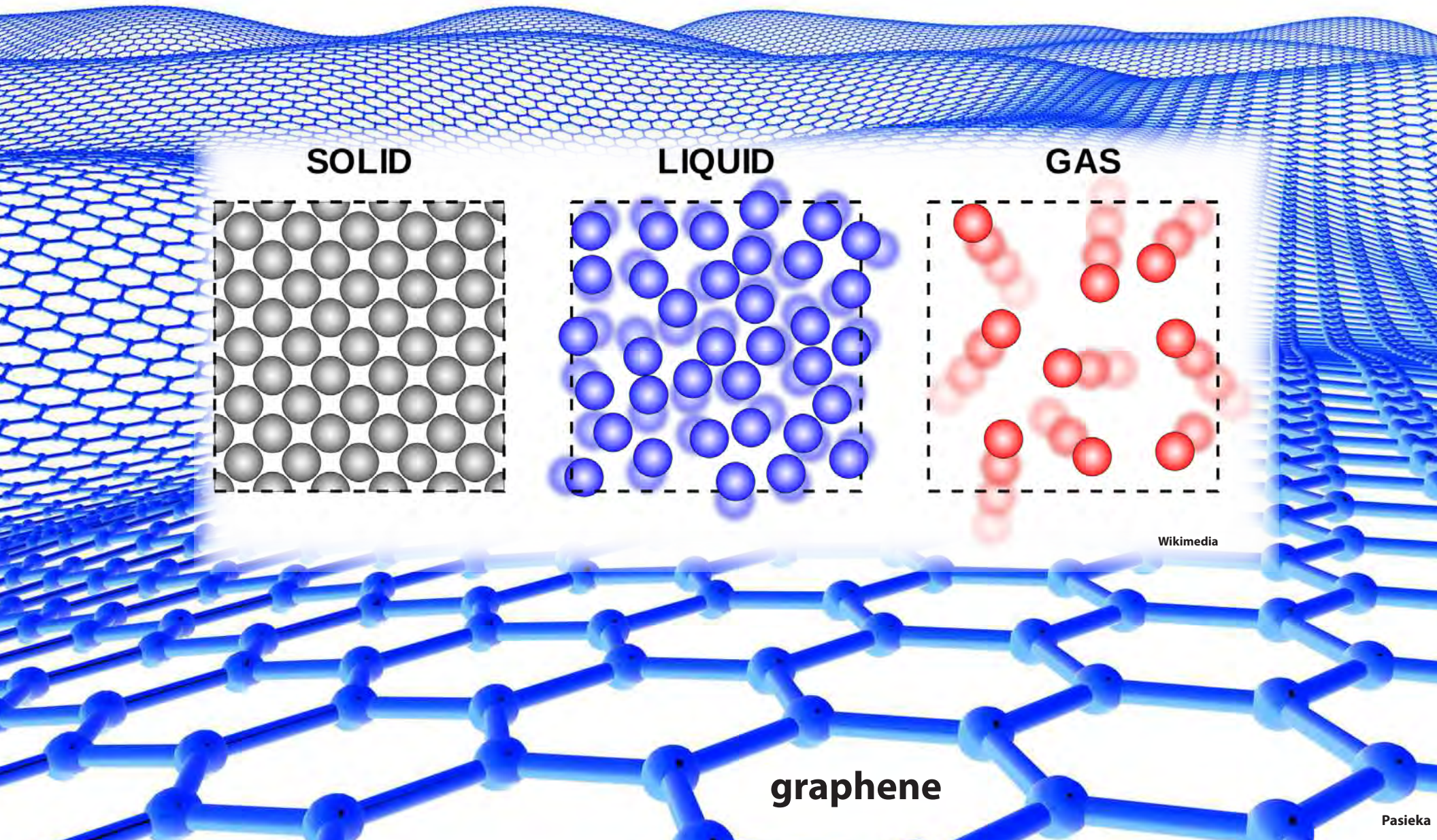
Wiener 1912, Hashin and Shtrikman 1962

STATISTICAL PHYSICS

percolation, phase transitions
solid state, semiconductors

How do microscopic laws determine macroscopic behavior?

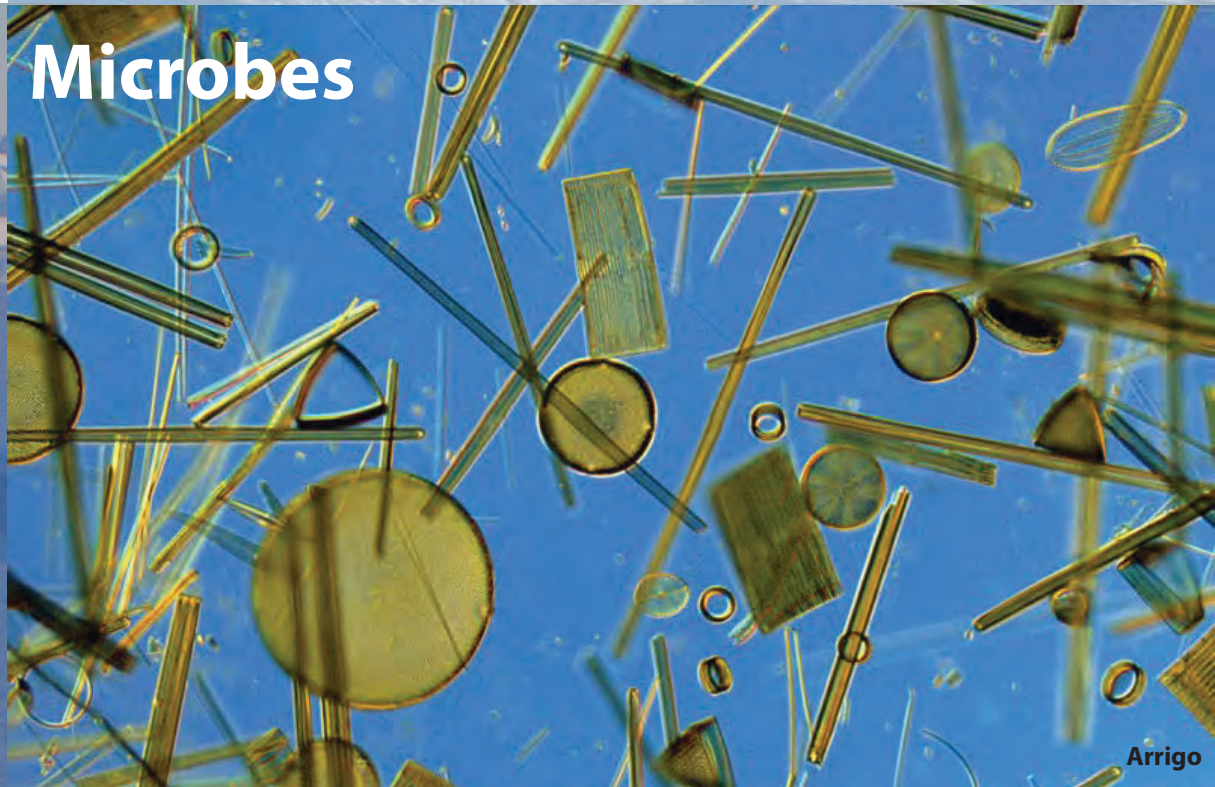
Banwell, Burton, Cenedese, Golden, Astrom, Physics of the Cryosphere, *Nature Reviews Physics* 2023



Polar Ecology and the Physics of Sea Ice

How do sea ice properties affect the life it hosts?

How does life in and on sea ice affect its physical properties?



Tour a few examples of multiscale modeling of physical and biological processes in the sea ice system.

microscale

mesoscale

macroscale

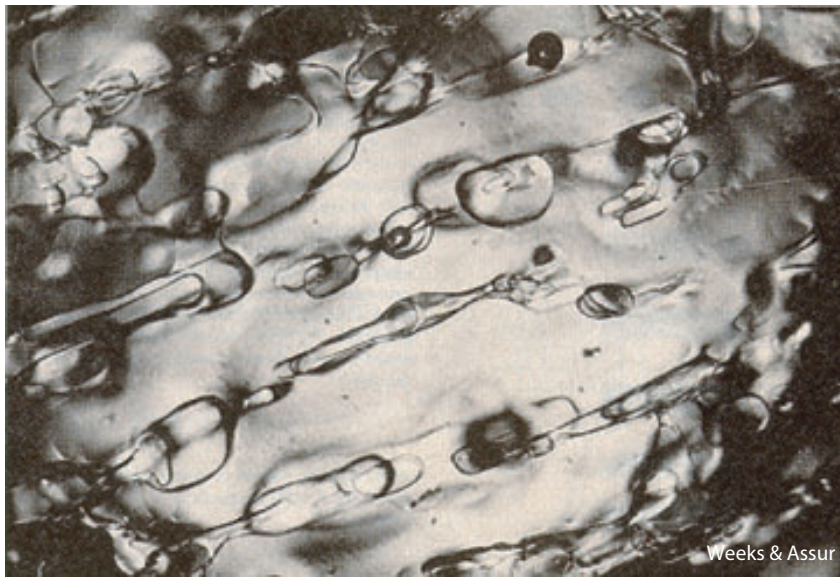
Take-away for mathematicians and physicists - our sea ice studies lead us into:

**spectral analysis, random matrix theory, topological data analysis,
UQ, anomalous diffusion, dynamical systems**

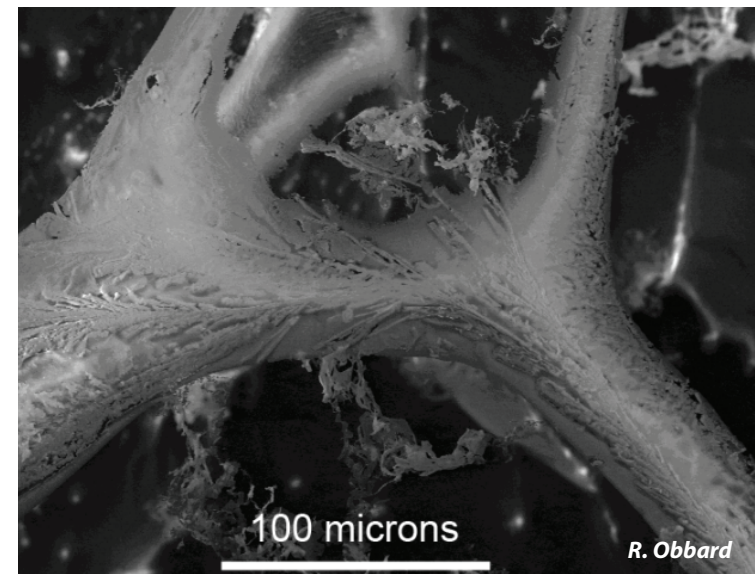
**percolation, Anderson localization, mushy layers, phase transitions
semiconductors, Ising models, quasicrystals**

+ fractal geometry

microscale



brine inclusions in sea ice (mm)



micro - brine channel (SEM)

***sea ice is a
porous composite***

pure ice with brine, air, and salt inclusions

brine channels (cm)



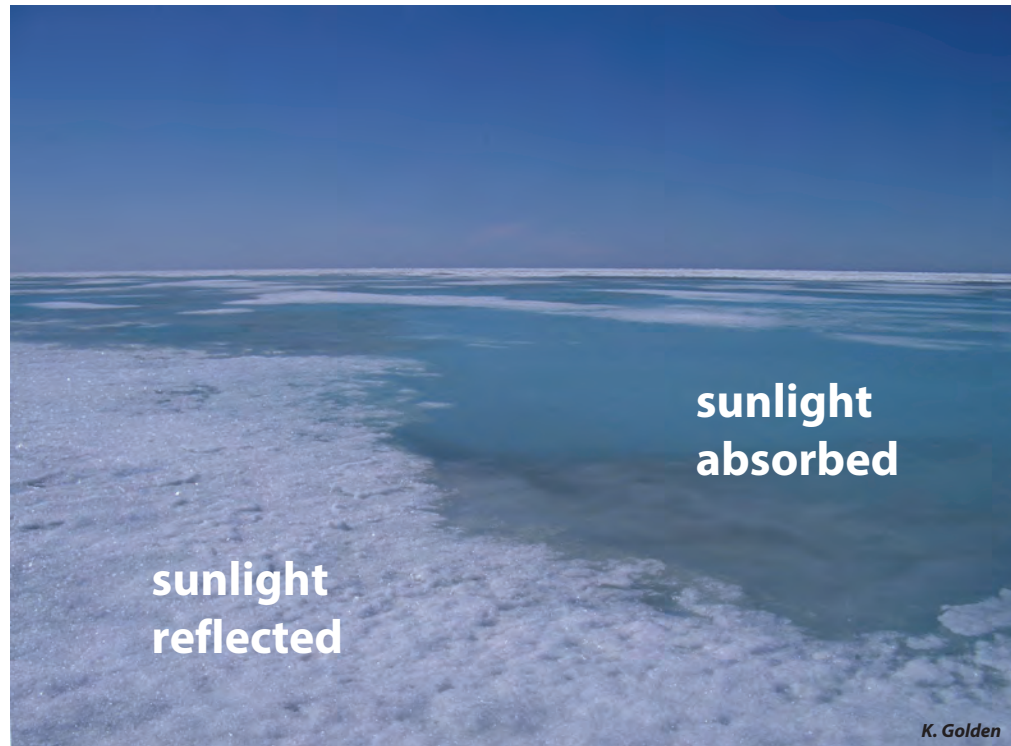
horizontal section



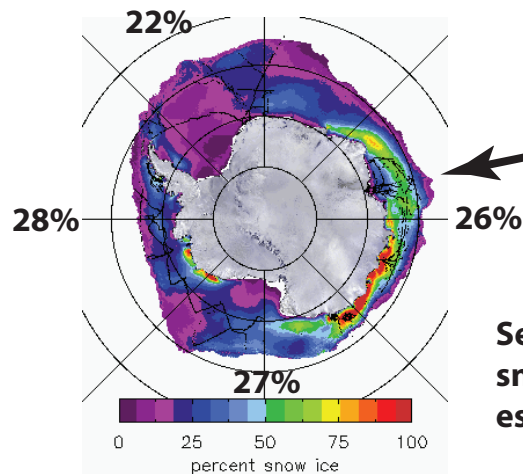
vertical section

fluid flow through the porous microstructure of sea ice governs key processes in polar climate and ecosystems

*evolution of Arctic melt ponds and sea ice **albedo***



nutrient flux for algal communities



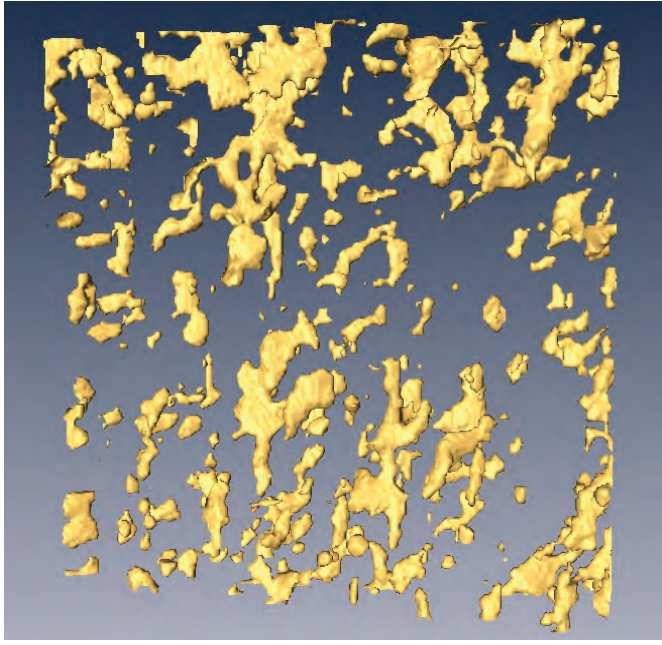
T. Maksym and T. Markus, 2008

***Antarctic surface flooding
and snow-ice formation***

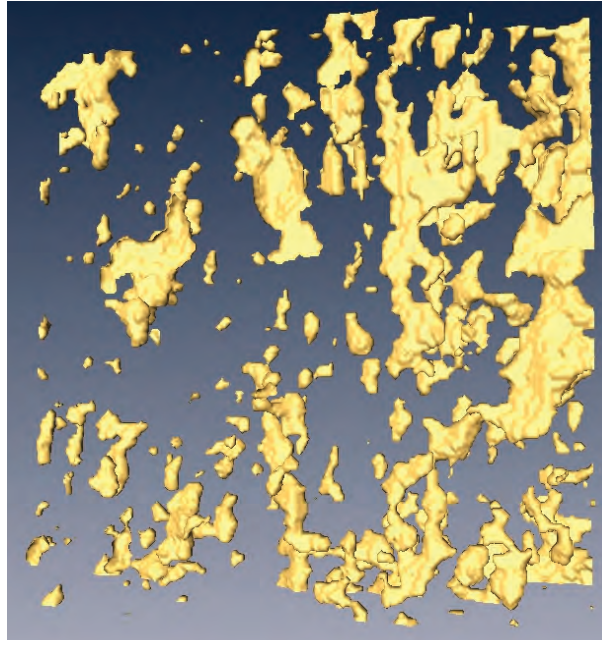
September
snow-ice
estimates

- *evolution of salinity profiles*
- *ocean-ice-air exchanges of heat, CO₂*

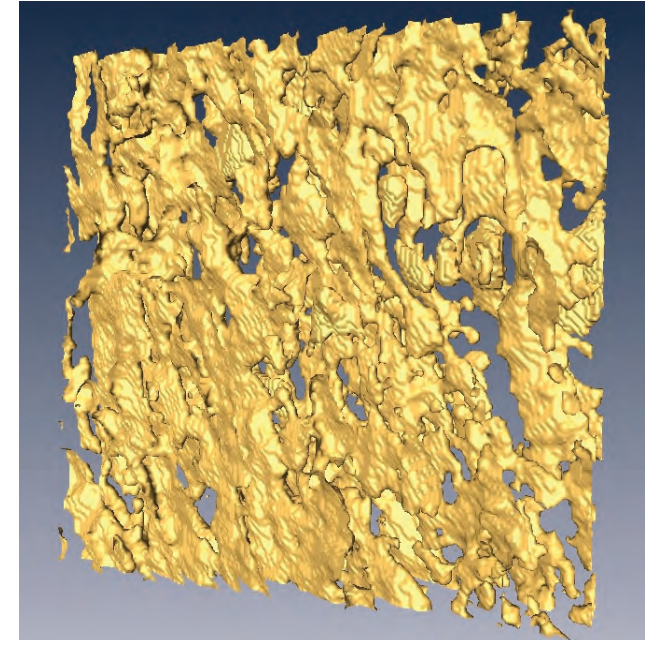
brine volume fraction and **connectivity** increase with temperature



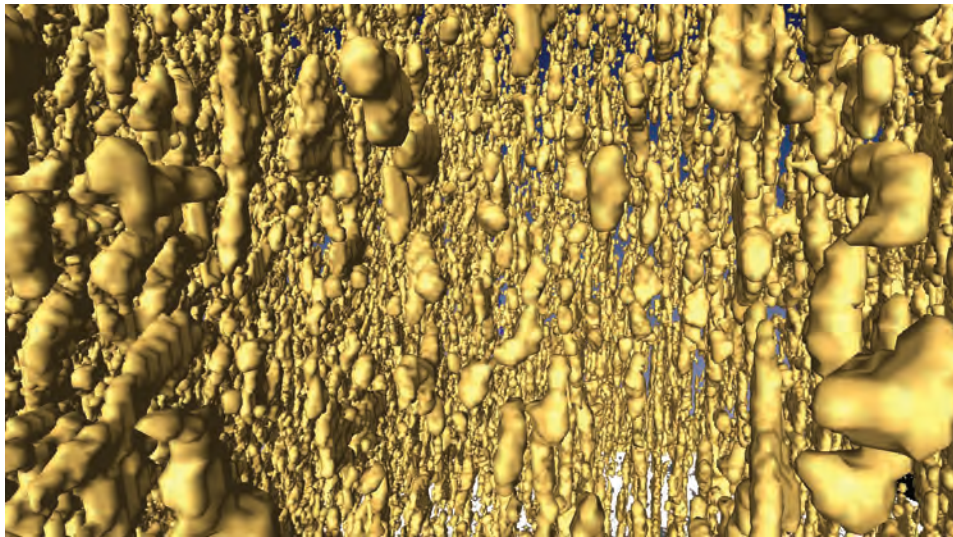
$T = -15\text{ }^{\circ}\text{C}$, $\phi = 0.033$



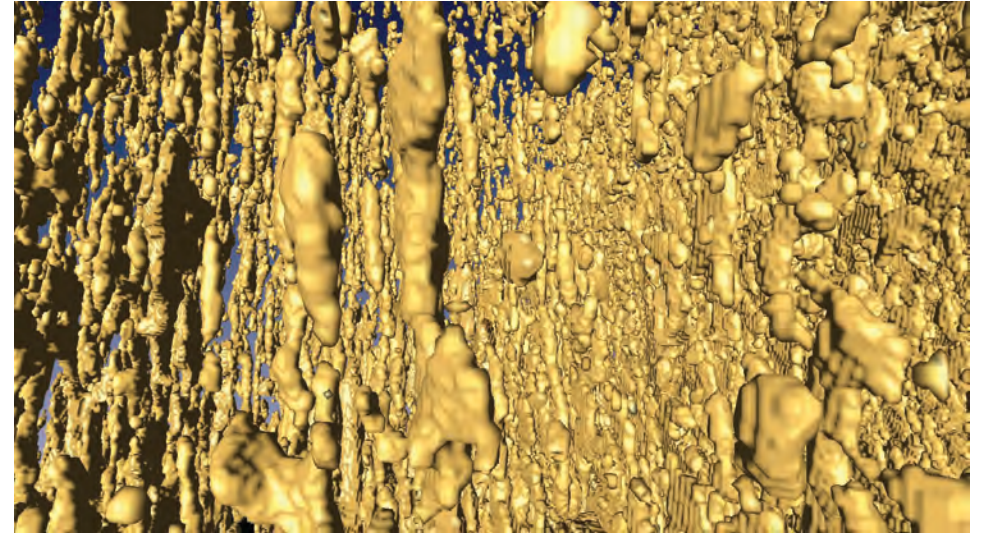
$T = -6\text{ }^{\circ}\text{C}$, $\phi = 0.075$



$T = -3\text{ }^{\circ}\text{C}$, $\phi = 0.143$



$T = -8\text{ }^{\circ}\text{C}$, $\phi = 0.057$



$T = -4\text{ }^{\circ}\text{C}$, $\phi = 0.113$

X-ray tomography for brine in sea ice

Golden et al., *Geophysical Research Letters*, 2007

Critical behavior of fluid transport in sea ice

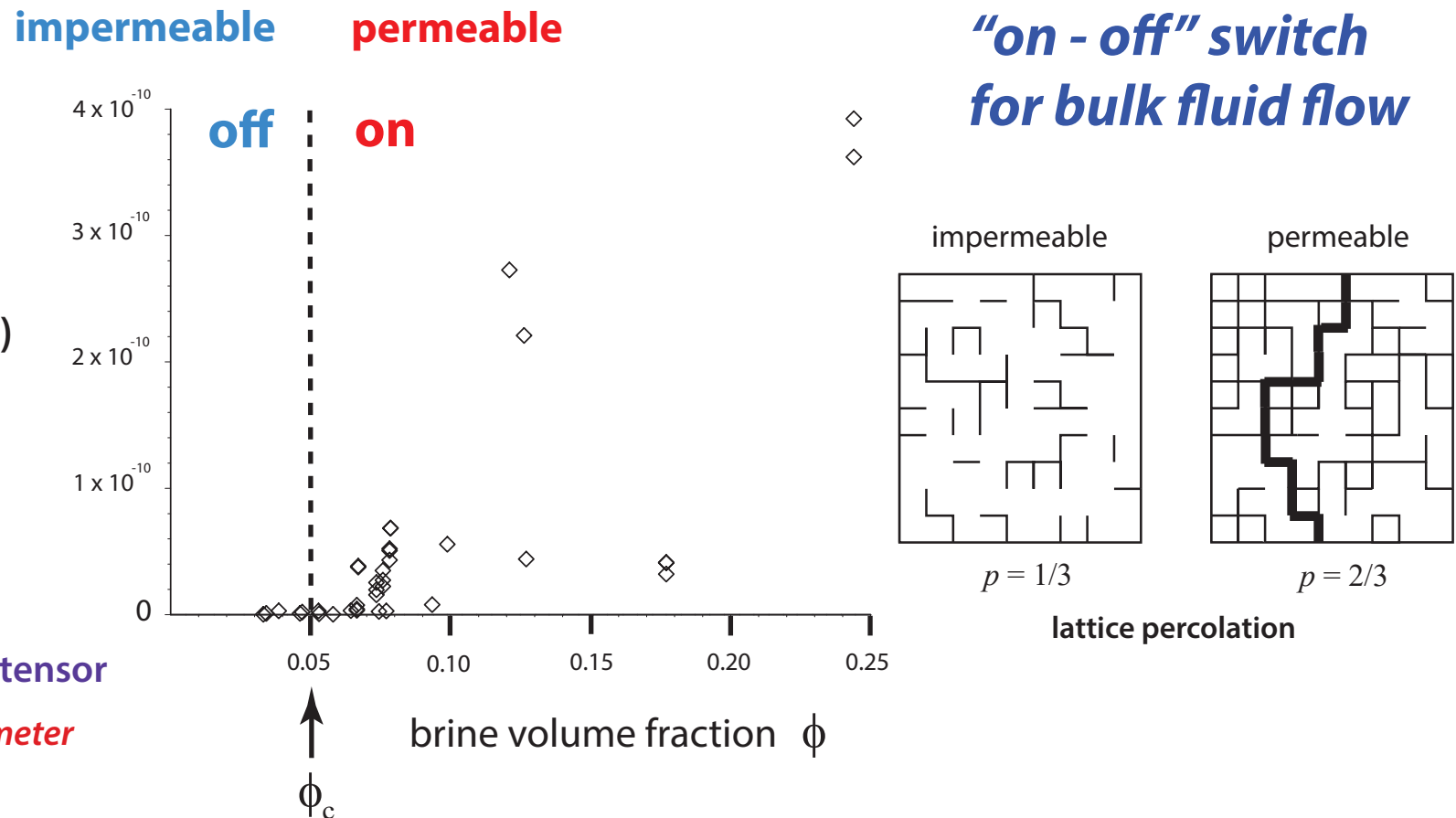
Arctic field data

vertical fluid permeability k (m^2)

Darcy's Law

$$\mathbf{v} = -\frac{\mathbf{k}}{\eta} \nabla p$$

\mathbf{k} = fluid permeability tensor
homogenized parameter



PERCOLATION THRESHOLD $\phi_c \approx 5\% \longleftrightarrow T_c \approx -5^\circ \text{C}, S \approx 5 \text{ ppt}$

RULE OF FIVES

Golden, Ackley, Lytle *Science* 1998

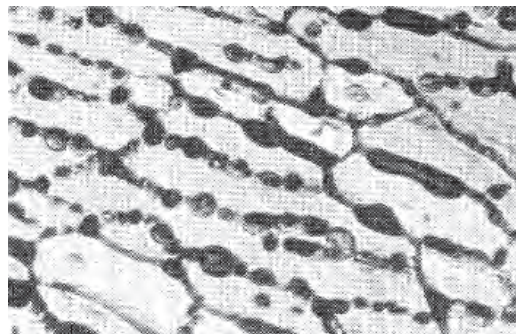
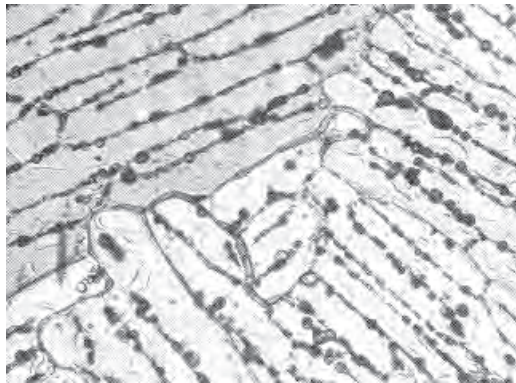
Golden, Eicken, Heaton, Miner, Pringle, Zhu *GRL* 2007

Pringle, Miner, Eicken, Golden *J. Geophys. Res.* 2009

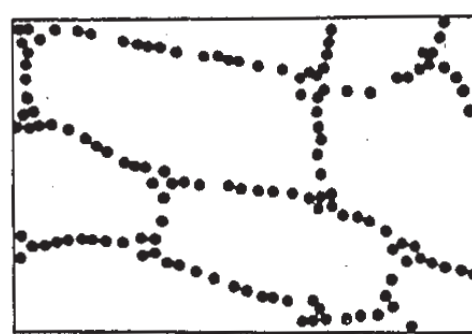
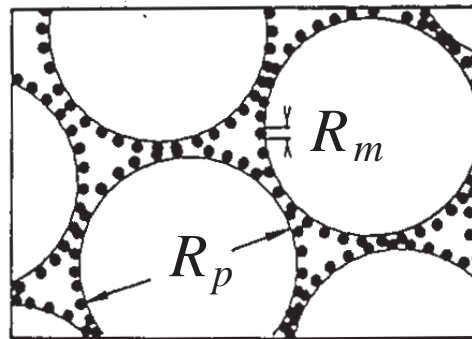
Continuum percolation model for **stealthy** materials applied to sea ice microstructure explains **Rule of Fives** and Antarctic data on **ice production** and **algal growth**

$$\phi_c \approx 5 \%$$

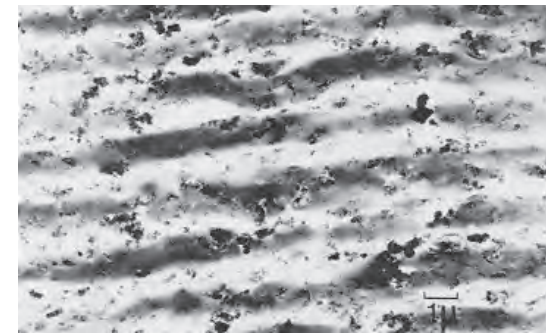
Golden, Ackley, Lytle, *Science*, 1998



sea ice



compressed
powder



radar absorbing
composite

sea ice is radar absorbing

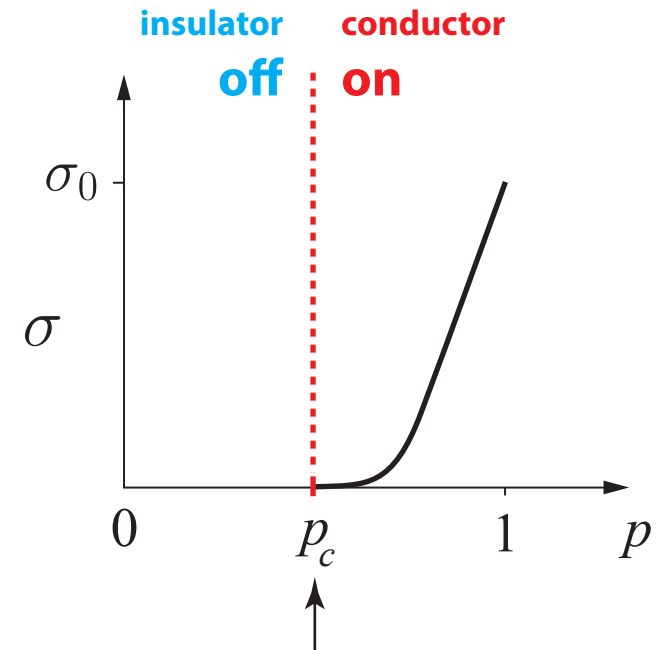
transport in percolation theory

MICRO $\xrightarrow{\text{lattice homogenization}}$ MACRO

local conductivity (electrical or fluid)

effective conductivity or fluid permeability

bond $\rightarrow \begin{cases} \sigma_0 & \text{probability } p \\ 0 & \text{probability } 1 - p \end{cases}$



percolation threshold

$$\sigma(p) \sim \sigma_0 (p - p_c)^t \quad p \rightarrow p_c^+$$

consider local conductivities

1 and $h > 0$

smooths, softens transition

UNIVERSAL critical exponents for lattices -- depend only on dimension

$1 \leq t \leq 2$ (for idealized model), Golden, *Phys. Rev. Lett.* 1990 ; *Comm. Math. Phys.* 1992

non-universal behavior in continuum



sea ice algal communities

D. Thomas 2004

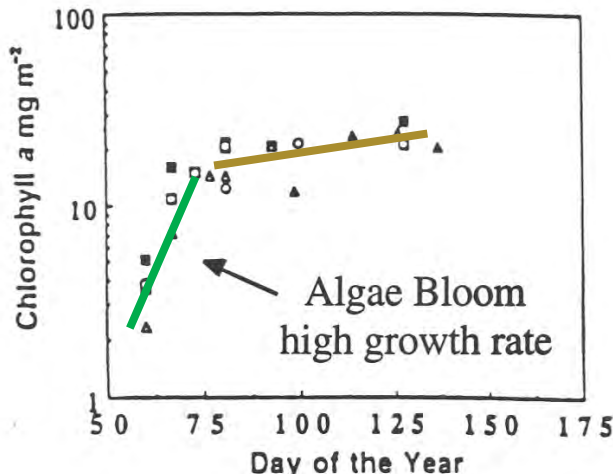
nutrient replenishment
controlled by ice permeability

biological activity turns on
or off according to
rule of fives

Golden, Ackley, Lytle *Science* 1998

Fritsen, Lytle, Ackley, Sullivan *Science* 1994

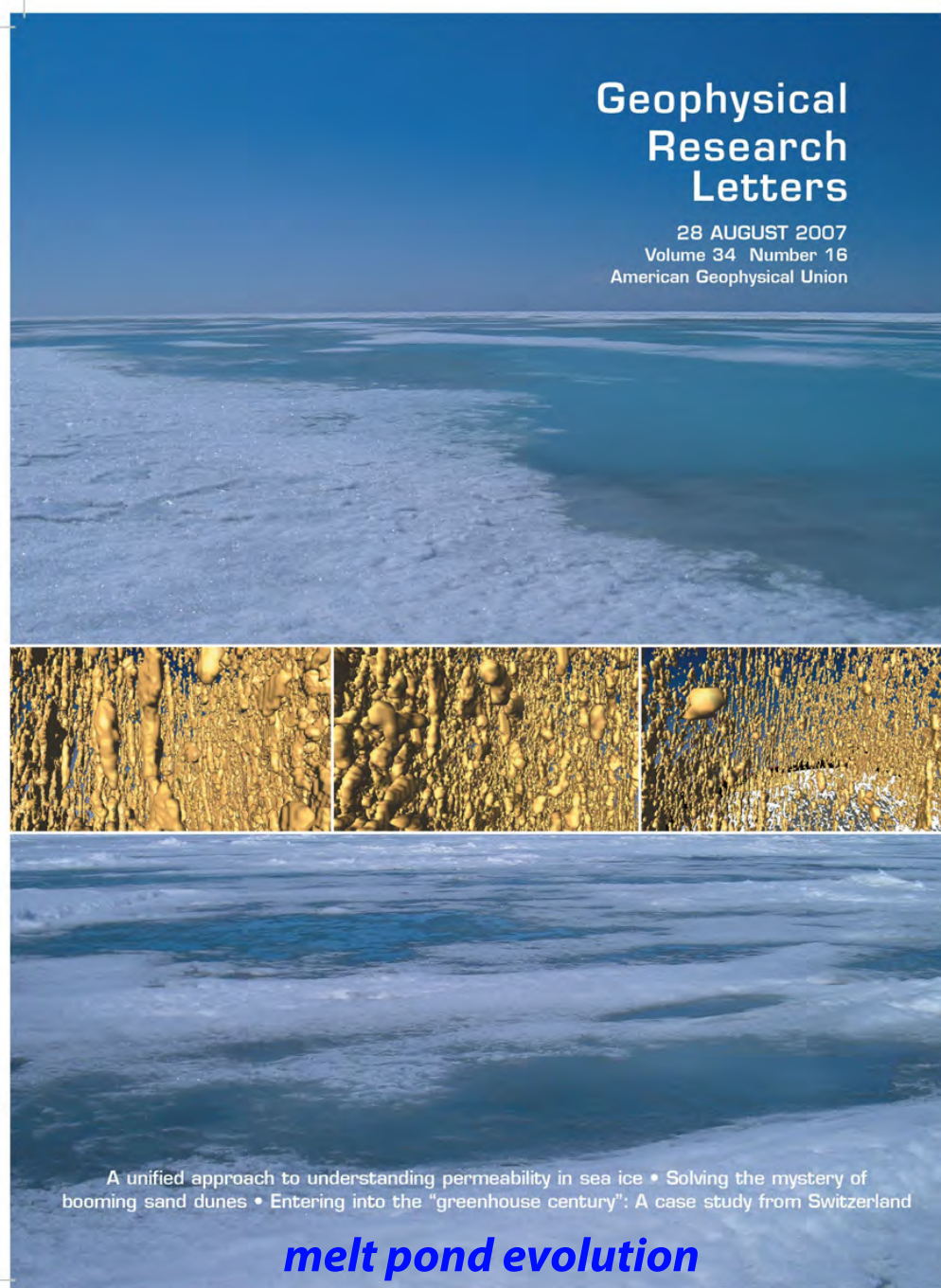
critical behavior of microbial activity



Convection-fueled algae bloom
Ice Station Weddell

Thermal evolution of permeability and microstructure in sea ice

Golden, Eicken, Heaton, Miner, Pringle, Zhu, *Geophysical Research Letters* 2007



percolation theory
for fluid permeability

$$k(\phi) = k_0 (\phi - 0.05)^2$$

critical exponent t

$$k_0 = 3 \times 10^{-8} \text{ m}^2$$

from critical path analysis
in hopping conduction

hierarchical model
rock physics
network model
rigorous bounds

X-ray tomography for
brine inclusions

confirms rule of fives

brine percolation threshold
of $\phi = 5\%$ for bulk fluid flow

*Pringle, Miner, Eicken, Golden
J. Geophys. Res. 2009*

theories agree closely
with field data

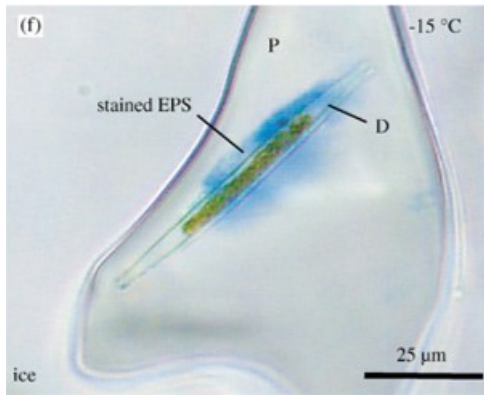
microscale
governs
mesoscale
processes

melt pond evolution

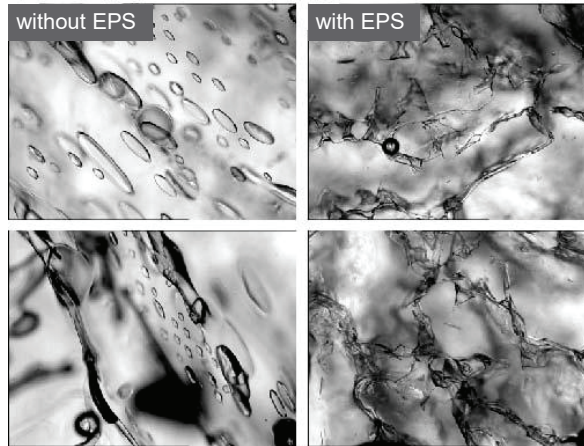
Sea ice algae secrete exopolymeric substances (EPS) affecting evolution of brine microstructure.

How does EPS affect fluid transport? How does the biology affect the physics?

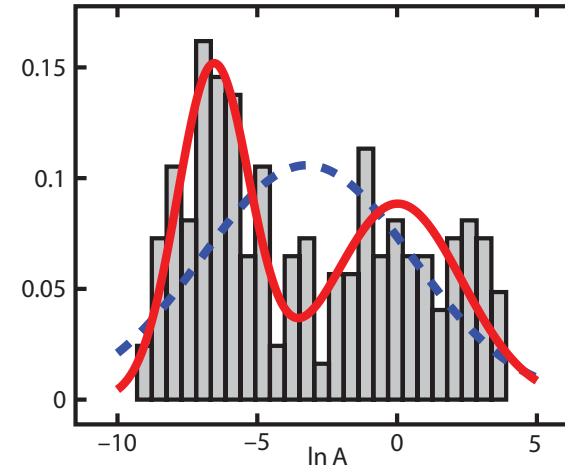
FRACTAL



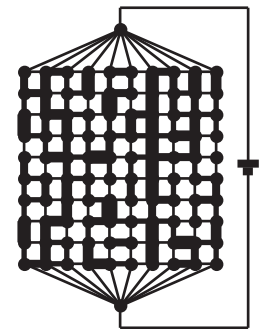
Krembs



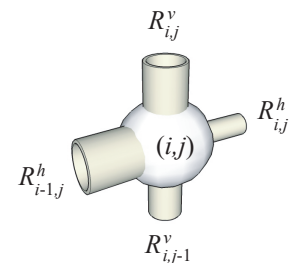
Krembs, Eicken, Deming, PNAS 2011



RANDOM PIPE MODEL



- 2D random pipe model with bimodal distribution of pipe radii
- Rigorous bound on permeability k ; results predict observed drop in k



Steffen, Epshteyn, Zhu, Bowler, Deming, Golden
Multiscale Modeling and Simulation, 2018

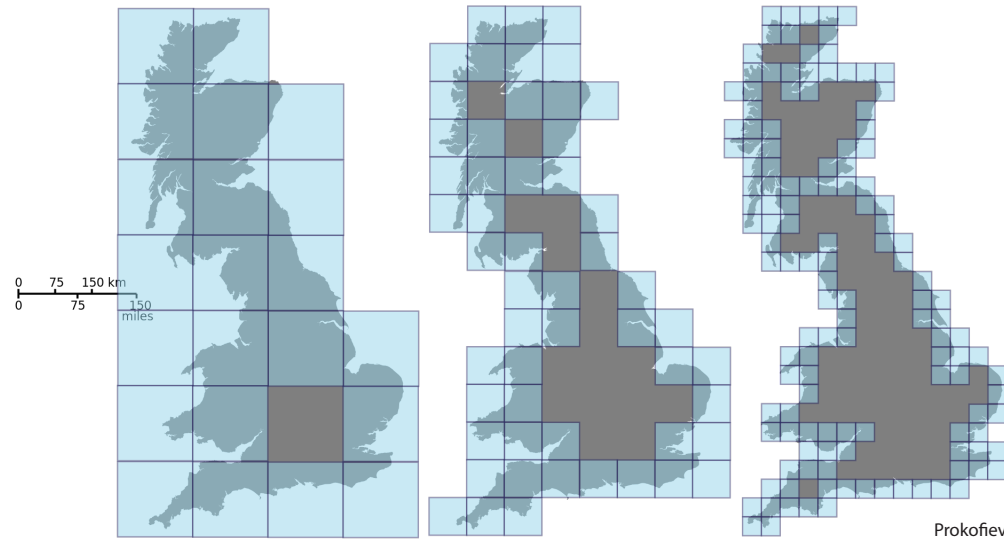
Zhu, Jabini, Golden,
Eicken, Morris
Ann. Glac. 2006

EPS - Algae Model Jajeh, Reimer, Golden, 2024

SIAM News
June 2024

Thermal Evolution of Brine Fractal Geometry in Sea Ice

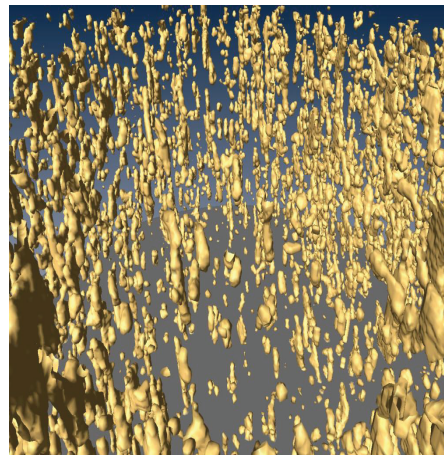
Nash Ward, Daniel Hallman, Benjamin Murphy, Jody Reimer,
Marc Oggier, Megan O'Sadnick, Elena Cherkaev and Kenneth Golden, 2024



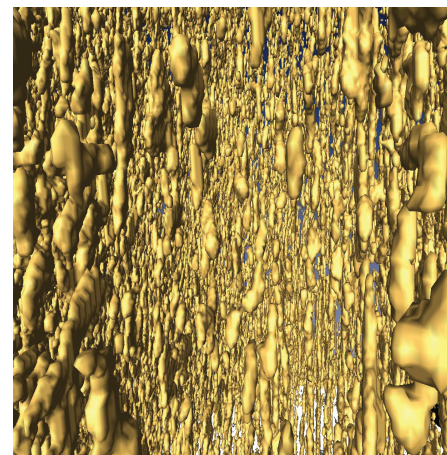
fractal dimension of the
coastline of Great Britain
by box counting

$$N(\epsilon) \sim \epsilon^{-D}$$

$T = -12^{\circ} \text{C}$, $\phi = 0.033$



$T = -8^{\circ} \text{C}$, $\phi = 0.057$



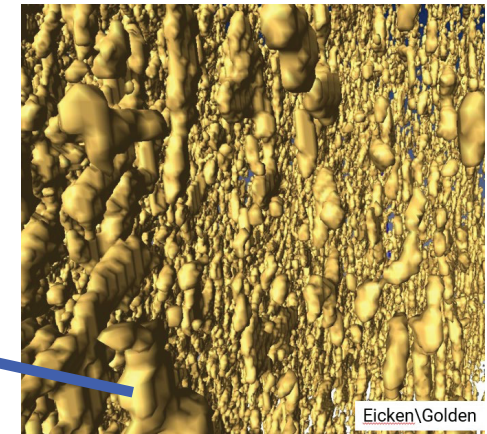
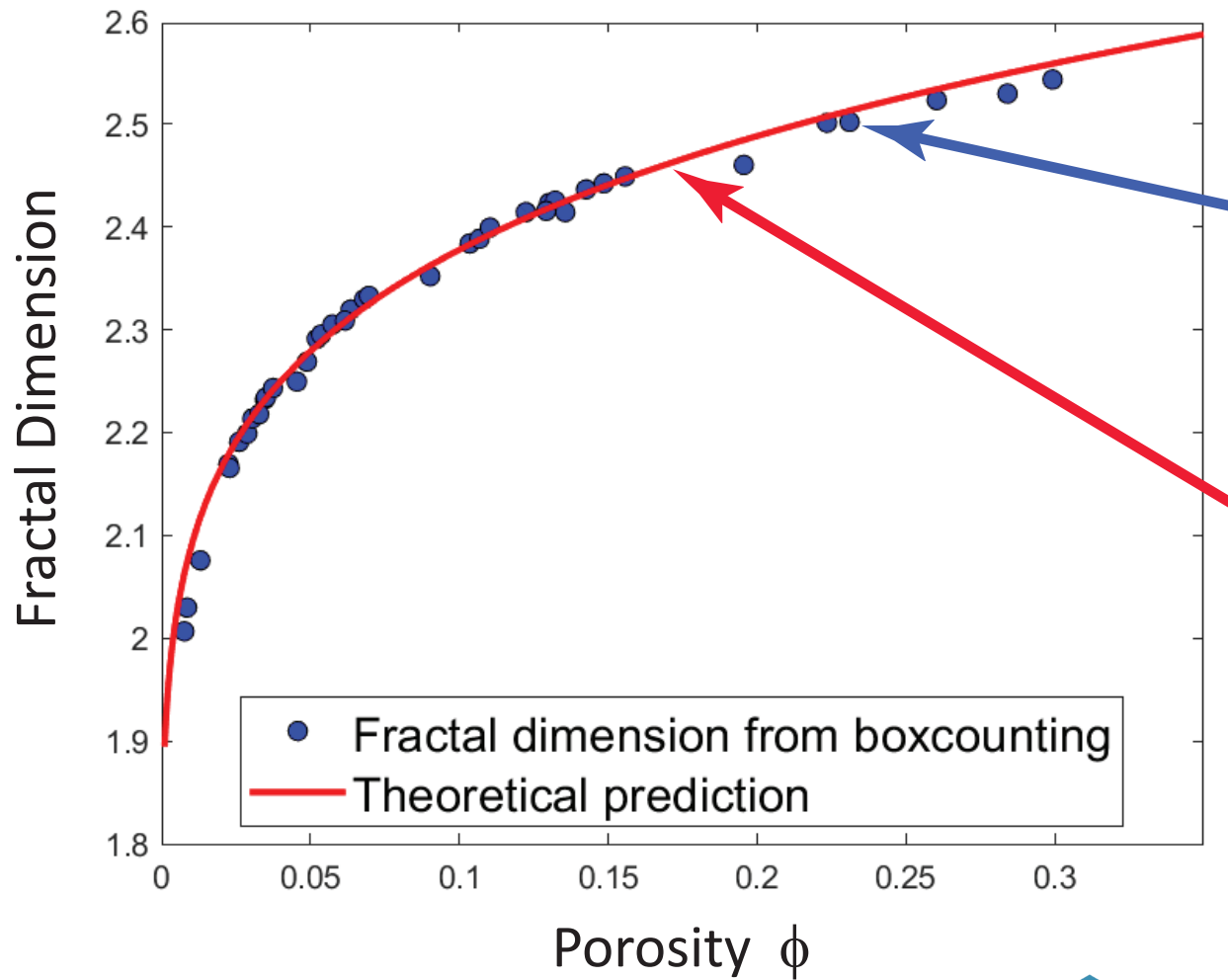
brine channels and
inclusions “look”
like fractals
(from 30 yrs ago)

X-ray computed
tomography of
brine in sea ice

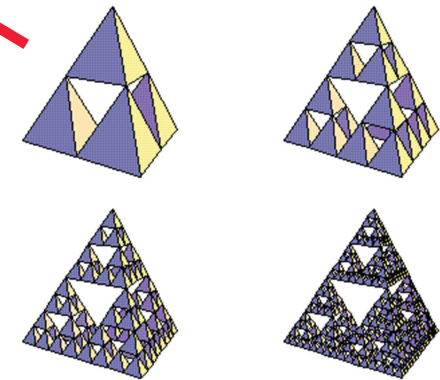
columnar and granular

Golden, Eicken, et al. *GRL*, 2007

The first quantitative study of the fractal dimension of brine in sea ice and its strong dependence on temperature and porosity.



Follows same curve as exactly self-similar Sierpinski tetrahedron



D. Eppstein

red curve

$$F_d = d_E - \frac{\ln \phi}{\ln(\lambda_{min}/\lambda_{max})}$$

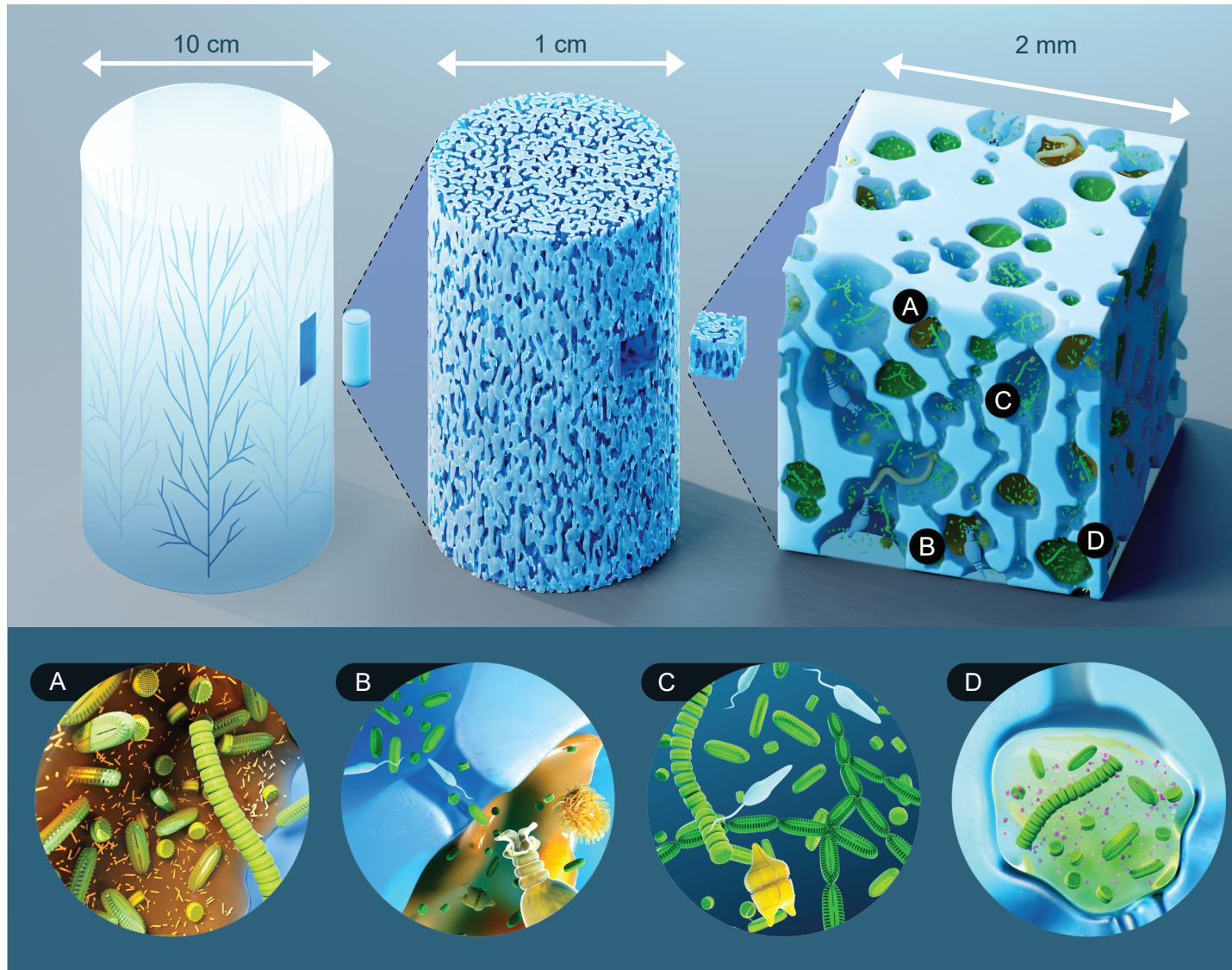
Katz and Thompson, 1985; Yu and Li, 2001

discovered for sandstones
statistically self-similar porous media



Fractal geometry of brine in sea ice, Ward, et al. 2024

Implications of brine fractal geometry on sea ice ecology and biogeochemistry



Brine inclusions are home to ice endemic organisms, e.g., bacteria, diatoms, flagellates, rotifers, nematodes.

The habitability of sea ice for these organisms is inextricably linked to its complex brine geometry.

- (A) Many sea ice organisms attach themselves to inclusion walls; inclusions with a higher fractal dimension have greater surface area for colonization.
- (B) Narrow channels prevent the passage of larger organisms, leading to refuges where smaller organisms can multiply without being grazed, as in (C).
- (D) Ice algae secrete extracellular polymeric substances (EPS) which alter inclusion geometry and may further increase the fractal dimension.

Arctic and Antarctic field experiments

*develop electromagnetic methods
of monitoring fluid transport and
microstructural transitions*

extensive measurements of fluid and
electrical transport properties of sea ice:

2007 Antarctic SIPEX

2010 Antarctic McMurdo Sound

2011 Arctic Barrow AK

2012 Arctic Barrow AK

2012 Antarctic SIPEX II

2013 Arctic Barrow AK

2014 Arctic Chukchi Sea

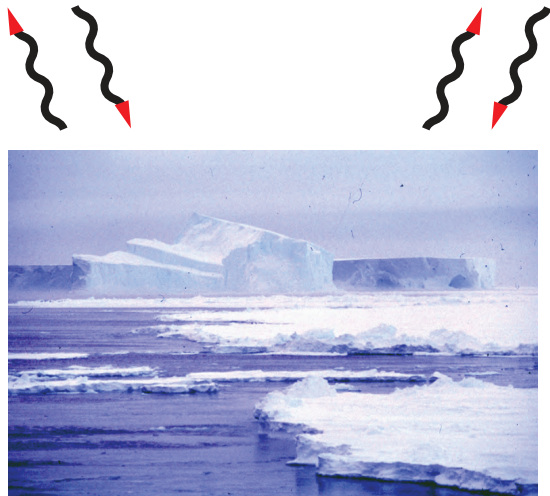


Remote Sensing of Sea Ice

with radar, microwaves, ...



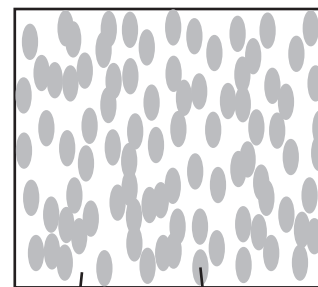
interaction of
EM waves with
brine and
polycrystalline
microstructures,
rough surfaces



INVERSE PROBLEM

Recover sea ice properties from
electromagnetic (EM) data ϵ^*

Effective complex permittivity of a composite
in the quasistatic (long wavelength) limit



ϵ_1 ϵ_2

ϵ^*

p_1, p_2 = volume fractions of
the components

$$D = \epsilon E$$

$$\nabla \cdot D = 0$$

$$\nabla \times E = 0$$

$$\langle D \rangle = \epsilon^* \langle E \rangle$$

electrical conductivity
thermal conductivity
magnetic permeability
diffusivity

$$\epsilon^* = \epsilon^* \left(\frac{\epsilon_1}{\epsilon_2}, \text{ composite geometry} \right)$$

**What are the effective propagation characteristics
of an EM wave (radar, microwaves) in the medium?**

Analytic Continuation Method for Homogenization

Bergman 1978, Milton 1979, Golden & Papanicolaou 1983, Milton 2002

Stieltjes integrals for homogenized parameters separate component parameters from geometry

$$F(s) = 1 - \frac{\epsilon^*}{\epsilon_2} = \int_0^1 \frac{d\mu(z)}{s - z} \quad s = \frac{1}{1 - \epsilon_1/\epsilon_2}$$

← geometry
← material parameters

- spectral measure of self adjoint operator $\Gamma\chi$ (matrix)

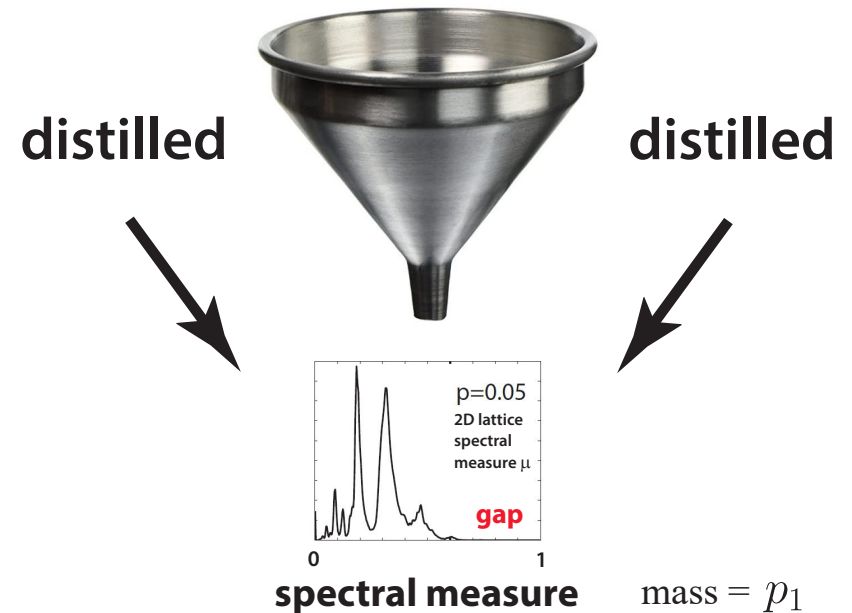
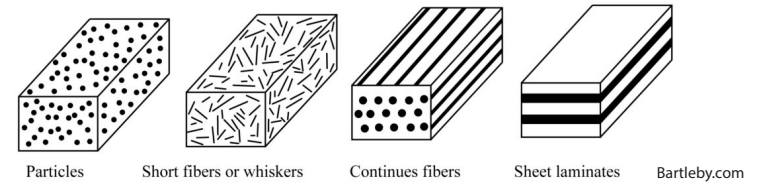
$$\Gamma = \nabla(-\Delta)^{-1}\nabla.$$

χ = characteristic function of the brine phase

- $E = s (s + \Gamma\chi)^{-1} e_k$ **resolvent**

- bounds in the complex plane; approximations
inverse bounds to recover porosity, connectivity

complexities of mixture geometry



spectral properties of operator (matrix)
~ quantum states, energy levels for atoms

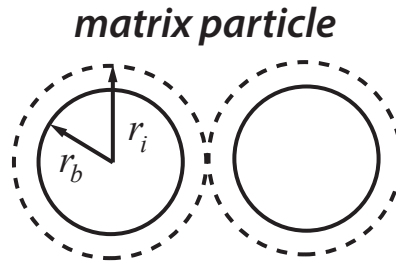
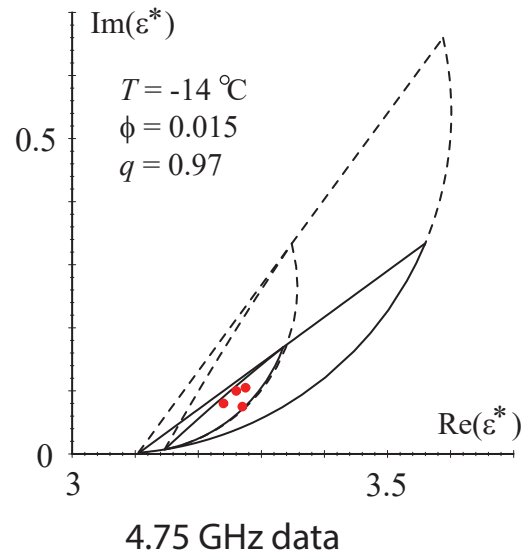
eigenvectors

eigenvalues

$\Gamma\chi$: microscale → macroscale

forward and inverse bounds on the complex permittivity of sea ice

forward bounds

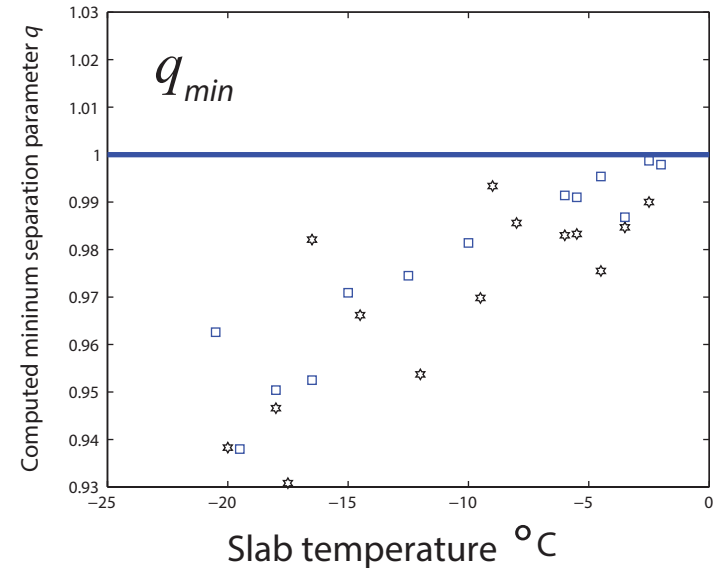


$$q = r_b / r_i$$

$$0 < q < 1$$

Golden 1995, 1997

inverse bounds



Inverse Homogenization

Cherkaev and Golden (1998), Day and Thorpe (1999), Cherkaev (2001), McPhedran, McKenzie, Milton (1982), *Theory of Composites*, Milton (2002)

ϵ^* \longrightarrow composite geometry
(spectral measure μ)

inverse bounds and recovery of brine porosity

Gully, Backstrom, Eicken, Golden
Physica B, 2007

inversion for brine inclusion separations in sea ice from measurements of effective complex permittivity ϵ^*

rigorous inverse bound on spectral gap

construct algebraic curves which bound admissible region in (p, q) -space

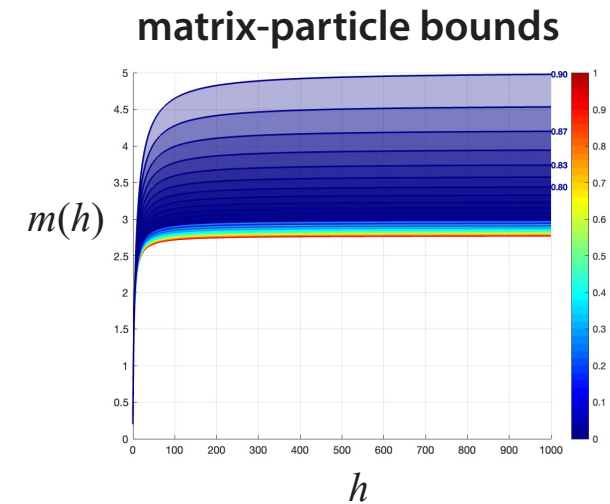
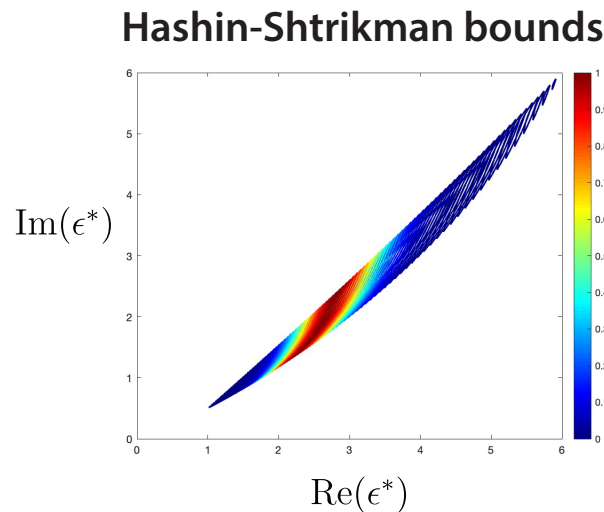
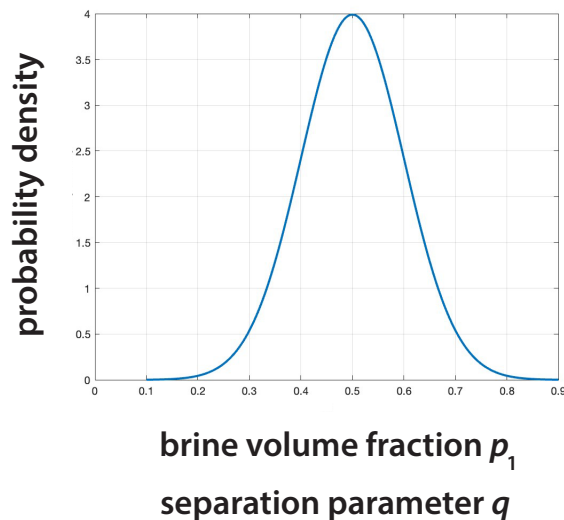
Orum, Cherkaev, Golden
Proc. Roy. Soc. A, 2012

Uncertainty Quantification for Homogenization via Stieltjes Integral Representations

Clara Platt, Elena Cherkaev, Akil Narayan, Debdeep Bhattacharya, Ken Golden 2025

Classical bounds in the analytic continuation method assume **fixed** microstructural parameters, such as porosity, local permittivities, or inclusion separations.

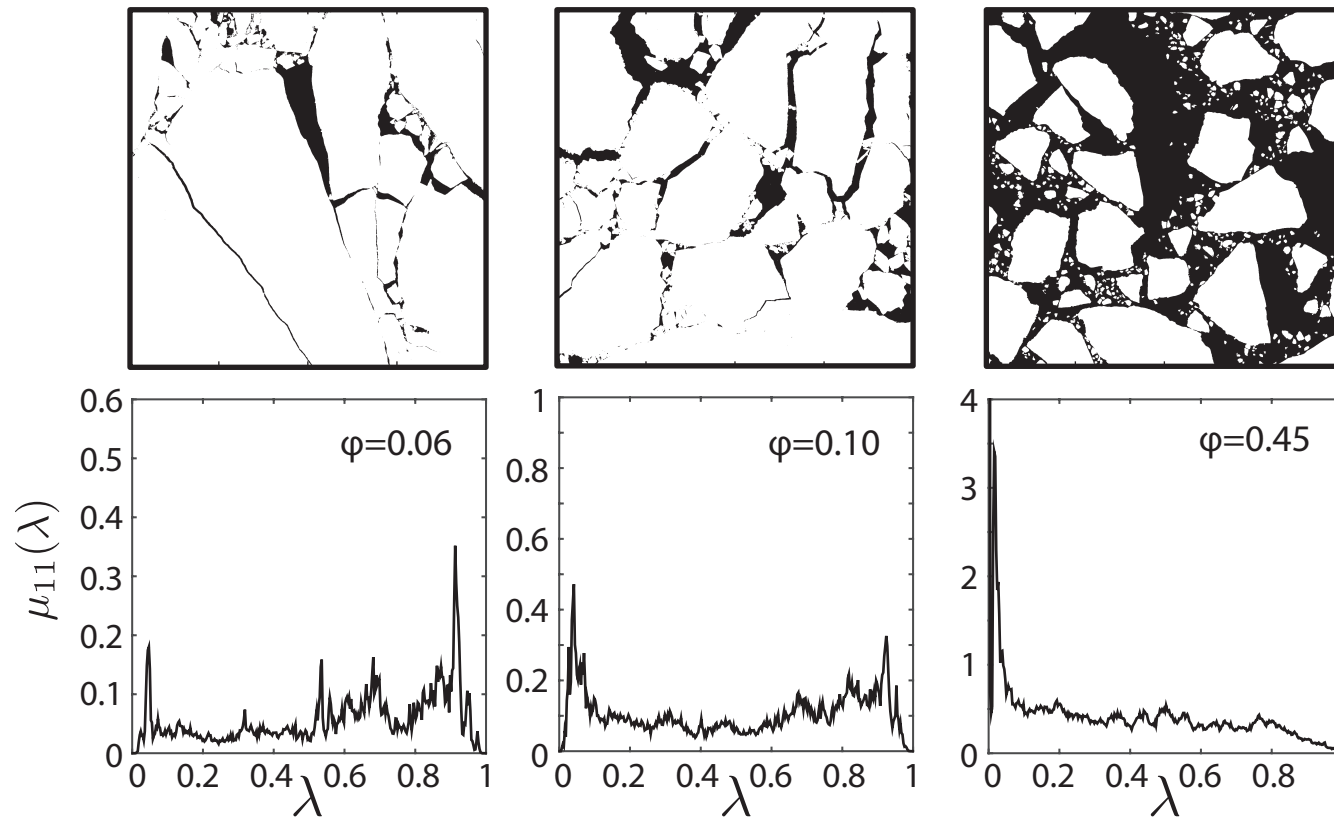
But what if there is uncertainty, and they are random variables?



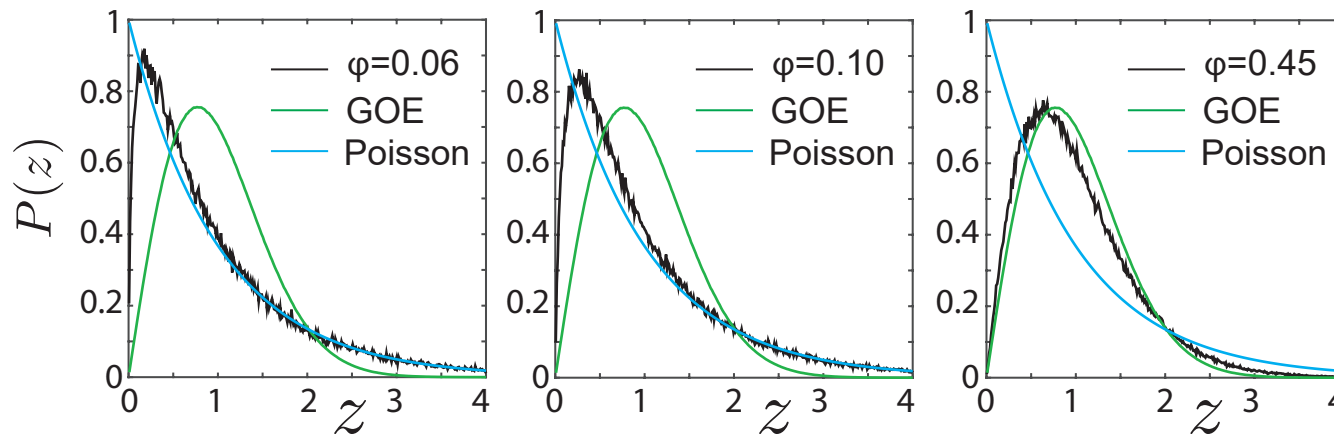
UQ for complex permittivity & thermal conductivity of sea ice

Spectral computations for sea ice floe configurations

spectral
measures



eigenvalue
spacing
distributions



**RANDOM
MATRIX
THEORY**

uncorrelated



level repulsion

**UNIVERSAL
Wigner-Dyson
distribution**

**Anderson
localization
transition**

Eigenvalue Statistics of Random Matrix Theory

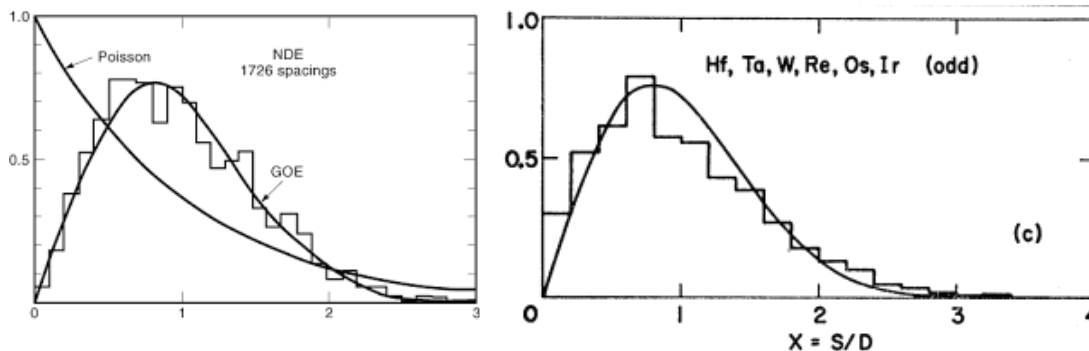
Wigner (1951) and Dyson (1953) first used random matrix theory (RMT) to describe quantized energy levels of heavy atomic nuclei.

$[N]_{ij} \sim N(0,1), \quad A = (N + N^T)/2 \quad \text{Gaussian orthogonal ensemble (GOE)}$

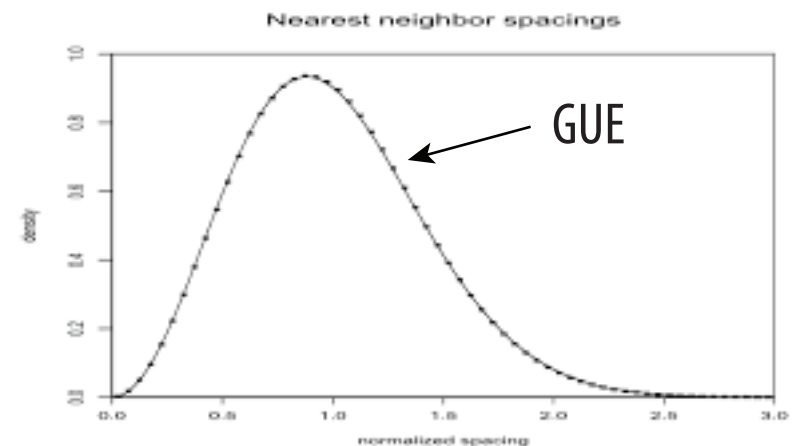
$[N]_{ij} \sim N(0,1) + iN(0,1), \quad A = (N + N^\dagger)/2 \quad \text{Gaussian unitary ensemble (GUE)}$

Short range and long range correlations of eigenvalues are measured by various eigenvalue statistics.

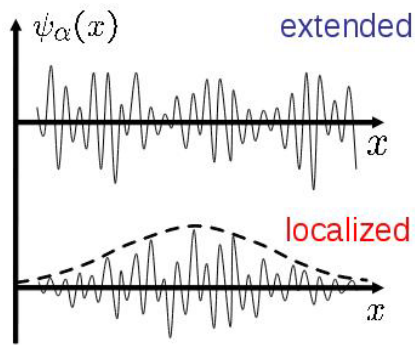
Spacing distributions of energy levels for heavy atomic nuclei



Spacing distributions of the first billion zeros of the Riemann zeta function



Universal eigenvalue statistics arise in a broad range of “unrelated” problems!



Anderson localization

disorder-driven

metal / insulator transition

Anderson 1958
Mott 1949
Evangelou 1992
Shklovshii et al 1993

propagation vs. localization in wave physics:
quantum, optics, acoustics, water waves

Wave equations

Laplace + Diffusion
equations

we find percolation-driven

Anderson transition for classical transport in composites

mobility edges, localization, universal spectral statistics

Murphy, Cherkaev, Golden Phys. Rev. Lett. 2017

but no wave interference or scattering effects at play!

local conductivity in 1D inhomogeneous material

$$\sigma(x) = 3 + \cos x + \cos kx$$

effective conductivity

$$\sigma^*(k) = \begin{cases} \text{constant} & k \text{ irrational} & \text{quasiperiodic} \\ f(k) & k \text{ rational} & \text{periodic} \end{cases}$$

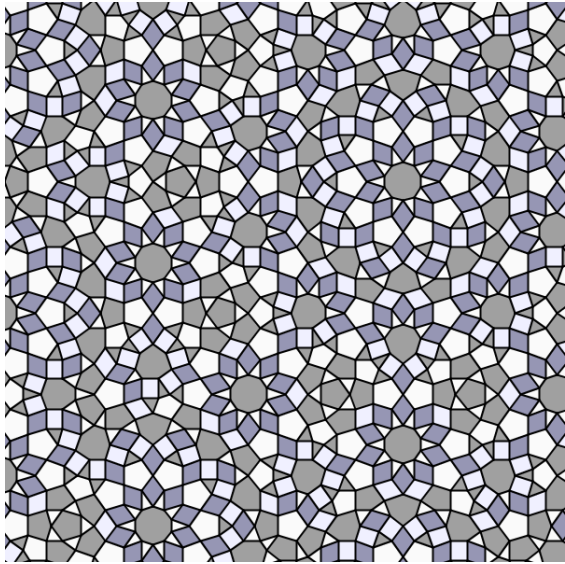
Golden, Goldstein, Lebowitz, Phys. Rev. Lett. 1985

Order to Disorder in Quasiperiodic Composites

D. Morison (Physics), N. B. Murphy, E. Cherkaev, K. M. Golden, *Communications Physics* 2022

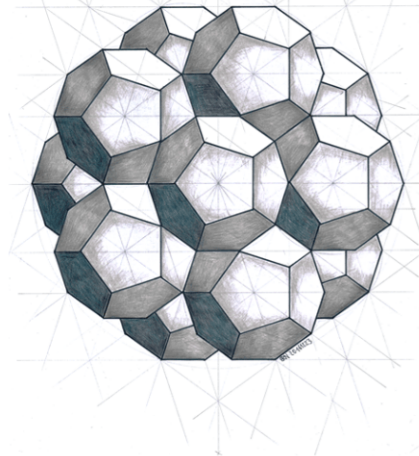
quasiperiodic crystal

quasicrystal



quasiperiodic checkerboard

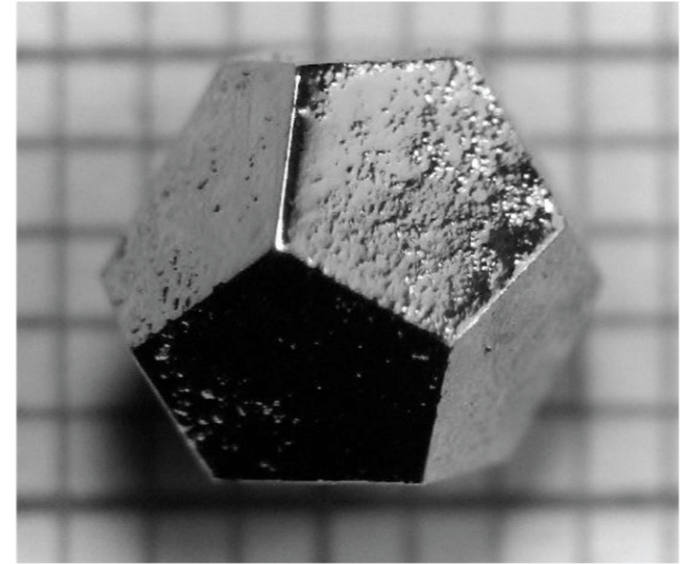
Stampfli, 2013



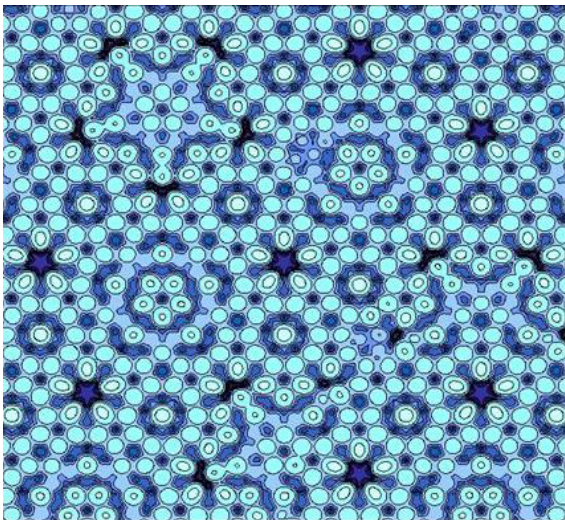
dense packing of dodecahedra

3D Penrose tiling

Tripkovic, 2019



Holmium-magnesium-zinc quasicrystal



energy surface Al-Pd-Mn quasicrystal

Unal et al., 2007

ordered but aperiodic

lacks translational symmetry

Shechtman et al., *Phys. Rev. Lett.*, 1984

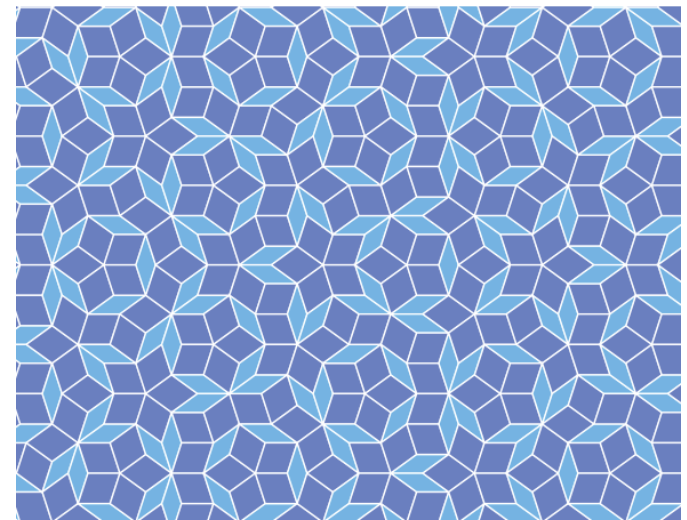
Levine & Steinhardt, *Phys. Rev. Lett.*, 1984

**classical transport in
quasiperiodic media**

Golden, Goldstein & Lebowitz, *Phys. Rev. Lett.*, 1985

Golden, Goldstein & Lebowitz, *J. Stat. Phys.*, 1990

⋮

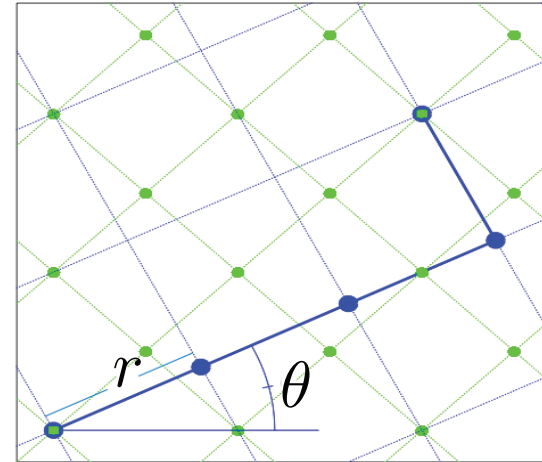


aperiodic tiling of the plane - R. Penrose 1970s

Moiré patterns generate two component composites on any scale

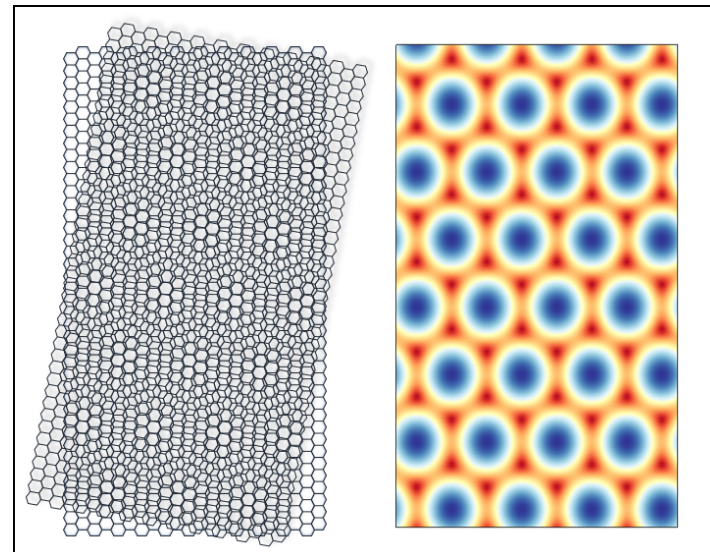
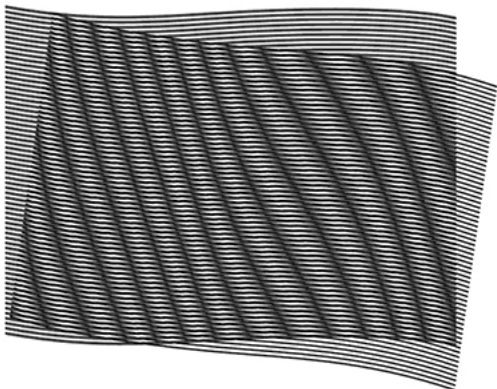
rotation
dilation

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = r \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$



$$\psi(x', y') = \cos 2\pi x' \cos 2\pi y'$$

$$\chi = \begin{cases} 1, & \psi \geq 0 \\ 0, & \psi < 0 \end{cases}$$



quantum dots
artificial atoms

Tran et al.
Nature 2019

Order to disorder in quasiperiodic composites

Morison, Murphy, Cherkaev, Golden, Comm. Phys. 2022

sea ice inspired - twisted bilayer composites

tunable quasiperiodic composites with exotic properties

(optical, electrical, thermal) Anderson localization; our Moiré patterned geometries are similar to **twisted bilayer graphene**

increasing twist angle between two lattices

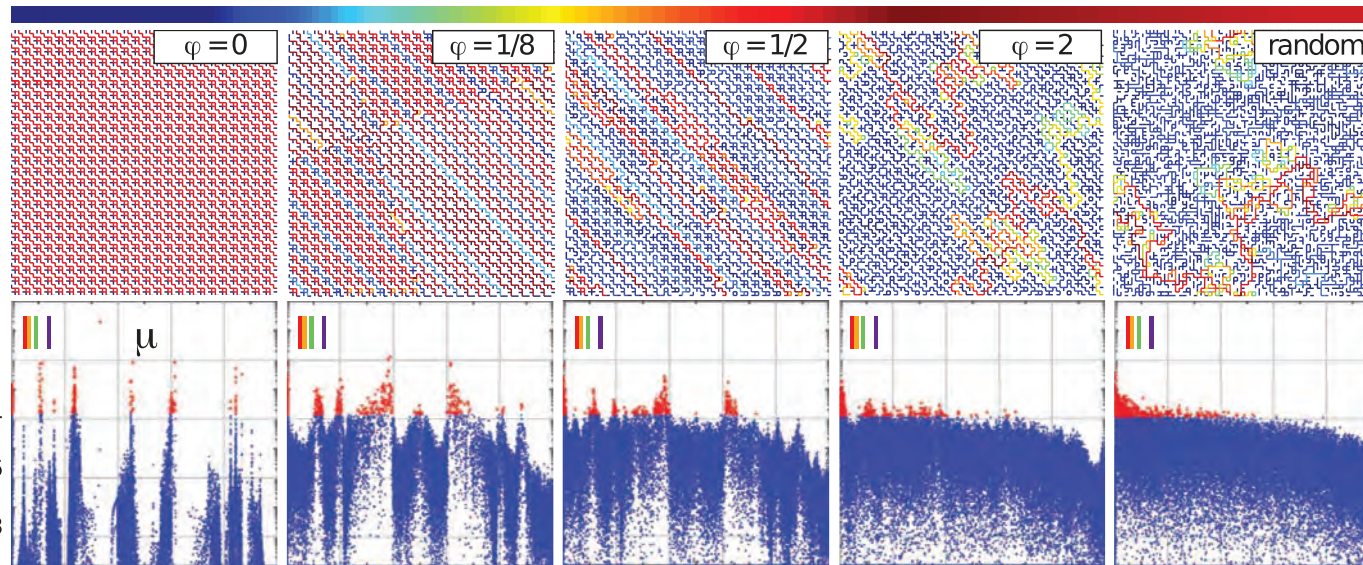
periodic

quasiperiodic

electric field strength

spectral measure

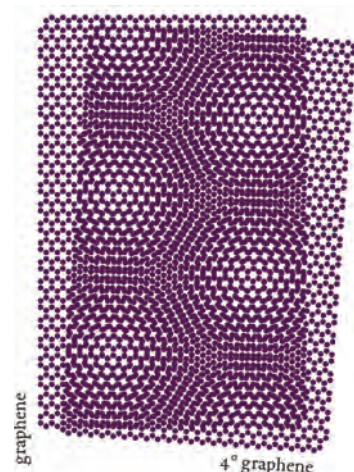
10^{-4}
 10^{-6}
 10^{-8}



RRN at percolation threshold

twisted bilayer graphene

superconducting magic twist angle



communications physics

[View all journals](#) [Search](#) [Log in](#)

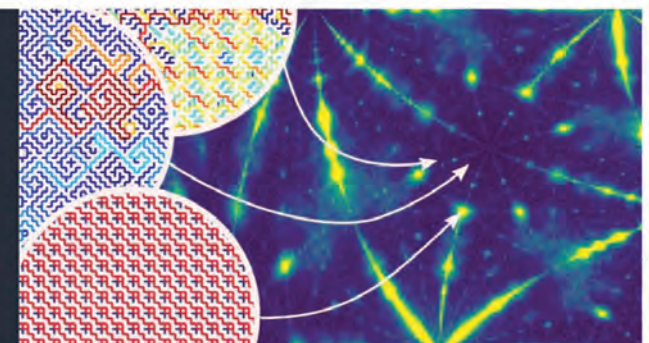
[Explore content](#) [About the journal](#) [Publish with us](#)

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[nature](#) > communications physics

Order to disorder in quasiperiodic composites

David Morison, N. Benjamin Murphy ... Kenneth M. Golden
Article | 14 June 2022

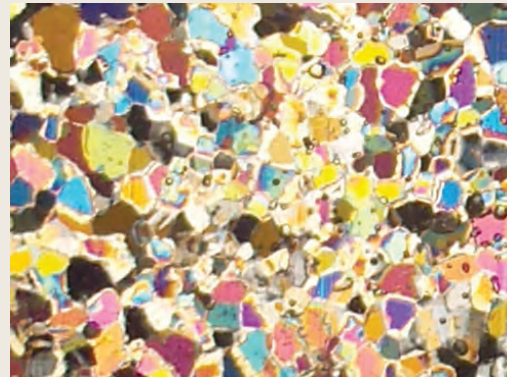


constellation of periodic systems in a sea of randomness

Bounds on the complex permittivity of polycrystalline materials by analytic continuation

Adam Gully, Joyce Lin,
Elena Cherkaev, Ken Golden

- **Stieltjes integral representation for effective complex permittivity**
Milton (1981, 2002), Barabash and Stroud (1999), ...
- **Forward and inverse bounds**
orientation statistics
- **Applied to sea ice using two-scale homogenization**
- **Inverse bounds give method for distinguishing ice types using remote sensing techniques**



PROCEEDINGS A

350 YEARS
OF SCIENTIFIC
PUBLISHING

An invited review
commemorating 350 years
of scientific publishing at the
Royal Society

A method to distinguish
between different types
of sea ice using remote
sensing techniques

A computer model to
determine how a human
should walk so as to expend
the least energy



THE
ROYAL
SOCIETY
PUBLISHING

higher threshold for fluid flow in granular sea ice

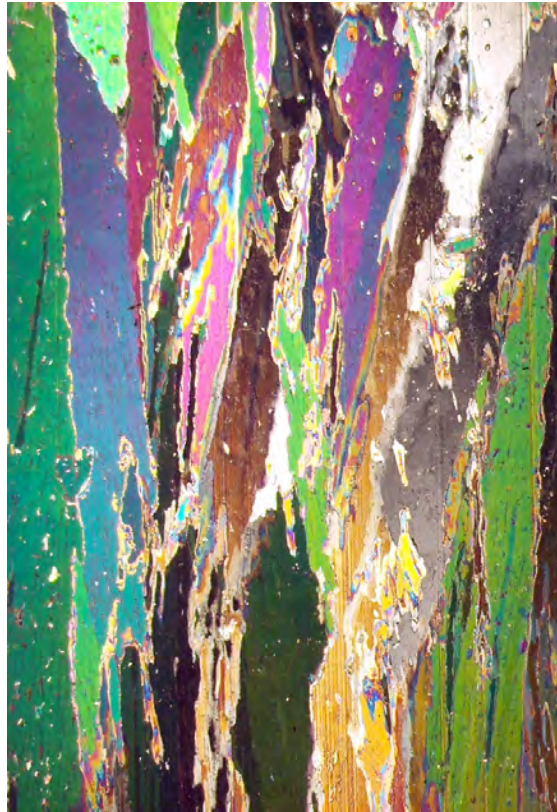
microscale details impact “mesoscale” processes

nutrient fluxes for microbes
melt pond drainage
snow-ice formation

columnar

granular

5%



10%



Golden, Furse, Gully, Lin, Mosier, Sampson, Tison 2025

electromagnetically distinguish ice types
inverse homogenization for polycrystals

mesoscale

advection enhanced diffusion

effective diffusivity

nutrient and salt transport in sea ice
heat transport in sea ice with convection
sea ice floes in winds and ocean currents
tracers, buoys diffusing in ocean eddies
diffusion of pollutants in atmosphere

advection diffusion equation with a velocity field \vec{u}

$$\frac{\partial T}{\partial t} + \vec{u} \cdot \vec{\nabla} T = \kappa_0 \Delta T$$

$$\vec{\nabla} \cdot \vec{u} = 0$$



homogenize

$$\frac{\partial \bar{T}}{\partial t} = \kappa^* \Delta \bar{T}$$

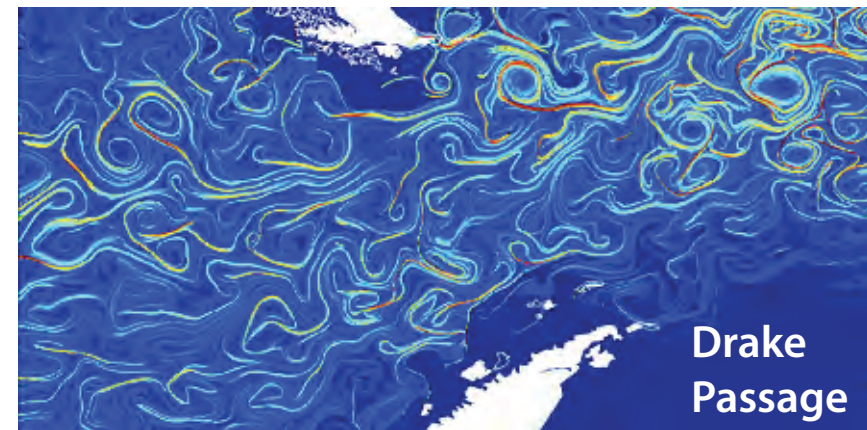
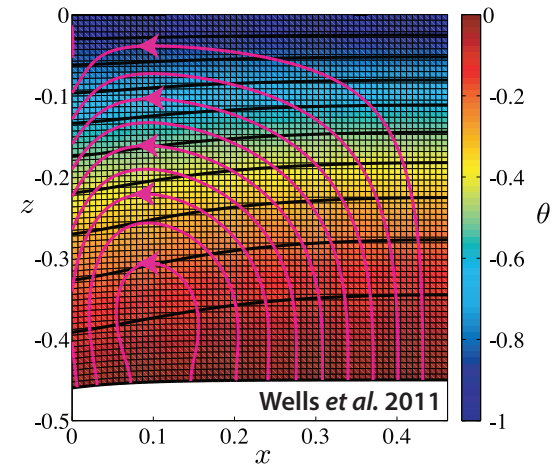
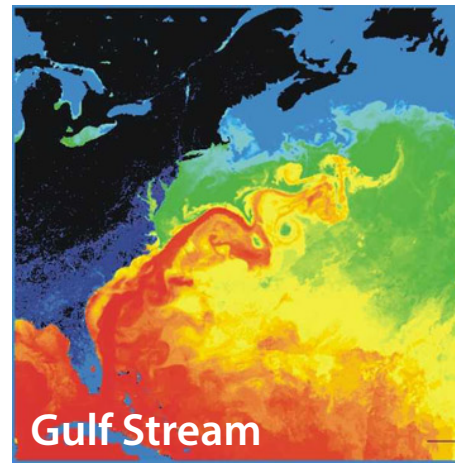
κ^* effective diffusivity

Stieltjes integral for κ^* with spectral measure

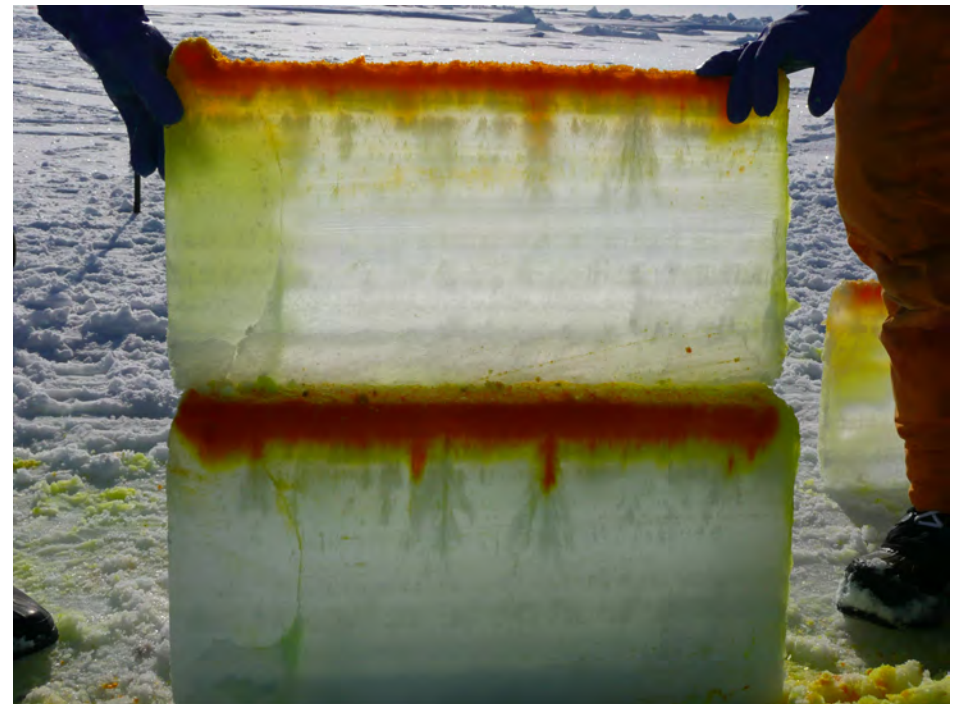
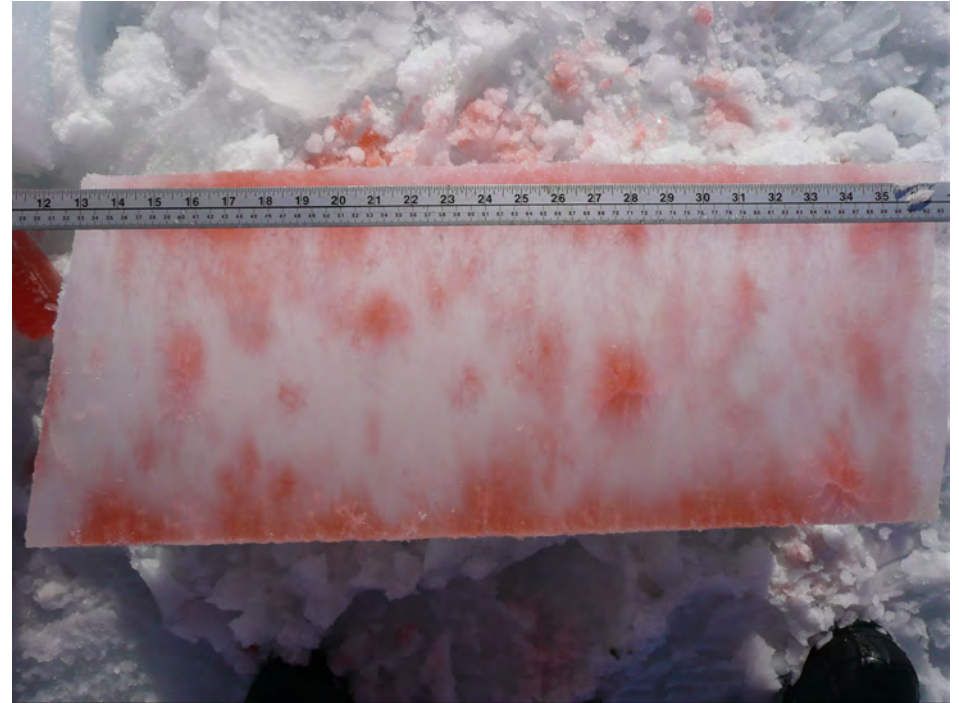
Avellaneda and Majda, PRL 89, CMP 91

Murphy, Cherkaev, Xin, Zhu, Golden, *Ann. Math. Sci. Appl.* 2017

Murphy, Cherkaev, Zhu, Xin, Golden, *J. Math. Phys.* 2020



tracers flowing through inverted sea ice blocks



Stieltjes Integral Representation for Advection Diffusion

Murphy, Cherkaev, Zhu, Xin, Golden, *J. Math. Phys.* 2020

$$\kappa^* = \kappa \left(1 + \int_{-\infty}^{\infty} \frac{d\mu(\tau)}{\kappa^2 + \tau^2} \right), \quad F(\kappa) = \int_{-\infty}^{\infty} \frac{d\mu(\tau)}{\kappa^2 + \tau^2}$$

- μ is a positive definite measure corresponding to the spectral resolution of the self-adjoint operator $i\Gamma H\Gamma$
- H = stream matrix , κ = local diffusivity
- $\Gamma := -\nabla(-\Delta)^{-1}\nabla$, Δ is the Laplace operator
- $i\Gamma H\Gamma$ is bounded for time independent flows
- $F(\kappa)$ is analytic off the spectral interval in the κ -plane

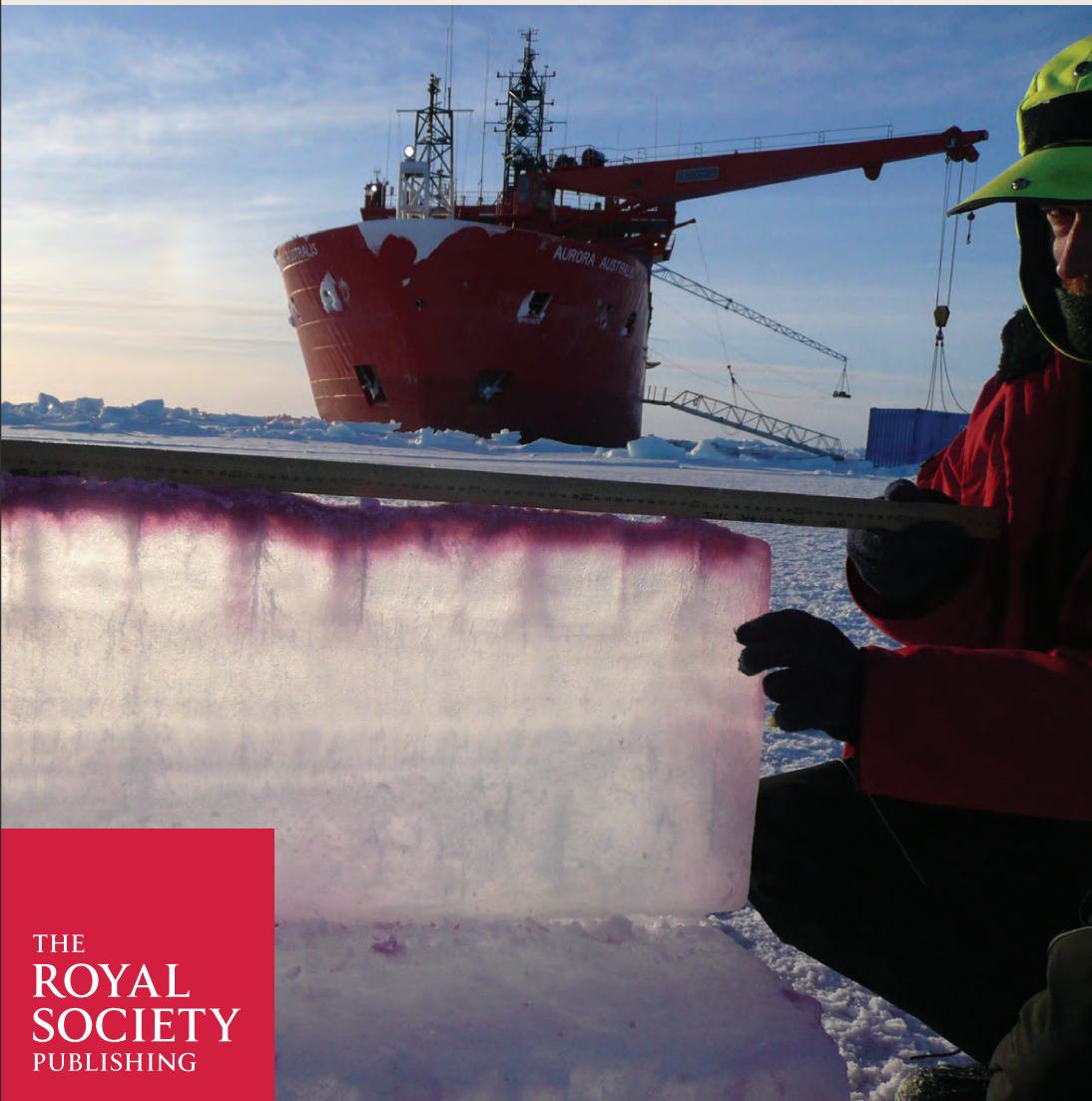
rigorous framework for numerical computations of spectral measures and effective diffusivity for model flows

new integral representations, theory of moment calculations

separation of material properties and flow field

PROCEEDINGS OF THE ROYAL SOCIETY A

MATHEMATICAL, PHYSICAL AND ENGINEERING SCIENCES



Homogenization for convection-enhanced thermal transport in sea ice

N. Kraitzman, R. Hardenbrook,
H. Dinh, N. B. Murphy, E. Cherkaev,
J. Zhu and K. M. Golden

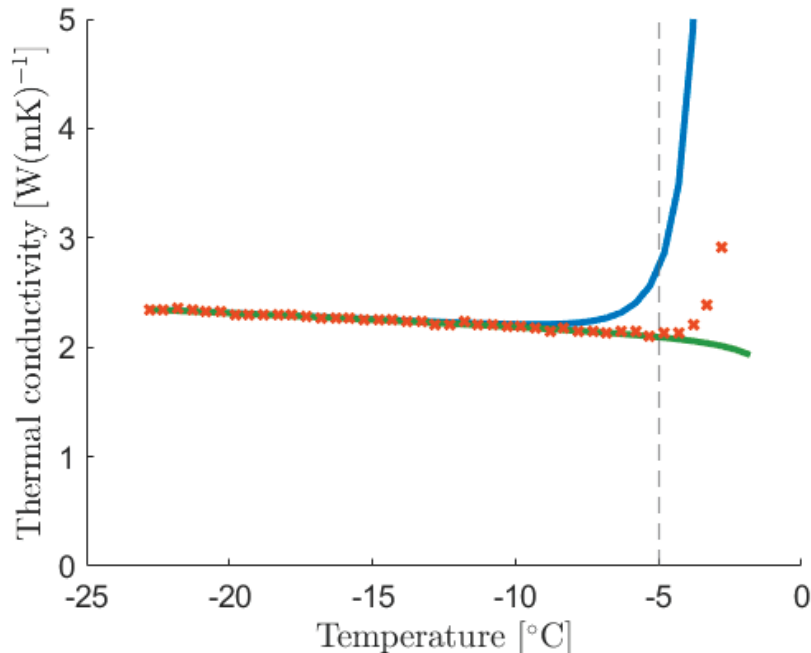
August 2024

First rigorous mathematical theory of
thermal conductivity of sea ice with
convective fluid flow; captures data.

missing in climate models

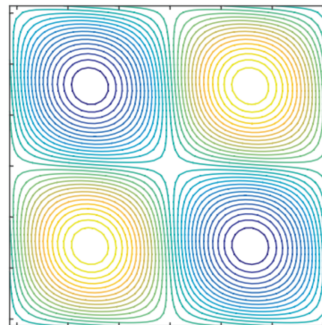
Bounds on Convection Enhanced Thermal Transport

simulations



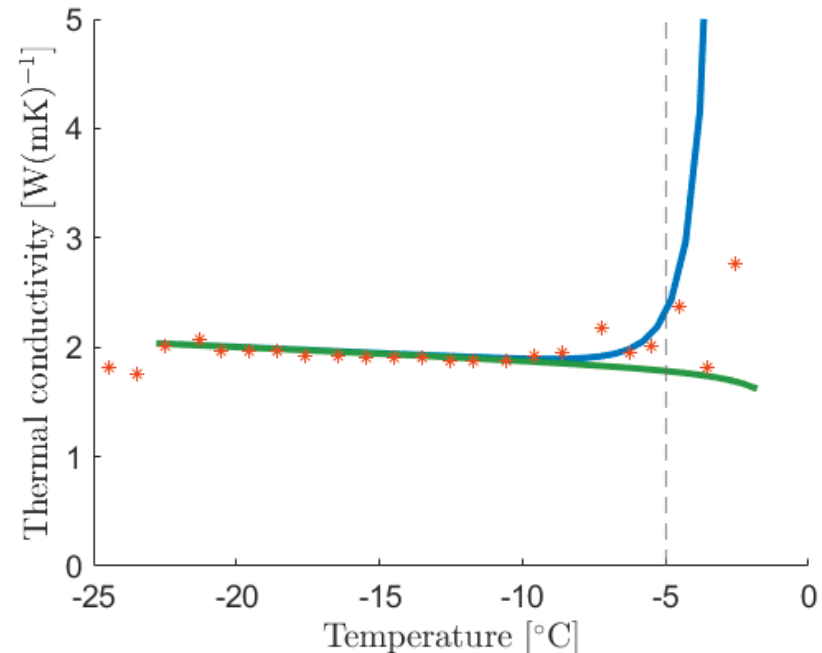
Monte-Carlo simulations of SDE with temperature dependent Péclet number P

strength of advection $B = \kappa P / 2\pi$
Euler-Maruyama and subsampling
methods for SDE



**cat's eye flow model for
brine convective flow**

data [Trodahl et al., 2001]



Rigorous Padé approximant bounds in terms of P using Stieltjes integral + analytic continuation method for the measure

Darcy velocity $v = 0.5$ $[\text{m/s}]$

ocean wave propagation through the sea ice pack



Stieltjes integral representation and bounds for
the complex viscoelasticity of the ice - ocean layer

Sampson, Murphy, Hallman, Cherkaev, Golden 2024

- wave-ice interactions critical to growth and melting processes
- break-up; pancake promotion floe size distribution

effective layer parameter
previously fit to wave data

Keller 1998

Mosig, Montiel, Squire 2015

Wang, Shen 2012

Analytic Continuation Method

Bergman 1978, Milton 1979

Golden and Papanicolaou 1983

Milton, *Theory of Composites* 2002

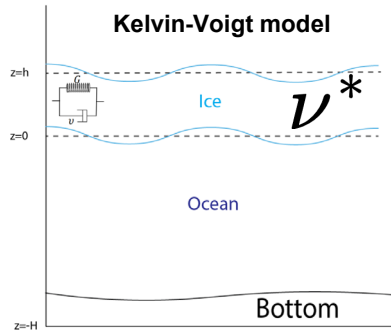


quasistatic, long wavelength regime

homogenized
parameter
depends on
sea ice
concentration
and ice floe
geometry

like EM waves





Single effective rheological parameter (Mosig et al. 2015)

$$\nu^* = G - i\omega\rho\nu$$

Effective complex viscoelasticity

Integral representation

$$\frac{\nu^*}{\nu_2} = \|\epsilon_s^0\|^2 (1 - F(s))$$

$$F(s) = \int_0^1 \frac{d\mu(\lambda)}{s-\lambda}$$

divergence-free deviatoric stress

$$\nabla \cdot \sigma_s = 0$$

microscale

$$\sigma_s = 2\nu\epsilon_s$$

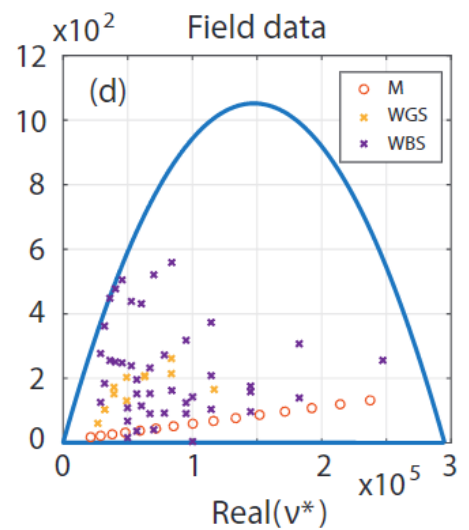
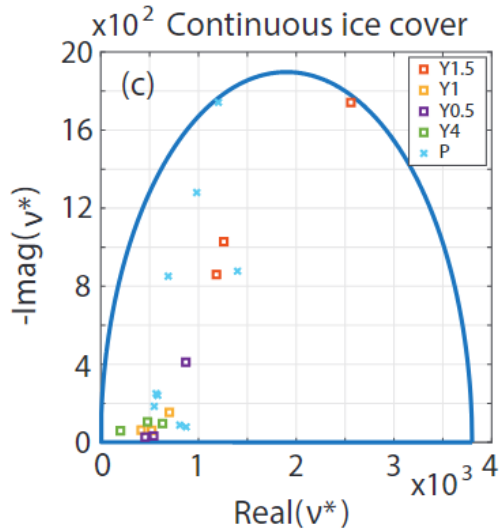
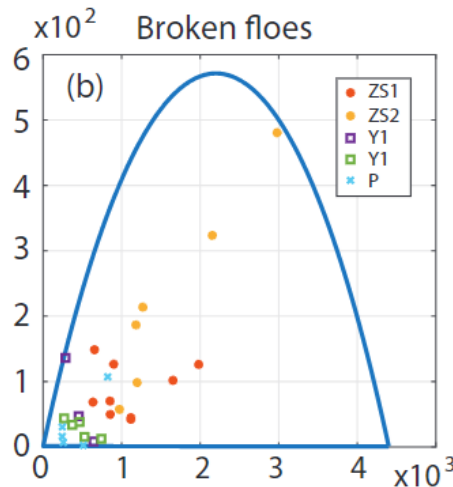
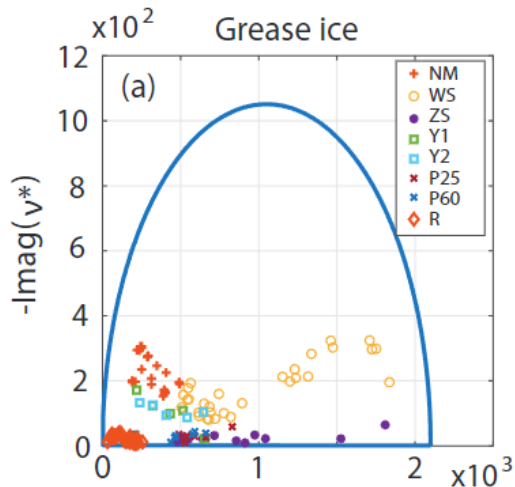
macroscale

$$\langle \sigma_s \rangle = 2\nu^*\epsilon_s^0$$

$$\nu(\vec{x}) = \chi_1\nu_1 + \chi_2\nu_2 \quad \langle \epsilon_s \rangle = \epsilon_s^0$$

Forward bounds for the effective viscoelasticity are fitted to well known wave-ice datasets, including [Wadhams et al. 1988](#), [Newyear & Martin 1997](#), [Wang & Shen 2010](#), [Meylan et al. 2014](#), and several others!

G	P	C	ρ	ν	g	u
shear modulus	pressure	elasticity	density	kinematic viscosity	gravity	displacement



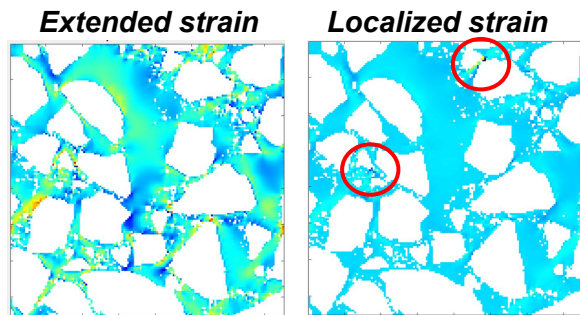
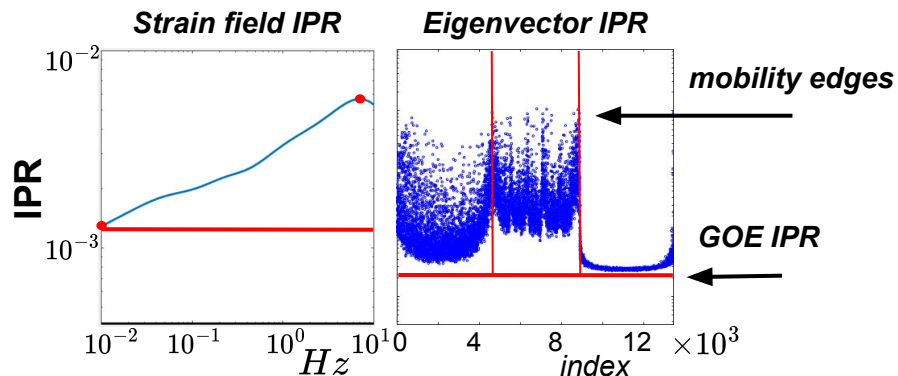
Waves in sea ice and solid state physics

Resolvent representation of the deviatoric **strain field**

$$\chi \epsilon_s = s(sI - \chi \Gamma^S \chi)^{-1} \chi \epsilon_s^0$$

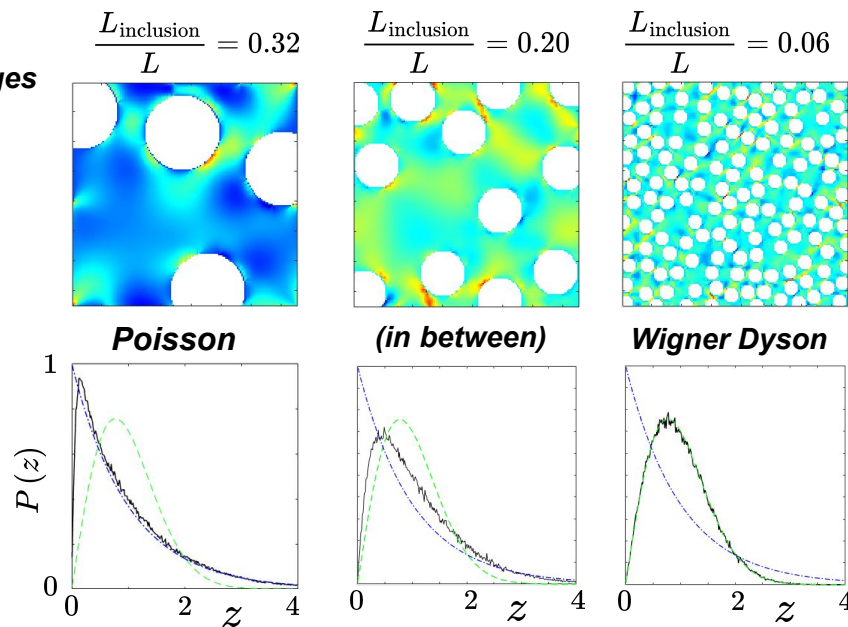
Stieltjes integral representation of effective complex viscoelasticity $\frac{\nu^*}{\nu_2} = \int_0^1 \frac{d\mu(\lambda)}{s-\lambda}$

Increasing geometric order \longrightarrow



$$f = 0.01 Hz$$

$$f = 7.079 Hz$$



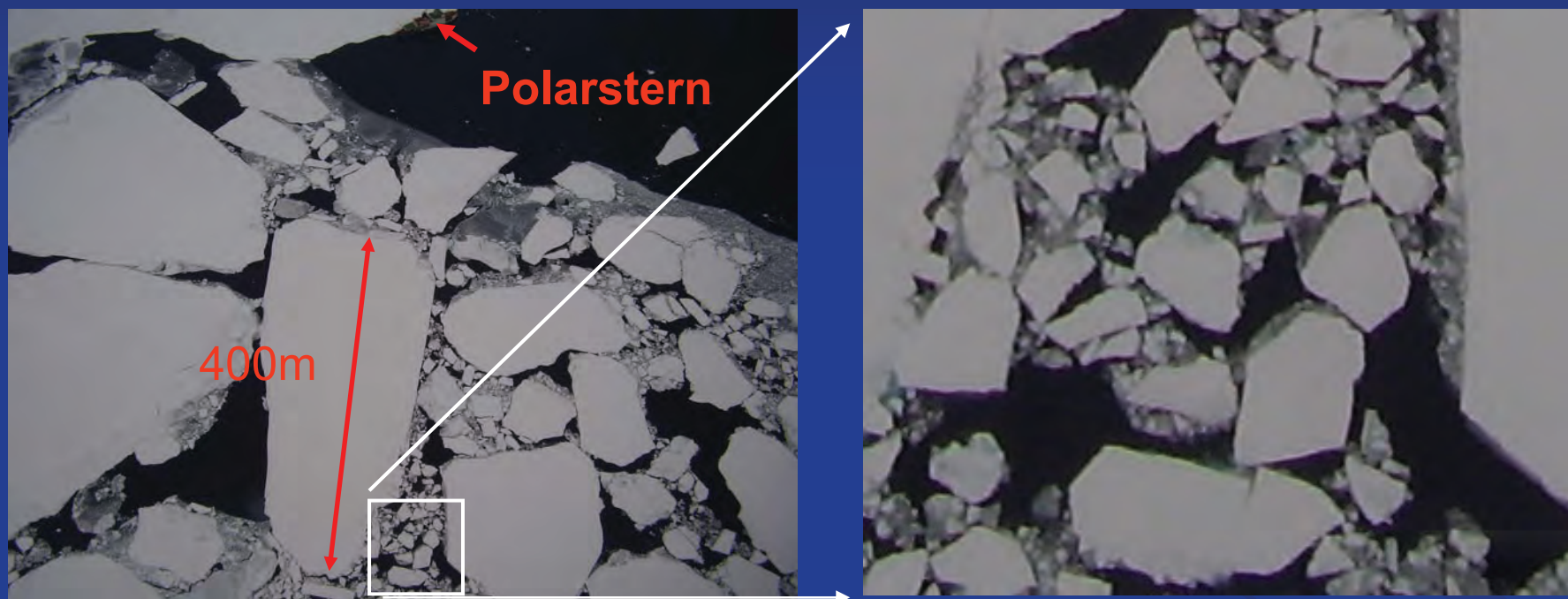
Transition in the eigenvalue spacing distribution of $\chi \Gamma^S \chi$

Large inclusions \longrightarrow **Small inclusions**
"Local to collective deformation transition"

The sea ice pack has fractal structure.

Self-similarity of sea ice floes

Weddell Sea, Antarctica



*fractal dimensions of Okhotsk Sea ice pack
smaller scales $D \sim 1.2$, larger scales $D \sim 1.9$*

fractal dim. vs. floe size exponent

Adam Dorsky, Nash Ward, Ken Golden 2024

Toyota, et al. *Geophys. Res. Lett.* 2006

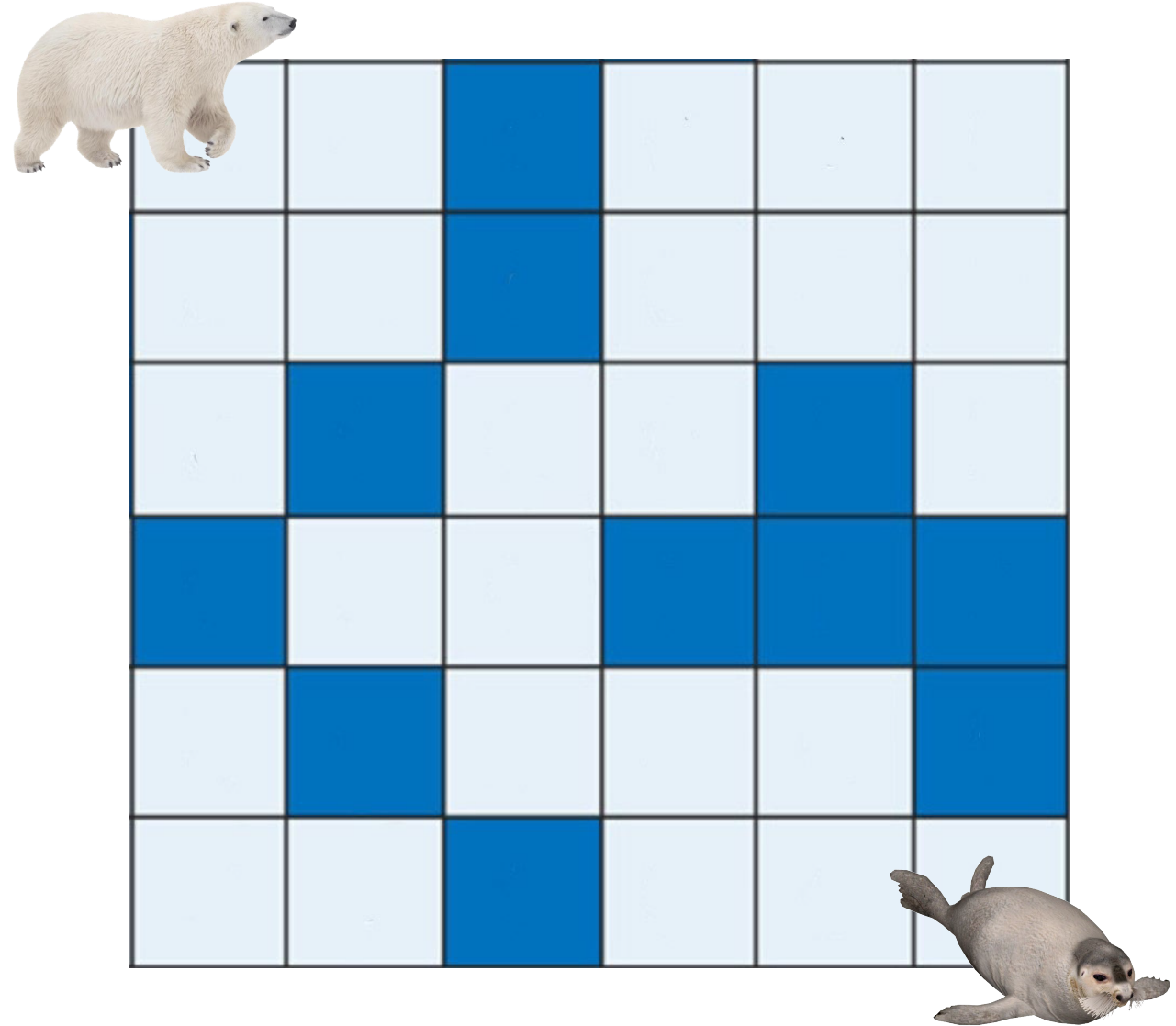
Rothrock and Thorndike, *J. Geophys. Res.* 1984

Optimal Movement of a Polar Bear in a Heterogenous Icescape

Nicole Forrester, Jody Reimer, Ken Golden 2024

Polar bears expend 5X more energy swimming than walking on sea ice.

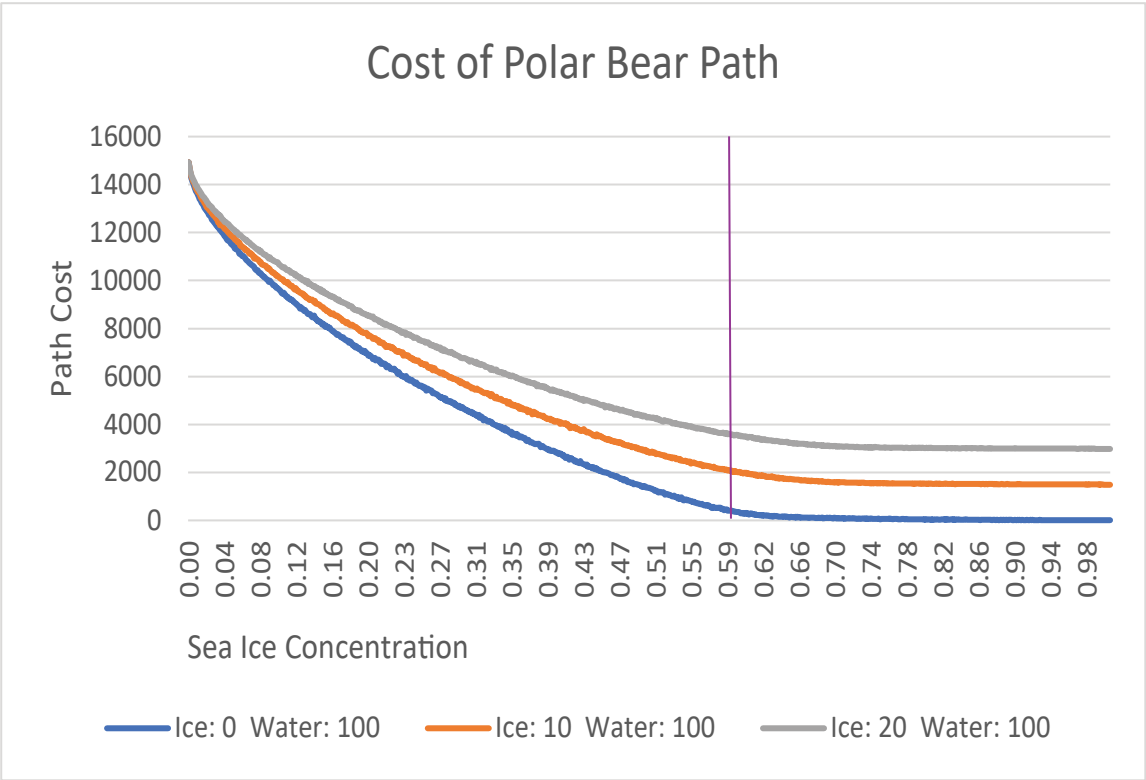
As sea ice is lost, how do polar bears optimize their movement to save energy and survive?



Polar Bear Percolation

To study the importance of ice connectedness, we exaggerate the data by setting the cost of walking on ice to 0 with the cost of swimming still at 5.

$C(p)$



$$h = \frac{C_i}{C_w}$$

ratio of local
“conductivities”

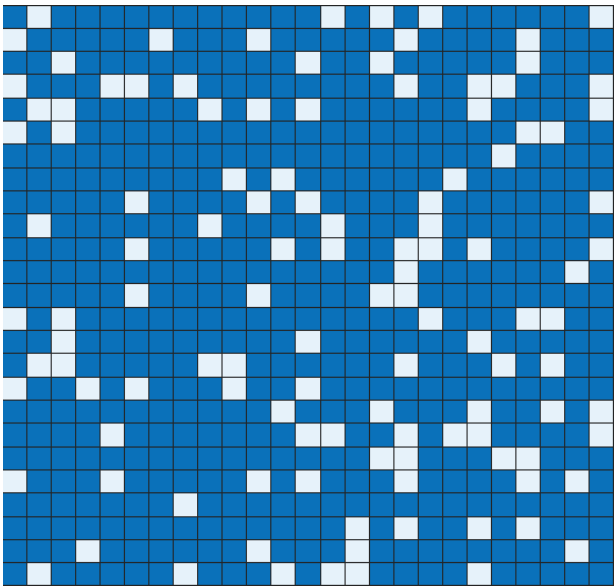
- ← $h = 0.2$
- ← $h = 0.1$
- ← $h = 0$

site percolation
threshold

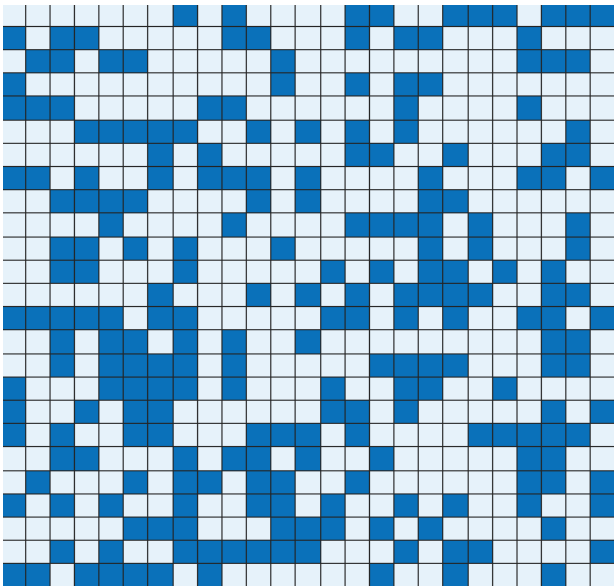
$p_c = 0.59$ for $d = 2$

Polar Bear
Critical
Exponent

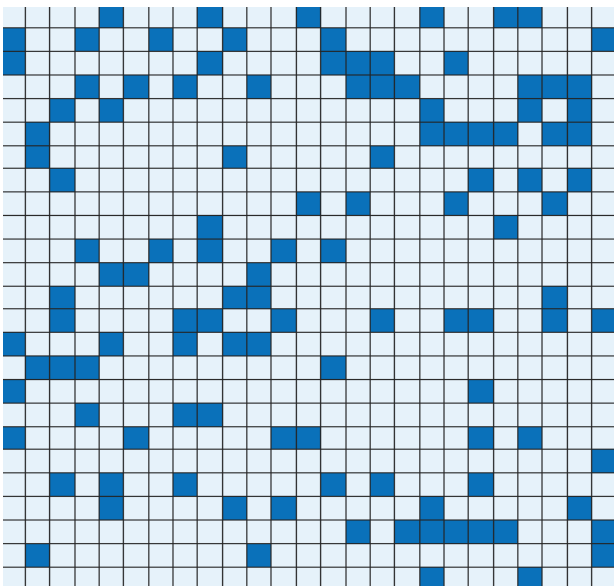
- ← $h = 0$



20% Ice

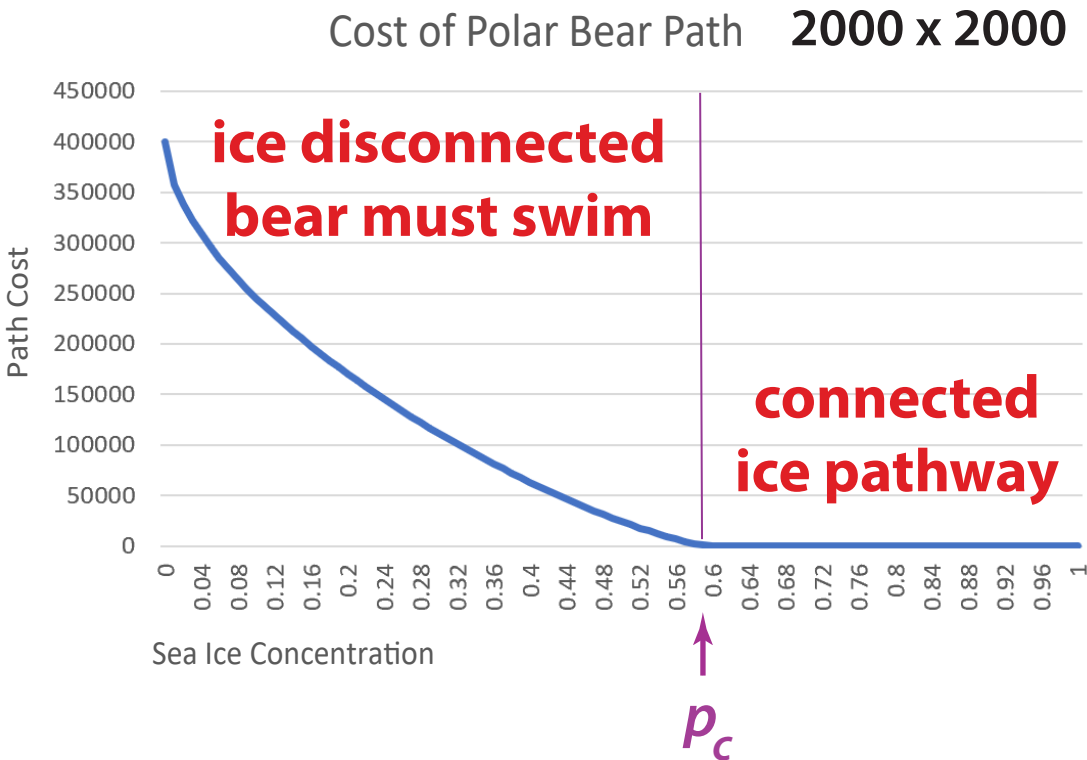


60% Ice

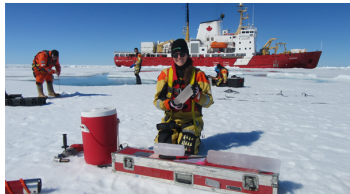
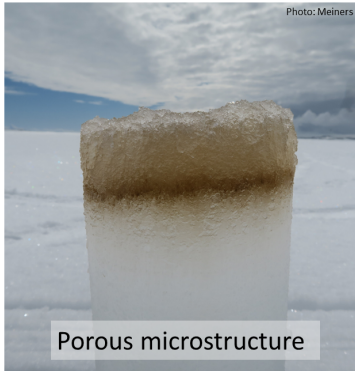


80% Ice

$C(p)$



SEA ICE ALGAE high level of local heterogeneity



Can we improve agreement between algae models and data?

80% of polar bear diet can be traced to ice algae*.

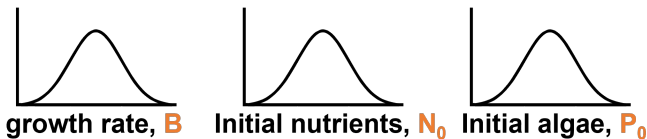
* Brown TA, et al. (2018). *PloS one*, 13(1), e0191631

HETEROGENEITY in PARAMETERS & CONDITIONS

At each location within a larger region, consider

$$\begin{aligned}\frac{dN}{dt} &= \alpha - \textcolor{brown}{B}NP - \eta N \\ \frac{dP}{dt} &= \gamma \textcolor{brown}{B}NP - \delta P\end{aligned}\quad \text{treating parameters as random variables}$$

$$N(0) = \textcolor{brown}{N}_0, \quad P(0) = \textcolor{brown}{P}_0$$



But, Monte Carlo for Full Algae Model: 8 hours X 10,000

METHOD

Uncertainty quantification for ecological models with random parameters

Jody R. Reimer^{1,2}  | Frederick R. Adler^{1,2}  | Kenneth M. Golden¹  | Akil Narayan^{1,3} 

¹Department of Mathematics, University of Utah, Salt Lake City, Utah, USA

²School of Biological Sciences, University of Utah, Salt Lake City, Utah, USA

³Scientific Computing and Imaging Institute, University of Utah, Salt Lake City, Utah, USA

Correspondences

Jody R. Reimer, Department of Mathematics and School of Biological Sciences, University of Utah, Salt Lake City, Utah, USA.

Email: reimer@math.utah.edu

Abstract

There is often considerable uncertainty in parameters in ecological models. This uncertainty can be incorporated into models by treating parameters as random variables with distributions, rather than fixed quantities. Recent advances in uncertainty quantification methods, such as polynomial chaos approaches, allow for the analysis of models with random parameters. We introduce these methods with a motivating case study of sea ice algal blooms in heterogeneous environments. We compare Monte Carlo methods with polynomial chaos techniques to help understand the dynamics of an algal bloom model with random parameters.

N-P Model

Introduce polynomial chaos approach to widely used ecological ODE models, but with random parameters.

POLYNOMIAL CHAOS EXPANSIONS

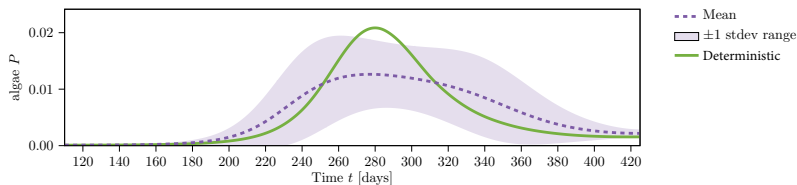
$$N(t; B, P_0, N_0) \approx N_V(t; B, P_0, N_0) := \sum_{j=1}^n \tilde{N}_j(t) \phi_j(B, P_0, N_0),$$

$$P(t; B, P_0, N_0) \approx P_V(t; B, P_0, N_0) := \sum_{j=1}^n \tilde{P}_j(t) \phi_j(B, P_0, N_0),$$

where

- $V := \text{span}\{\phi_j\}_{j=1}^n$
- ϕ_j are orthogonal polynomials that form a basis for V
- $(\tilde{N}_j, \tilde{P}_j)$ need to be computed

ECOLOGICAL INSIGHTS



- lower peak bloom intensity
- longer bloom duration
- able to compare variance to data

Inverse Problem: given algal and nutrient data, recover growth rate distribution
Anthony Lee, Jody Reimer, Akil Narayan, Ken Golden 2025

melt pond formation and albedo evolution:

- *major drivers in polar climate*
- *key challenge for global climate models*

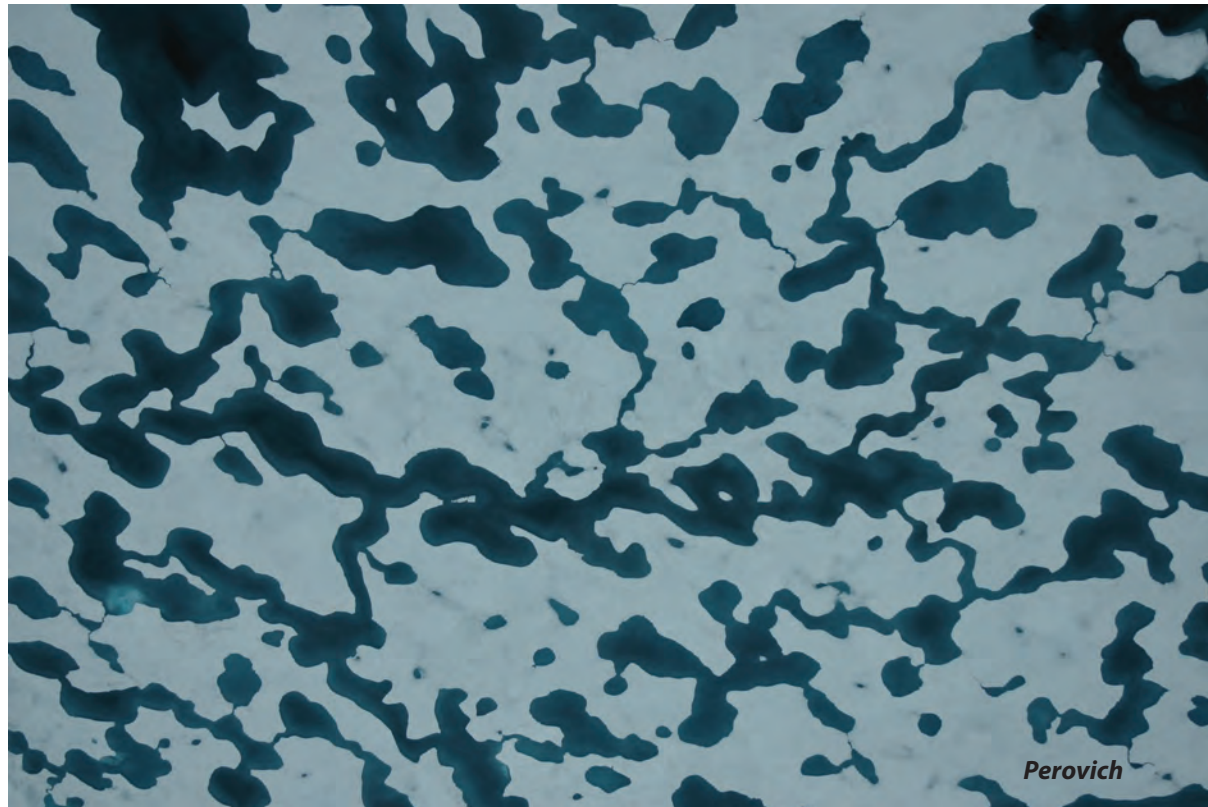
numerical models of melt pond evolution, including topography, drainage (permeability), etc.

Lüthje, Feltham,
Taylor, Worster 2006

Flocco, Feltham 2007

Skyllingstad, Paulson,
Perovich 2009

Flocco, Feltham,
Hunke 2012



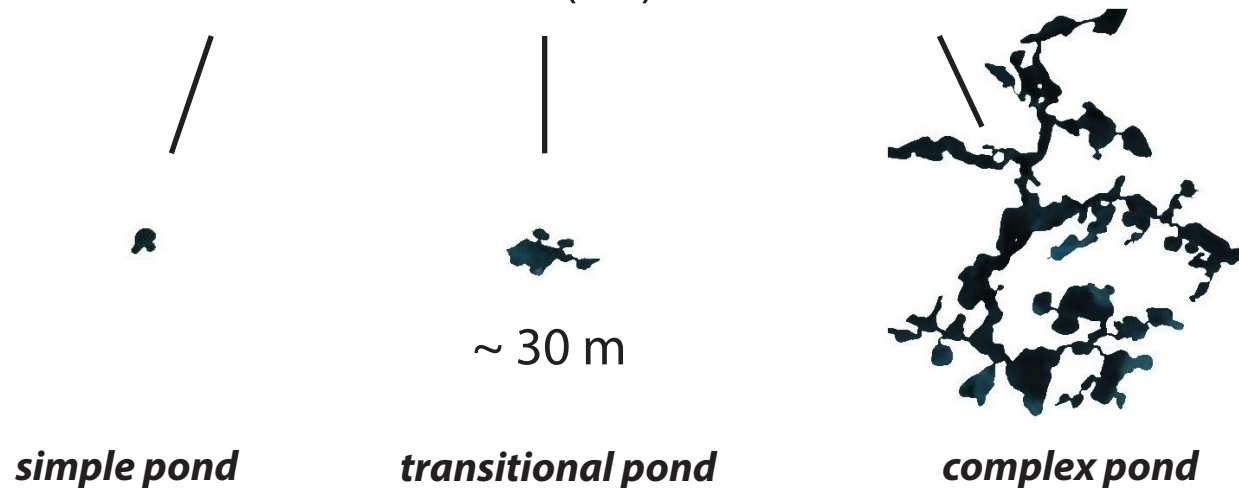
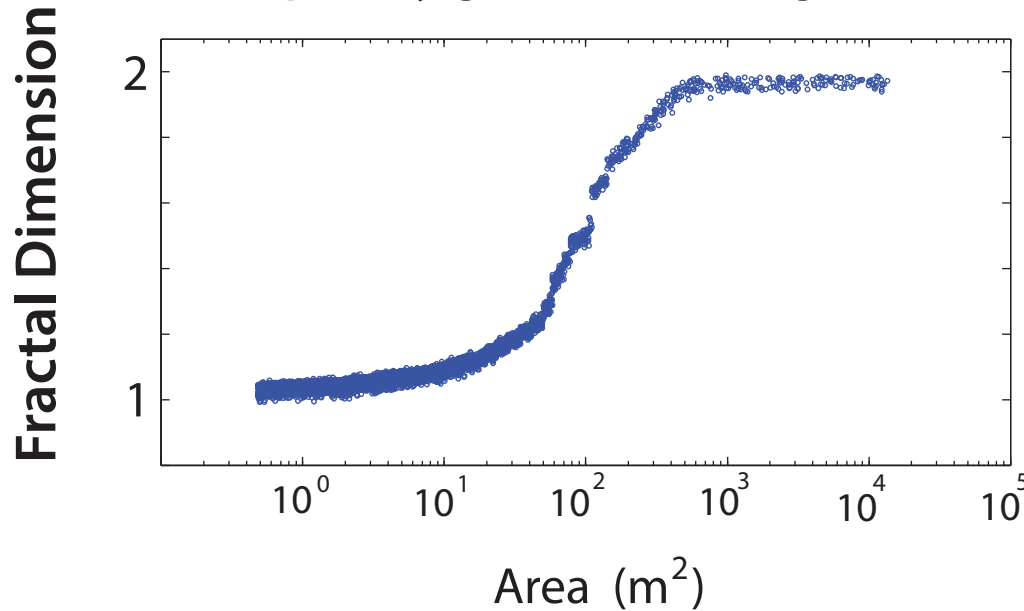
Are there universal features of the evolution similar to phase transitions in statistical physics?

Transition in the fractal geometry of Arctic melt ponds

Christel Hohenegger, Bacim Alali, Kyle Steffen, Don Perovich, Ken Golden

The Cryosphere, 2012

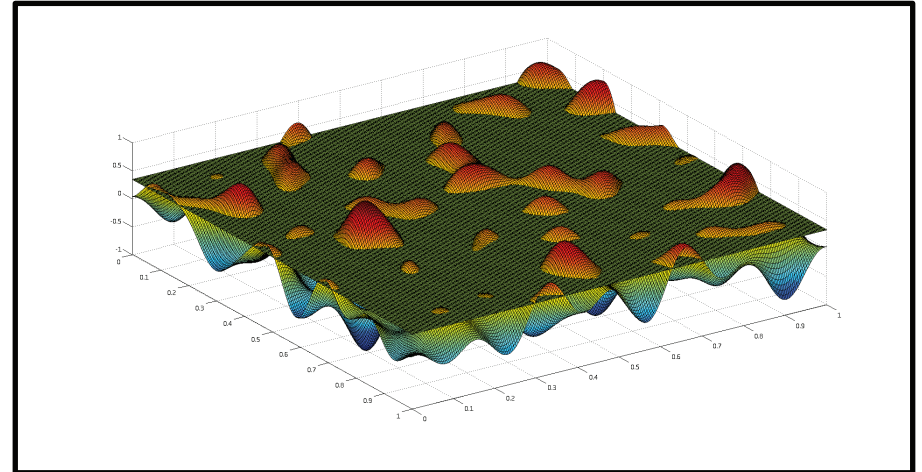
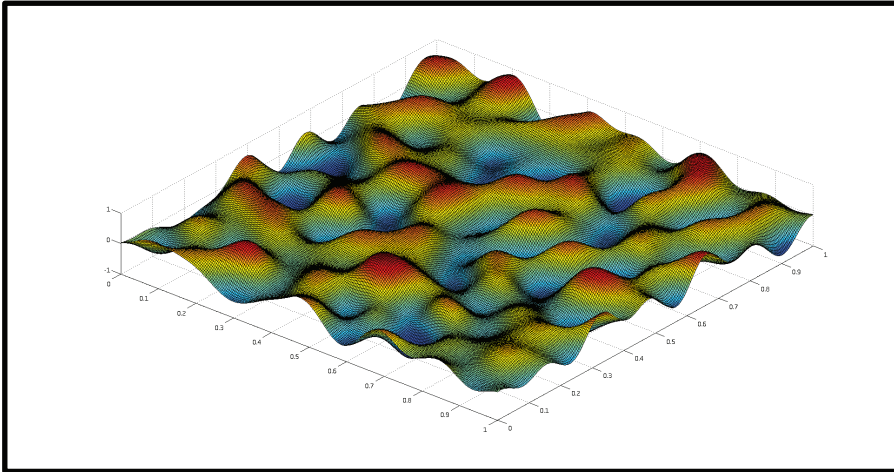
complexity grows with length scale



Continuum percolation model for melt pond evolution

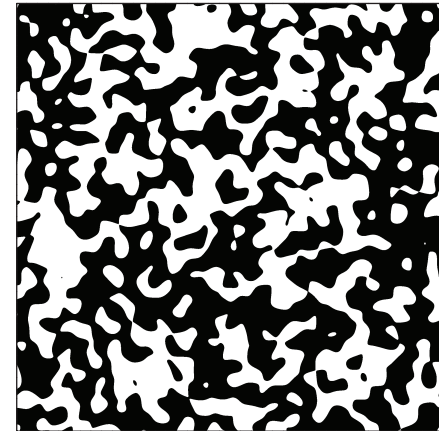
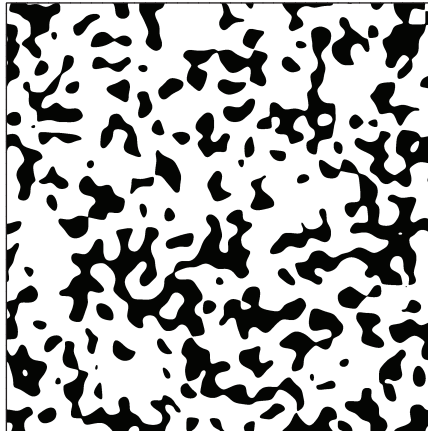
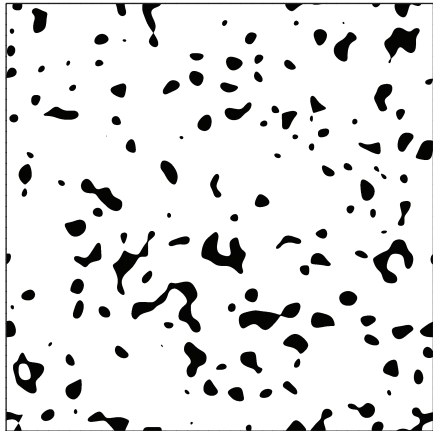
level sets of random surfaces

Brady Bowen, Court Strong, Ken Golden, J. Fractal Geometry 2018



random Fourier series representation of surface topography

intersections of a plane with the surface define melt ponds



electronic transport in disordered media

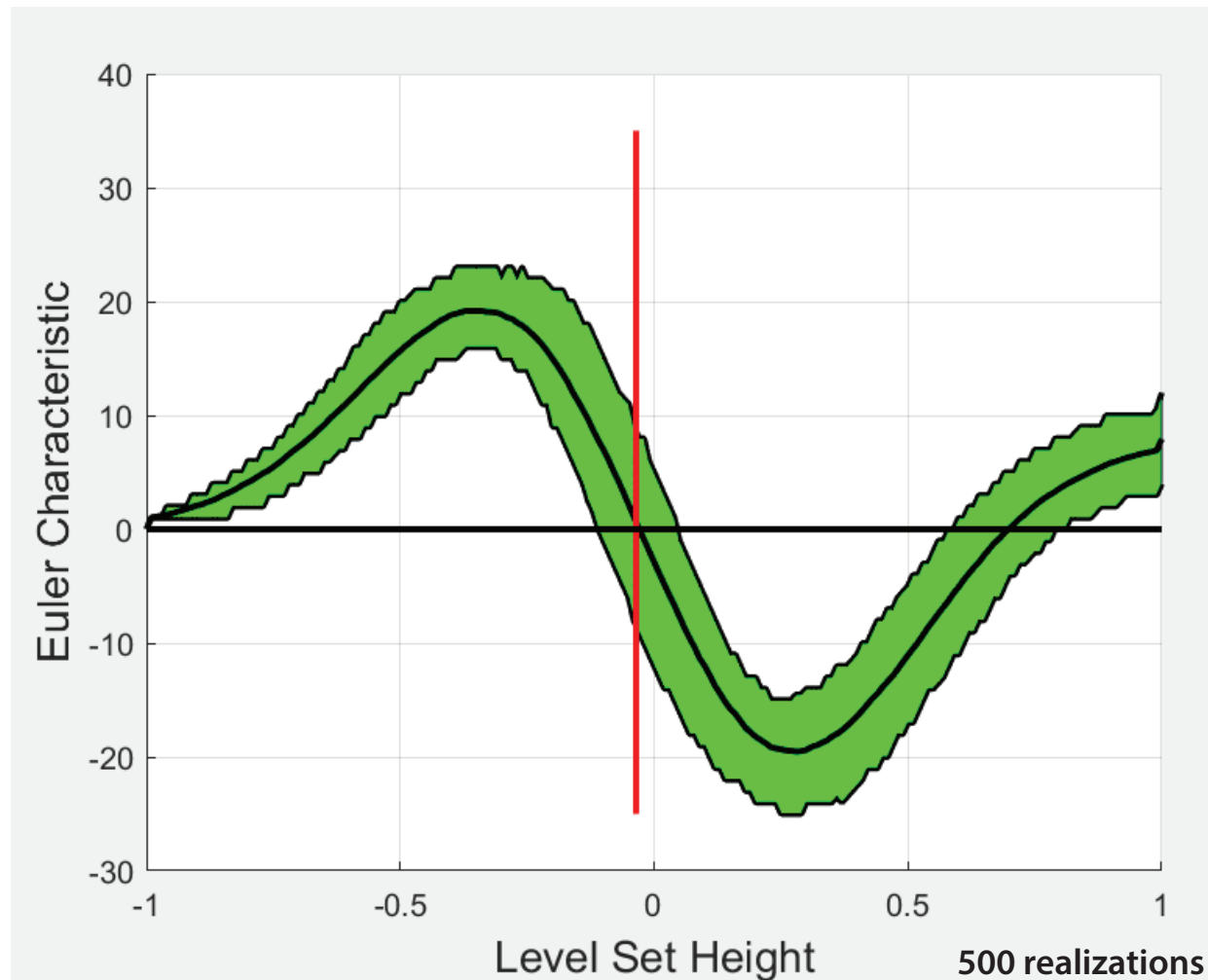
diffusion in turbulent plasmas

Isichenko, Rev. Mod. Phys., 1992

Topological Data Analysis

Euler characteristic = # maxima + # minima - # saddles
topological invariant

filtration - sequence of nested topological spaces, indexed by water level



Expected
Euler Characteristic Curve (ECC)

tracks the evolution of the EC of
the flooded surface as water rises

zero of ECC ~ percolation

percolation on a torus
creates a giant cycle

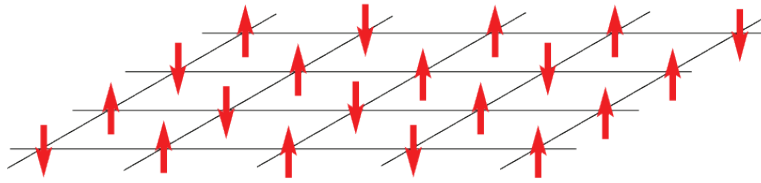
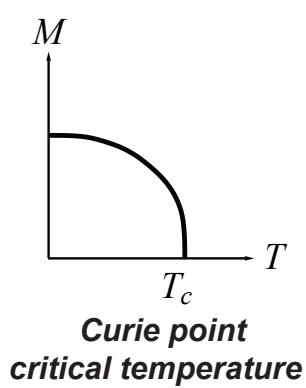
Bobrowski &
Skraba, 2020

Carlsson, 2009

Vogel, 2002 GRF

image analysis
porous media
cosmology
brain activity

Ising Model for a Ferromagnet



$$s_i = \begin{cases} +1 & \text{spin up} \\ -1 & \text{spin down} \end{cases} \quad \begin{matrix} \text{blue} \\ \text{white} \end{matrix}$$

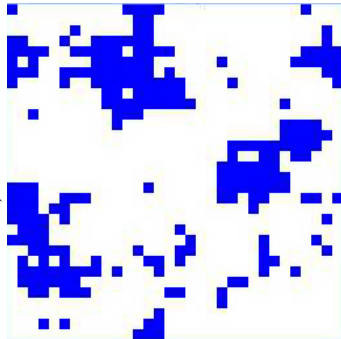
$$\mathcal{H} = -H \sum_i s_i - J \sum_{\langle i,j \rangle} s_i s_j$$

nearest neighbor Ising Hamiltonian

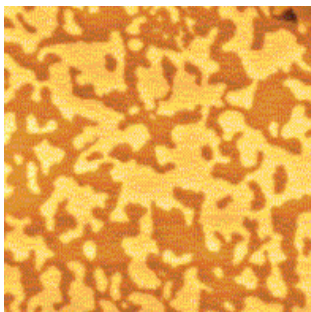
$$M(T, H) = \lim_{N \rightarrow \infty} \frac{1}{N} \left\langle \sum_j s_j \right\rangle$$

effective magnetization

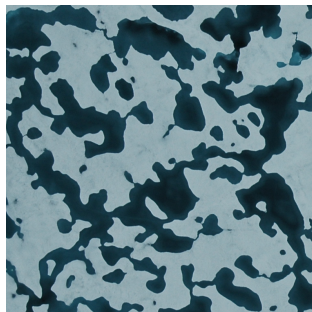
islands of like spins



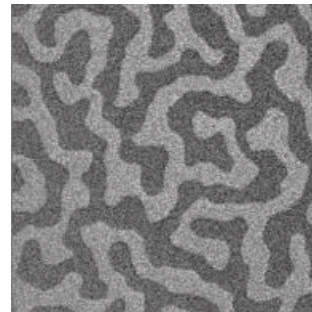
energy is lowered when nearby spins align with each other, forming **magnetic domains**



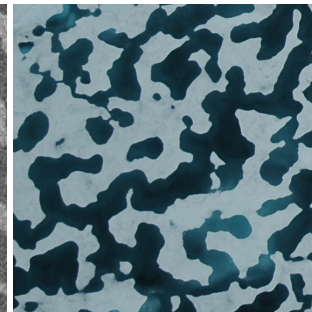
magnetic domains in cobalt



melt ponds (Perovich)



magnetic domains in cobalt-iron-boron



melt ponds (Perovich)

Ising model for ferromagnets \longrightarrow Ising model for melt ponds

Ma, Sudakov, Strong, Golden, *New J. Phys.*, 2019

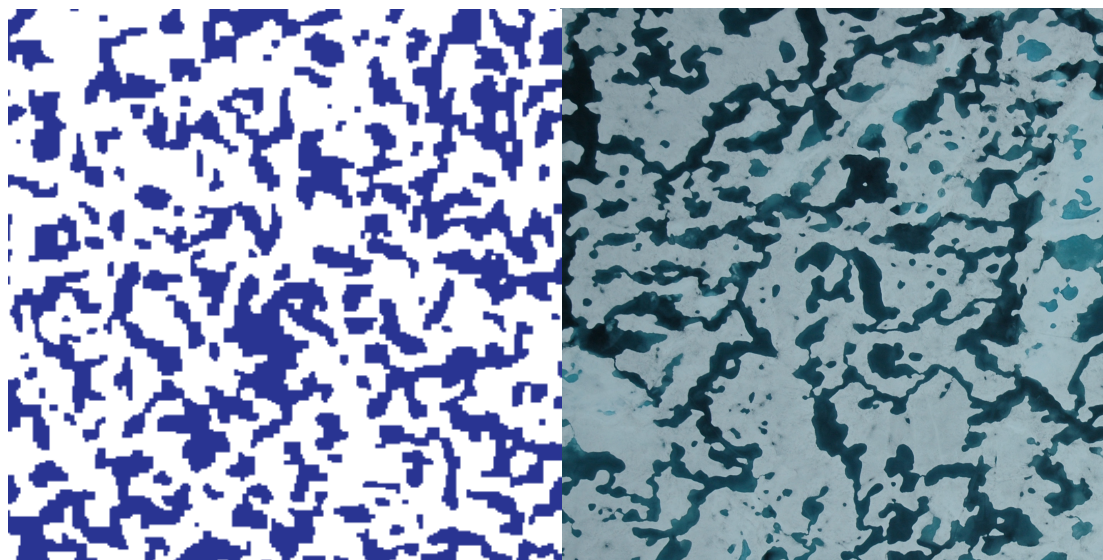
$$\mathcal{H} = - \sum_i^N H_i s_i - J \sum_{\langle i,j \rangle}^N s_i s_j \quad s_i = \begin{cases} \uparrow & +1 \text{ water (spin up)} \\ \downarrow & -1 \text{ ice (spin down)} \end{cases}$$

random magnetic field
represents snow topography

magnetization M pond area fraction $F = \frac{(M+1)}{2}$ only nearest neighbor patches interact
 \sim albedo

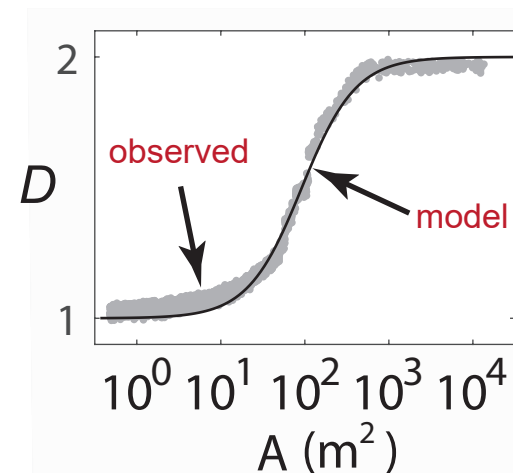
Starting with random initial configurations, as Hamiltonian energy is minimized by Glauber spin flip dynamics, system “flows” toward metastable equilibria.

Order from Disorder



Ising
model

melt pond
photo (Perovich)



pond size
distribution exponent

observed -1.5

(Perovich, et al. 2002)

model -1.58

*Scientific American
EOS, PhysicsWorld, ...*

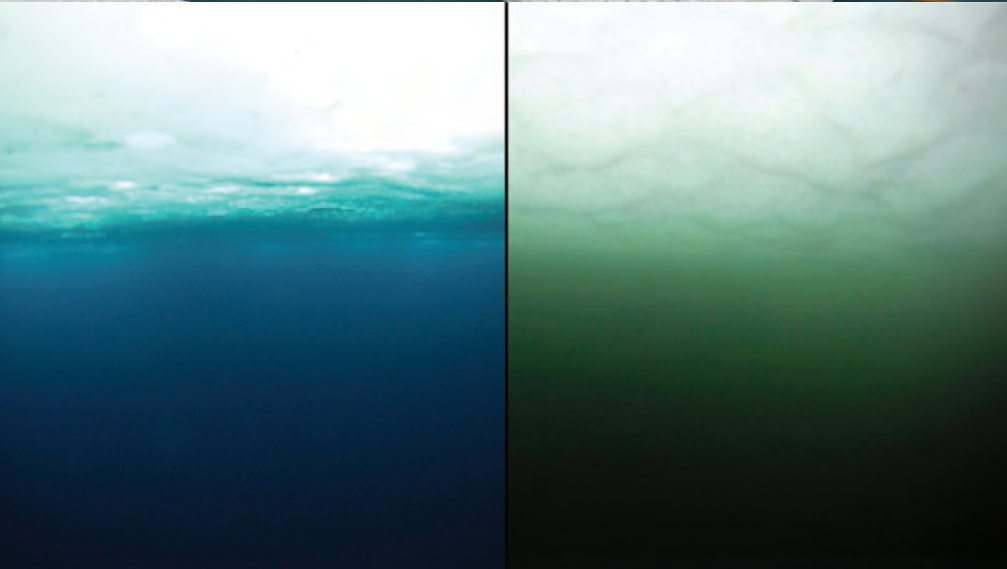
ONLY MEASURED INPUT = LENGTH SCALE (GRID SIZE) from snow topography data



Perovich

Melt ponds control transmittance of solar energy through sea ice, impacting upper ocean ecology.

WINDOWS



no bloom

bloom

massive under-ice **algal bloom**

Arrigo et al., *Science* 2012

Have we crossed into a new ecological regime?

The frequency and extent of sub-ice phytoplankton blooms in the Arctic Ocean

Horvat, Rees Jones, Iams, Schroeder, Flocco, Feltham, *Science Advances* 2017

The effect of melt pond geometry on the distribution of solar energy under first year sea ice

Horvat, Flocco, Rees Jones, Roach, Golden
Geophys. Res. Lett. 2019

(2015 AMS MRC)

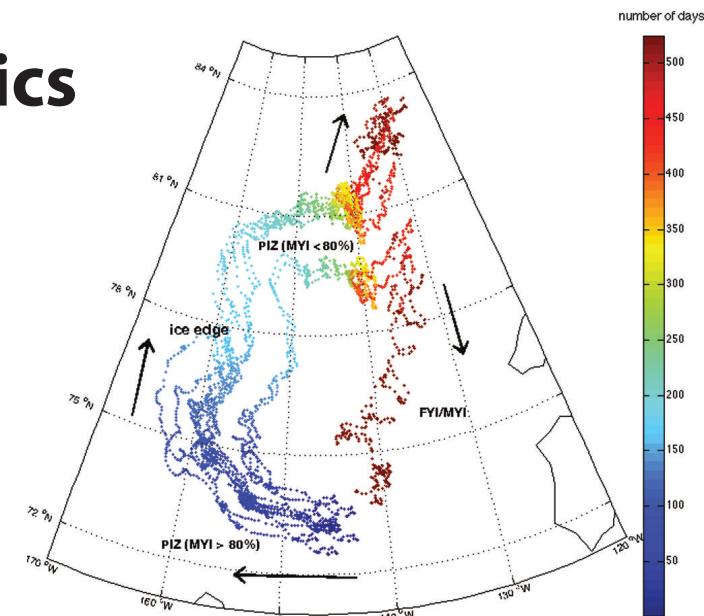
macroscale

Anomalous diffusion in sea ice dynamics

Ice floe diffusion in winds and currents

observations from GPS data

Lukovich, Hutchings, Barber, *Ann. Glac.* 2015



Floe scale model of advection diffusion

Huy Dinh, Tyler Evans, Kaeden George, Ben Murphy, Elena Cherkaev, Ken Golden 2025

$$\langle |\mathbf{x}(t) - \mathbf{x}(0) - \langle \mathbf{x}(t) - \mathbf{x}(0) \rangle|^2 \rangle \sim t^\alpha$$

$\alpha =$ **Hurst exponent**

diffusive $\alpha = 1$

sub-diffusive $\alpha < 1$

super-diffusive $\alpha > 1$

Model Approximations

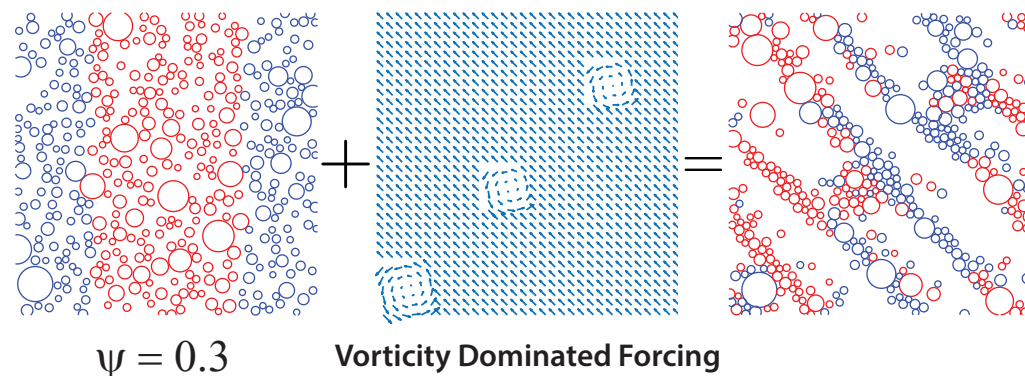
Power Law Size Distribution: $N(D) \sim D^{-k}$

D. A. Rothrock and A. S. Thorndike *Journal of Geophysical Research* 1984

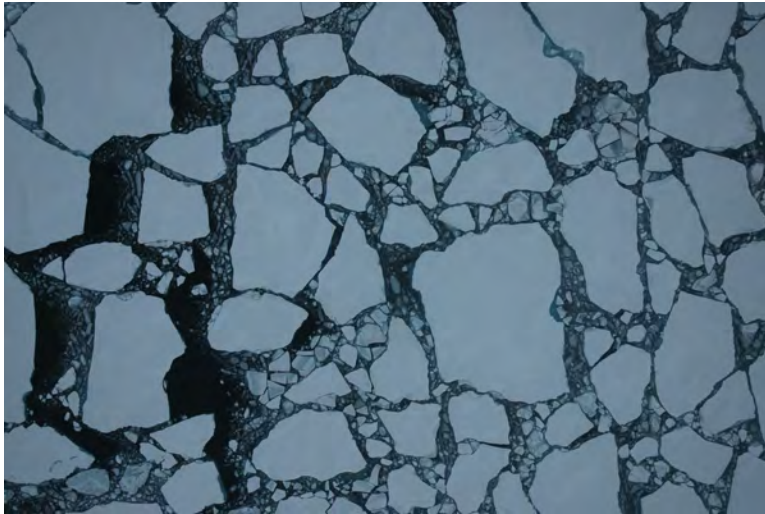
Floe-Floe Interactions: Linear Elastic Collisions

Advective Forcing: Passive, Linear Drag Law

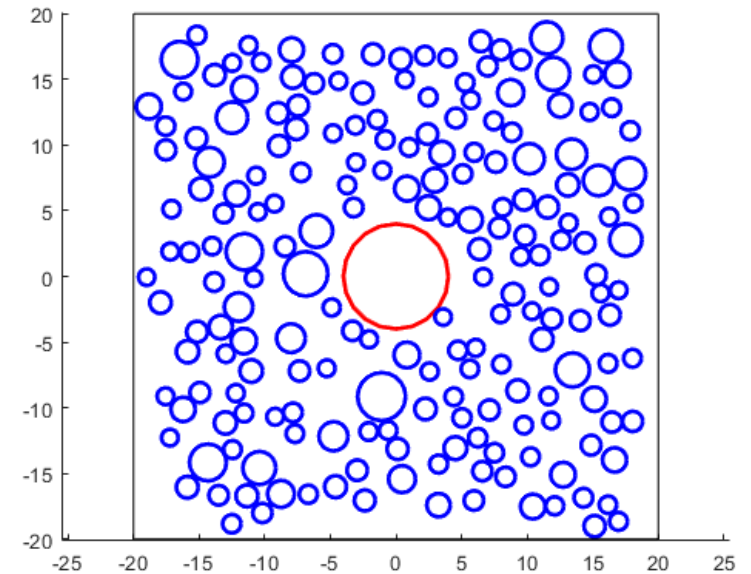
Fractional PDE



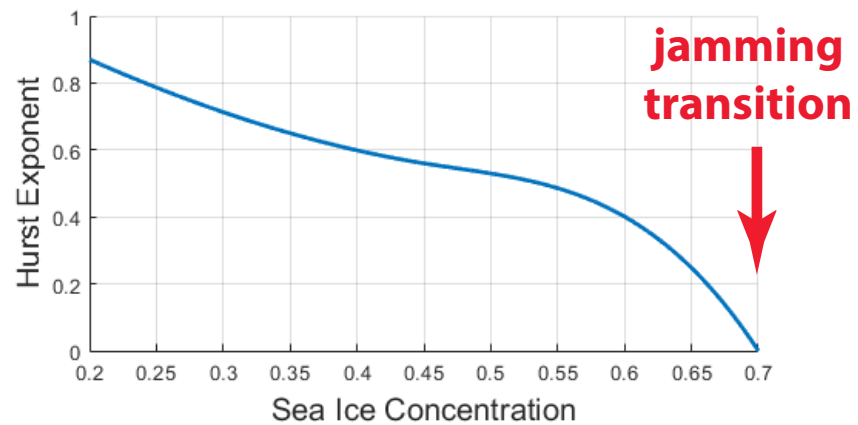
Arctic sea ice pack with tagged particle



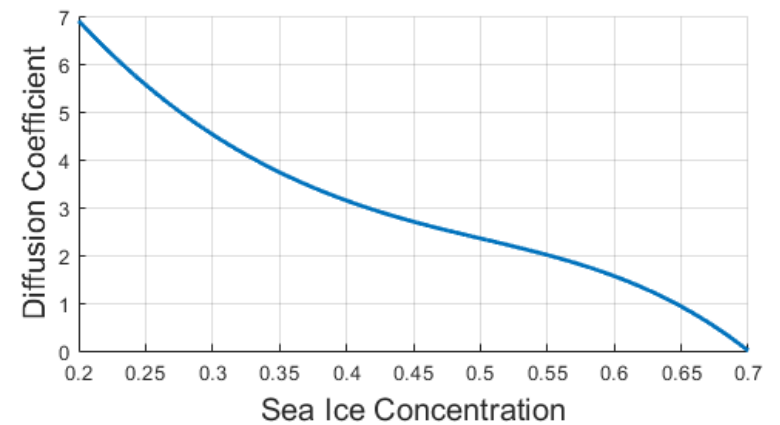
Einstein's pollen grain



Hurst exponent



diffusion coefficient



Marginal Ice Zone (MIZ)

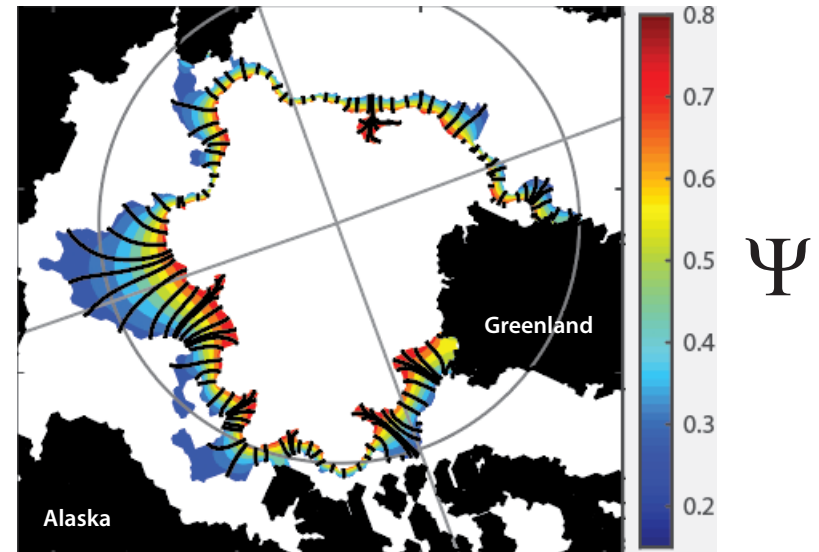
transitional region between
dense interior pack $\Psi > 0.8$
sparse outer fringes $\Psi < 0.15$

- biologically active region
- intense wave-ice interactions
- strong air-ice-ocean exchanges



MIZ WIDTH

fundamental length scale of
ecological and climate dynamics



streamlines of harmonic Ψ

MIZ width definition from medical imaging

Strong, *Climate Dynamics* 2012
Strong & Rigor, *GRL* 2013

**39% widening
1979 - 2012**

Strong, Foster, Cherkaev, Eisenman, Golden, *J. Atmos. Oceanic Tech.* 2017

Strong & Golden, *SIAM News* 2017

Multiscale mushy layer model for marginal ice zone dynamics

Strong, Cherkaev, Golden *Scientific Reports* 2024

MIZ - transitional region between dense pack ice and open ocean

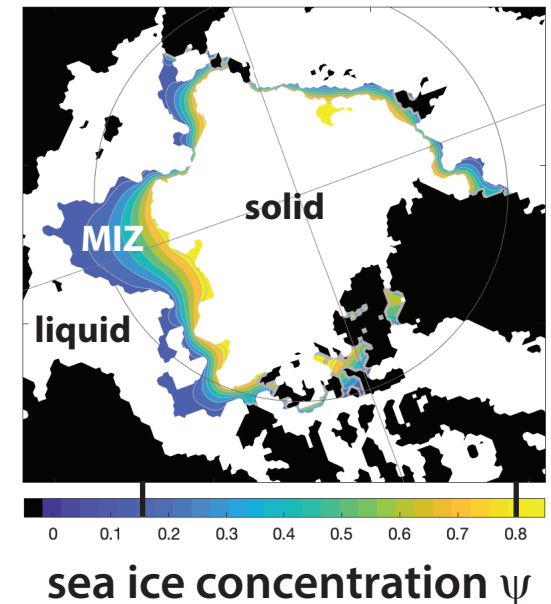
OBJECTIVE: model & predict dramatic annual cycle
impacts climate dynamics, polar ecology, human activities

mushy layer physics in the lab



NaCl-H₂O in lab
(Peppin et al., 2007, J. Fluid Mech.)

Arctic MIZ as a mushy layer



MIZ as a moving phase transition region

$$\rho c \frac{\partial T}{\partial t} = \nabla \cdot (k \nabla T) + S$$

$$S = [\rho(c_l - c_s)T + \rho L] \frac{\partial \psi}{\partial t}$$

$$\psi = 1 - \left(\frac{T - T_s}{T_l - T_s} \right)^\alpha$$

$$k_x = \left(\frac{\psi}{k_s} + \frac{1 - \psi}{k_l} \right)^{-1}$$

$$k_z = \psi k_s + (1 - \psi) k_l$$

homogenization

ρ effective density

T temperature

c specific heat

L latent heat of fusion

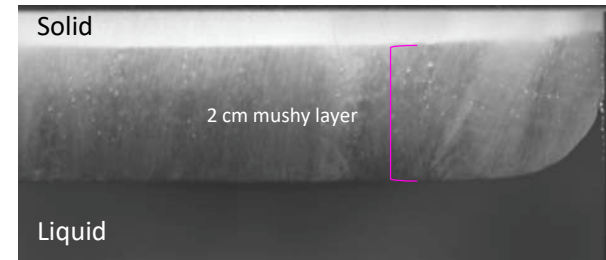
S models nonlinear phase change

ψ sea ice concentration

k effective diffusivity

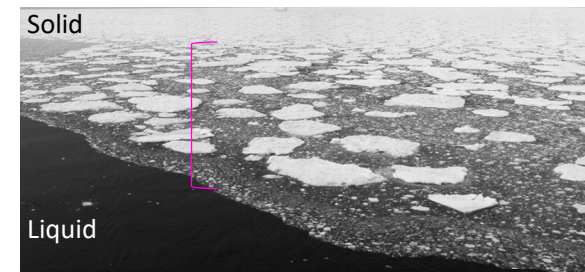
l liquid, s solid

Classical small-scale application



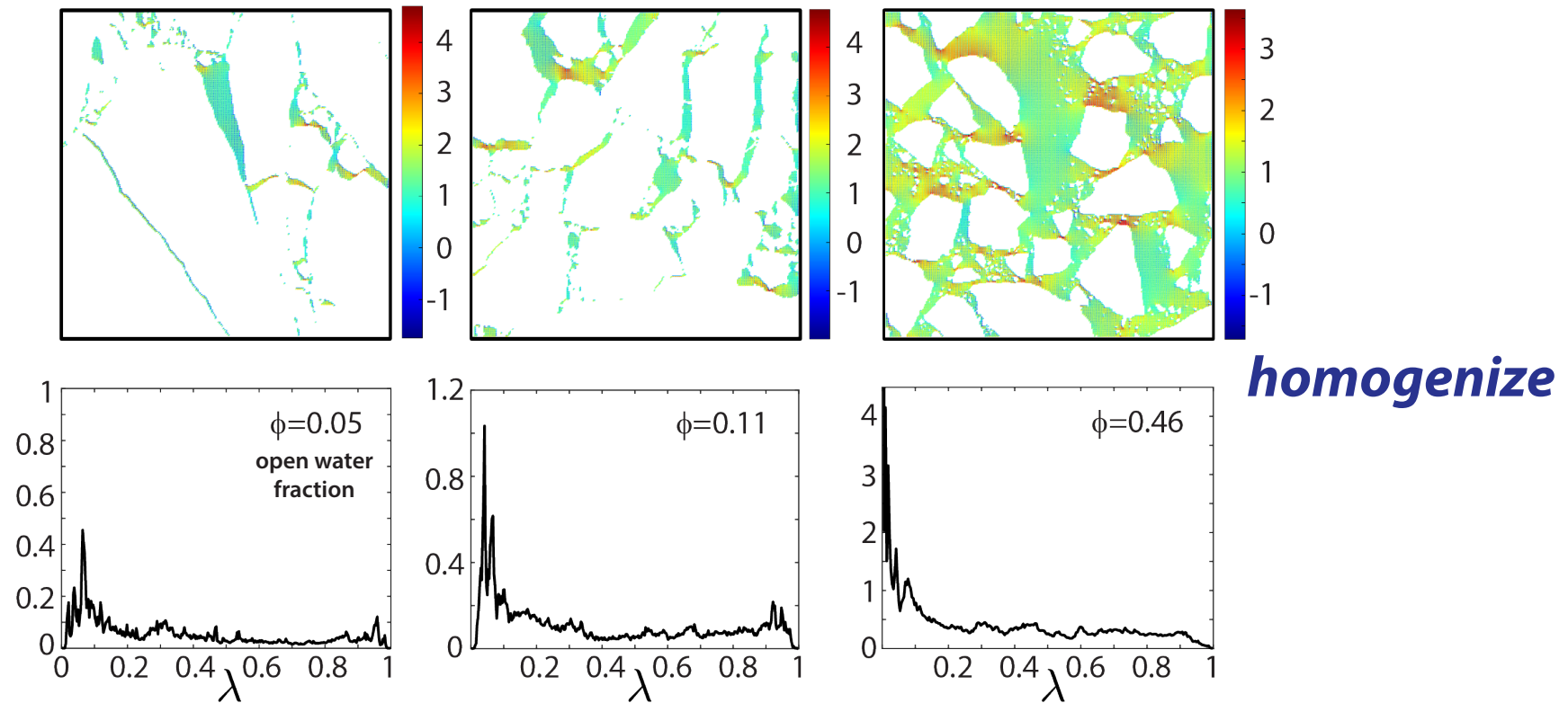
NaCl-H₂O in lab
(Peppin et al., 2007; J. Fluid Mech.)

Macroscale application



- Develop multiscale PDE model for simulating phase transition fronts to predict MIZ seasonal cycles and decadal trends
- Model simulates MIZ as a large-scale mushy layer with effective thermal conductivity derived from physics of composite materials

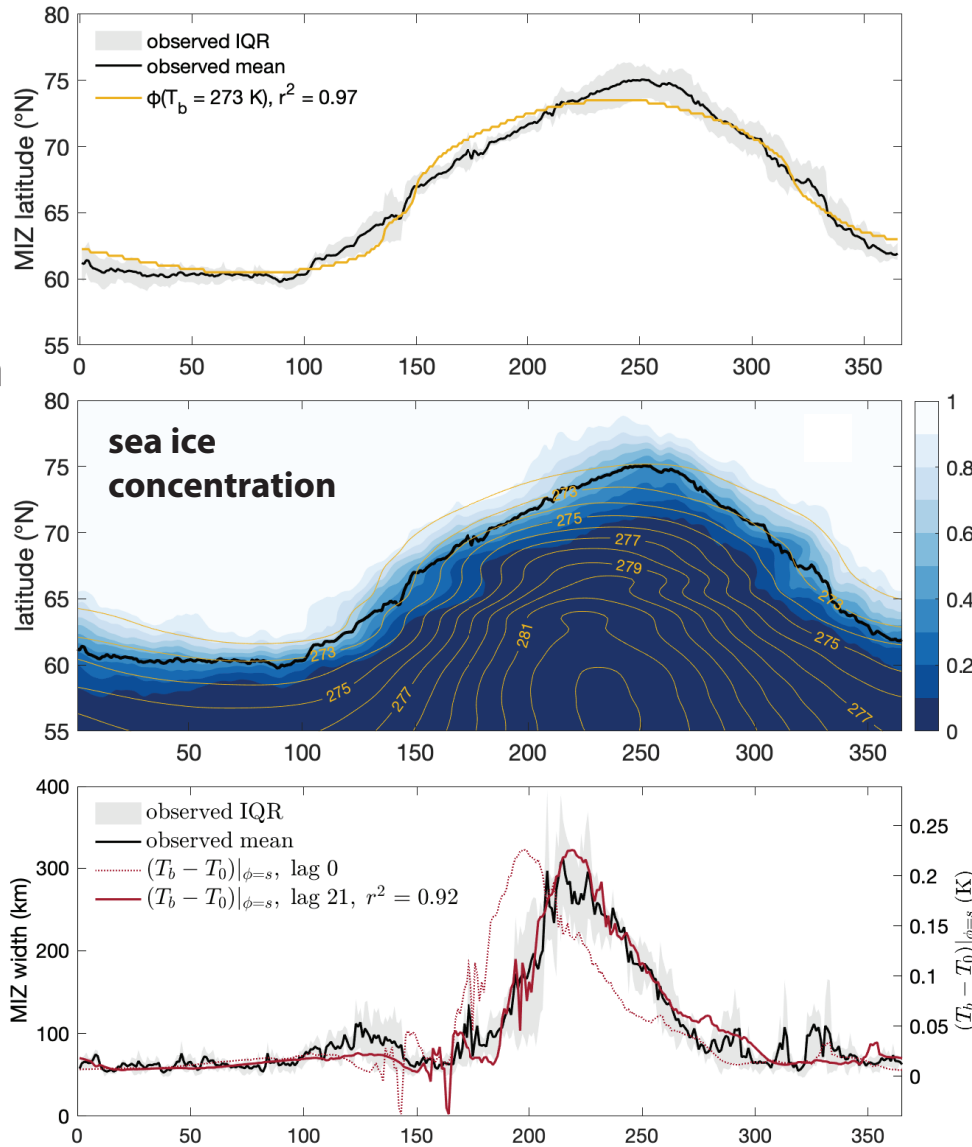
thermal flow field through the ice cover: multiscale granular composite



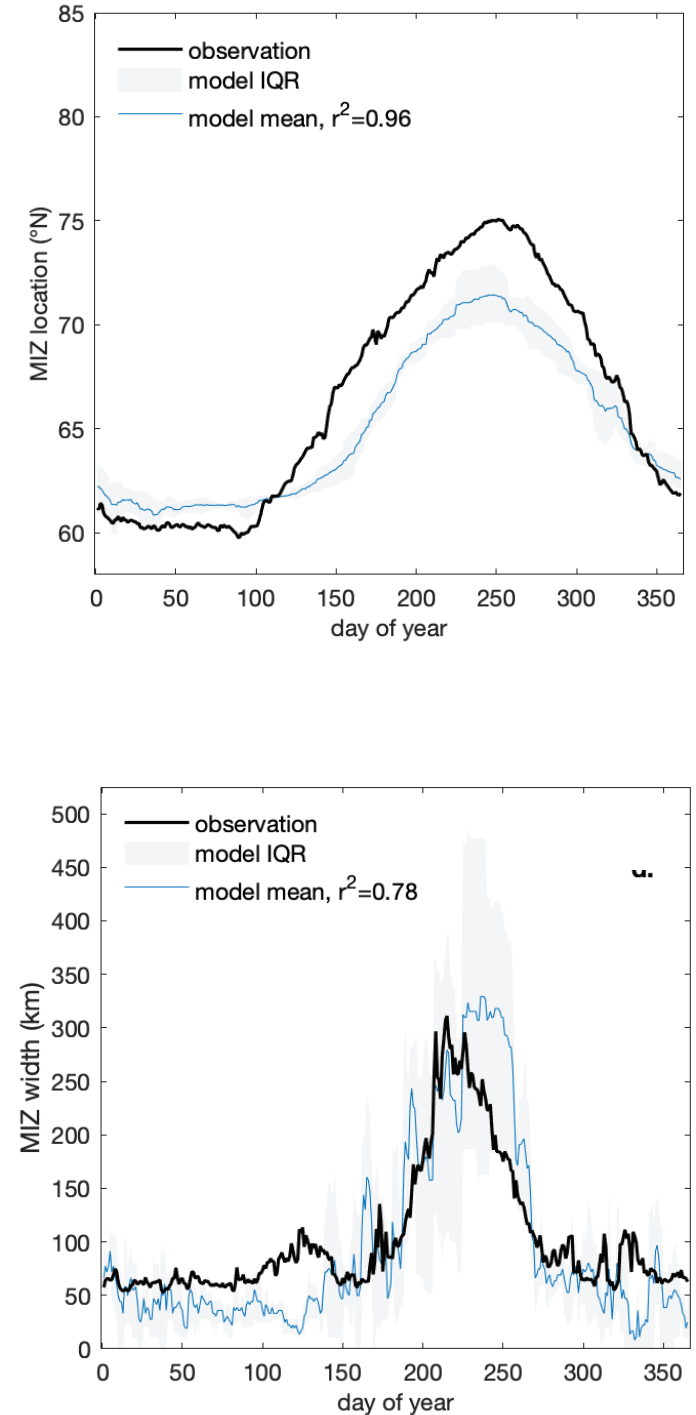
spectral measures for 2D
horizontal thermal conductivity

homogenized thermal conductivity is a key parameter in MIZ mushy layer model

MIZ observations



MIZ model vs. observations

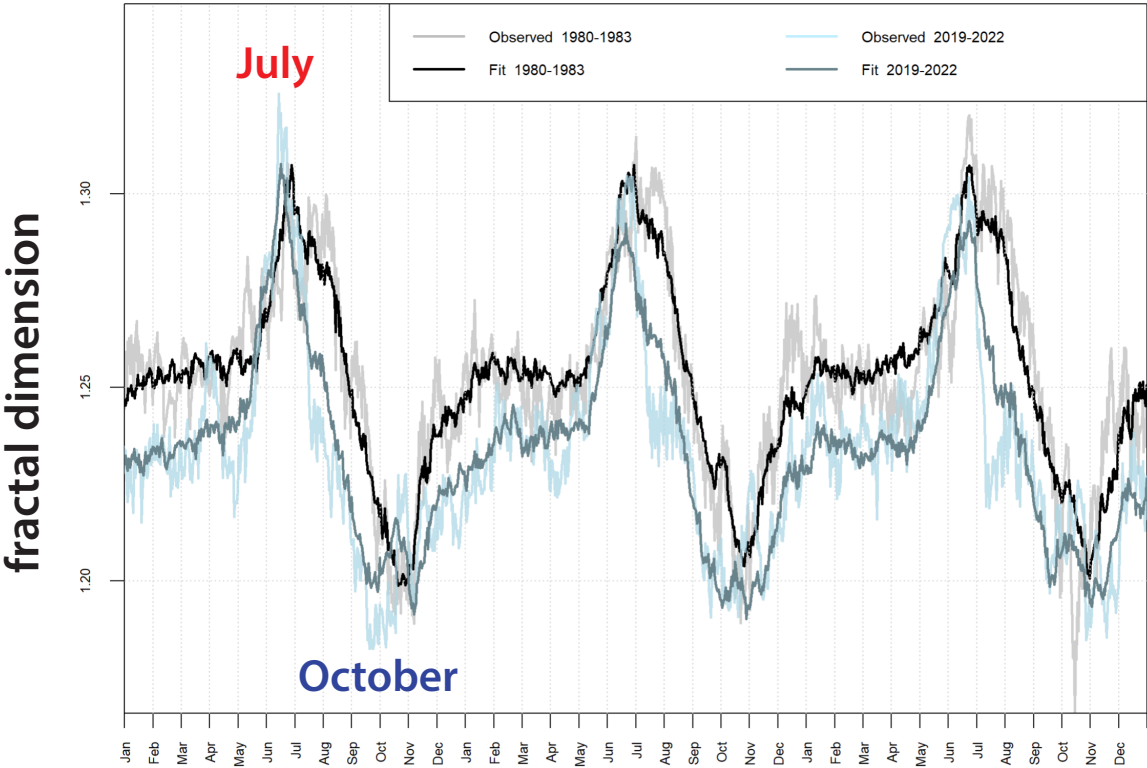


Model captures basic physics of MIZ dynamics.

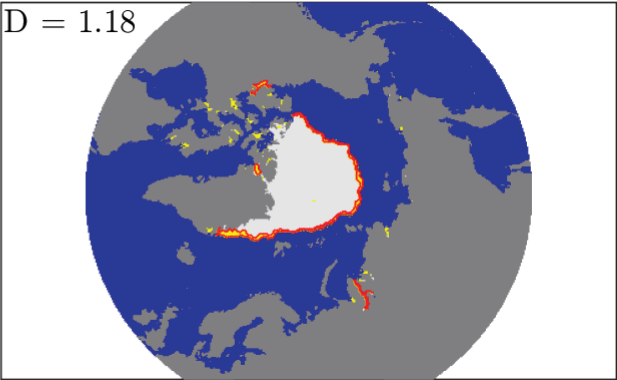
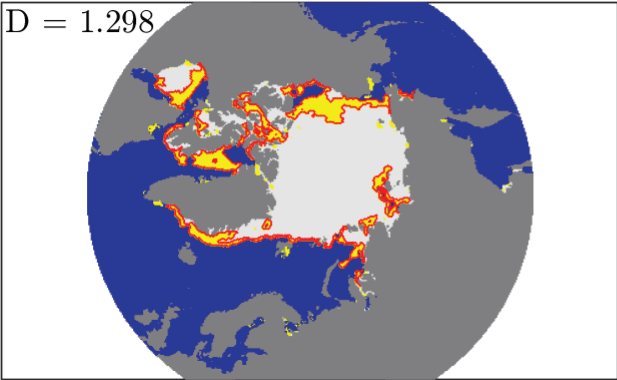
Identifying Fractal Geometry in Arctic Marginal Ice Zone Dynamics

Julie Sherman, Court Strong, Ken Golden 2024

Compute the fractal dimension of the boundary of the Arctic MIZ by boxcounting methods; analyze seasonal cycle and long term trends.



early summer



early autumn

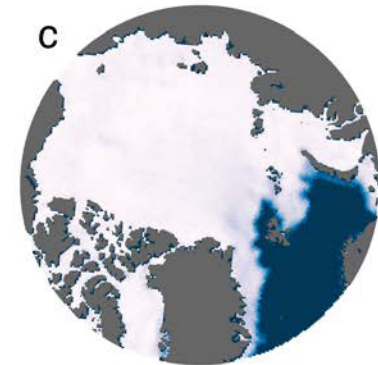
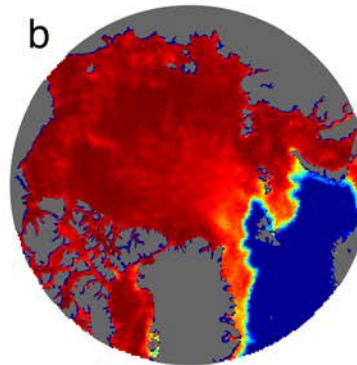
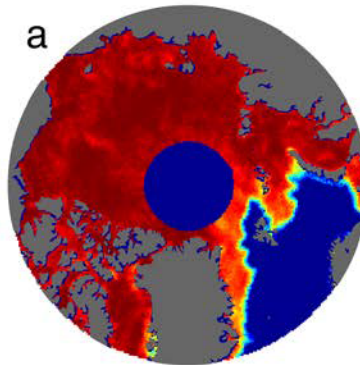
wave and thermal interactions with fractal boundary

Filling the polar data gap with partial differential equations

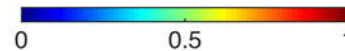
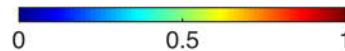
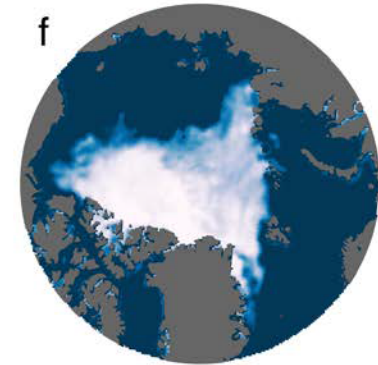
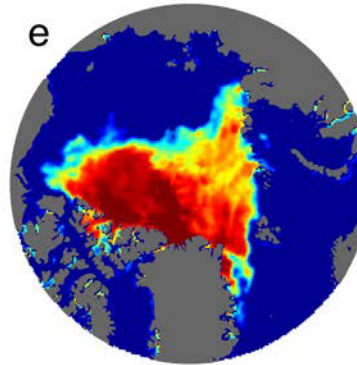
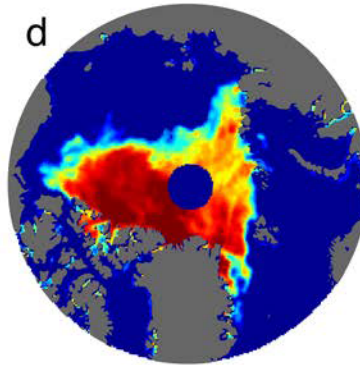
hole in satellite coverage
of sea ice concentration field

previously assumed
ice covered

Gap radius: 611 km
06 January 1985



Gap radius: 311 km
30 August 2007



$$\Delta\psi=0$$

fill = harmonic function satisfying
satellite BC's plus learned stochastic term

Strong and Golden, *Remote Sensing* 2016
Strong and Golden, *SIAM News* 2017

Global Sea Ice Concentration Climate Data Records, 2022
Lavergne, Sorensen, et al., Norwegian Met. Inst., ... OSI SAF

Conclusions

Our research is helping to improve projections of climate change, the fate of Earth's sea ice packs, and the ecosystems they support.

Mathematics for sea ice advances the theory of composites, inverse problems, and other areas of science and engineering.

**Modeling sea ice leads to unexpected
areas of math and physics.**



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Notices

of the American Mathematical Society

November 2020

Volume 67, Number 10



NSF Research Training Grant (RTG) with 15 Applied Math faculty:

optimization and inverse problems

July 2022 - June 2027

Overall goal: Build an advanced, competitive U.S. STEM workforce.

- Strengthen our graduate and postdoctoral programs in applied math to attract top students in the nation, and place them in top jobs.
- Provide transformative experiences that draw students into math.

Arctic Mathpeditions - May 2024 & 2026

OPEN POSITIONS:

Postdoctoral, Ph.D., Undergraduate

NSF RTG Arctic Mathpedition, May 2024

on the frozen Arctic Ocean north of Utqiagvik, AK

We took 7 math students working on sea ice models to the Arctic to do *experiments* on the physics and biology of sea ice.

Jody Reimer, Ken Golden
[Seth & Tarn]

Anthony Lee
David Gluckman
Kathy Lin
Nash Ward
Daniel Hallman
Anthony Jajeh
Delaney Mosier
Marco Lozzi

High School
Undergraduate
Undergraduate
Undergraduate
Graduate Student
Graduate Student
Graduate Student
Student Photojournalist

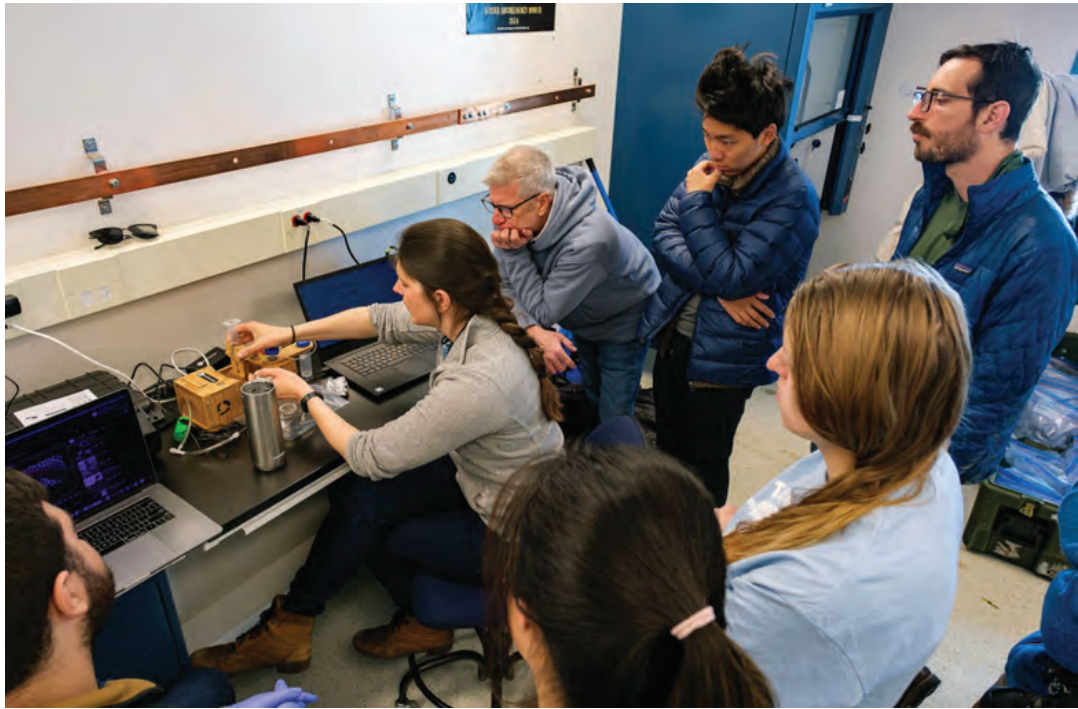
**see what you're modeling; close the gap between theory and experiment;
connect physics & bio; experience climate change first-hand; math outreach to locals**

Math Dept Colloquium, Nov 21

NSF RTG Arctic Mathpedition 2, May 2026







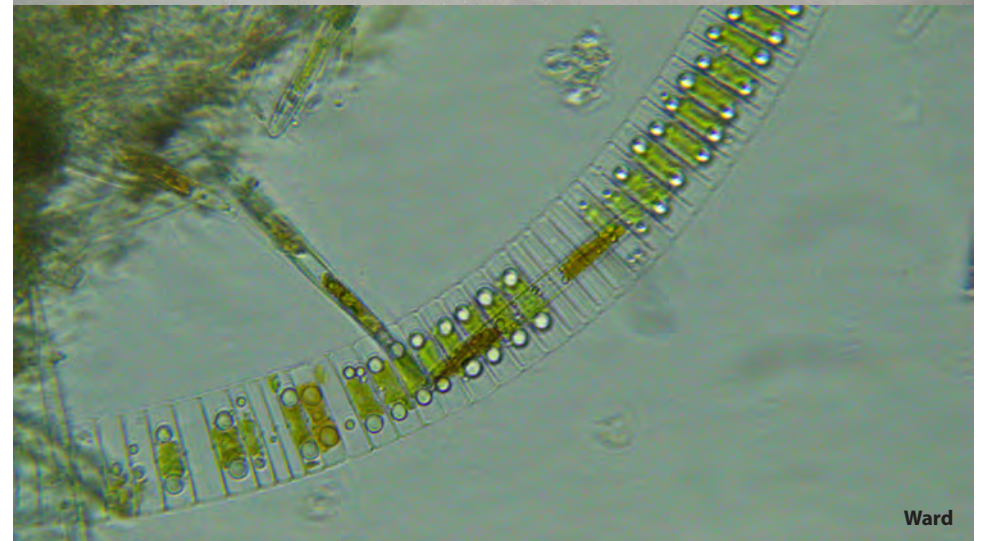


Reimer

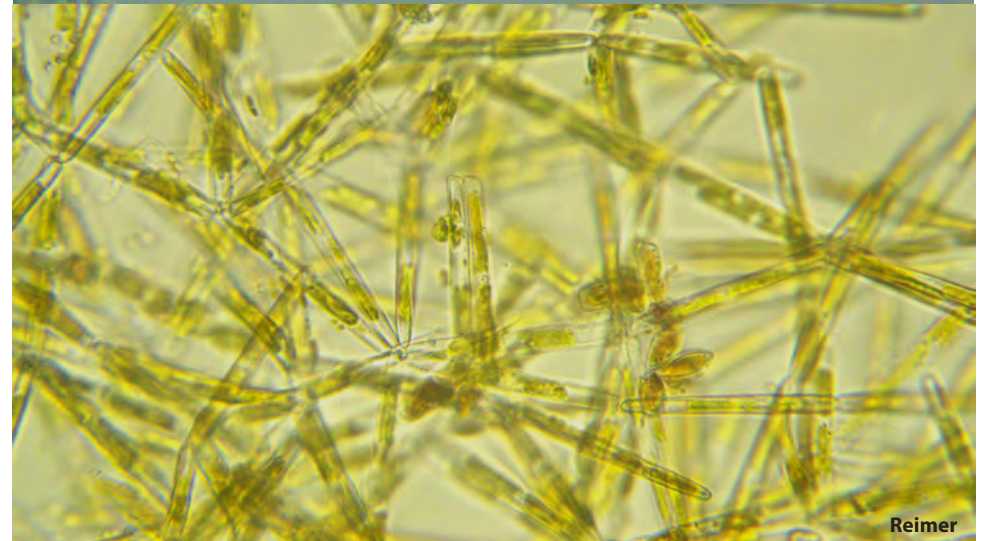
bottom of a sea ice core



Golden

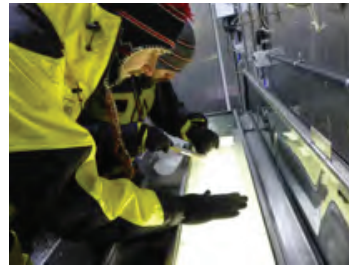
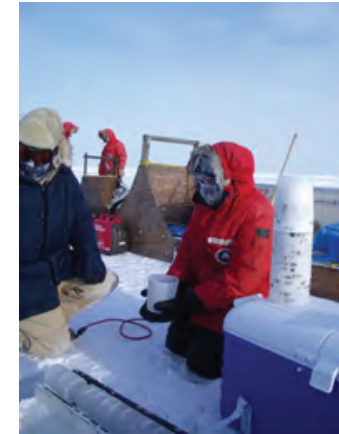


Ward



Reimer

Thank you to so many postdocs, graduate students, undergraduates, high school students and colleagues who contributed to this work!



U. of Utah students in the Arctic and Antarctic (2003-2022): closing the gap between theory and observation - making math models come alive and experiencing climate change firsthand.

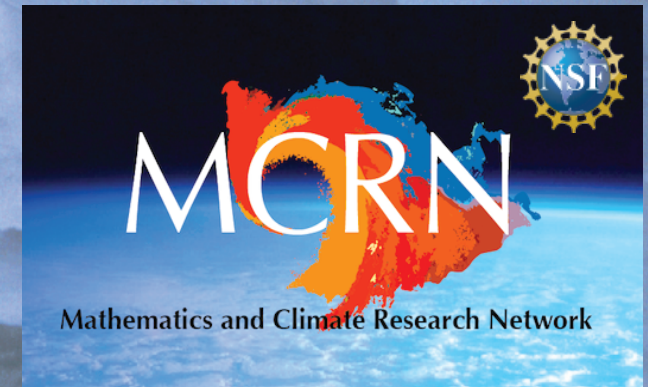
THANK YOU

Office of Naval Research

Applied and Computational Analysis Program
Arctic and Global Prediction Program

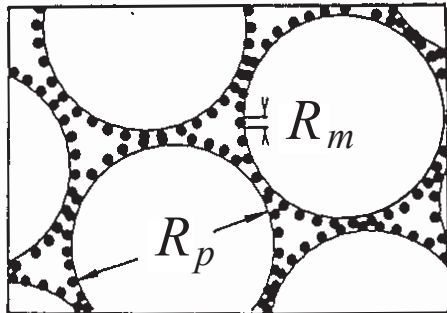
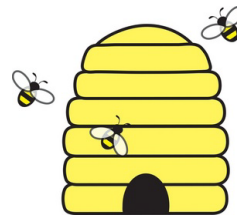
National Science Foundation

Division of Mathematical Sciences
Division of Polar Programs

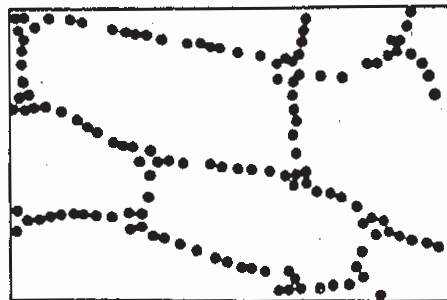


Buchanan Bay, Antarctica Mertz Glacier Polynya Experiment July 1999

cross pollination



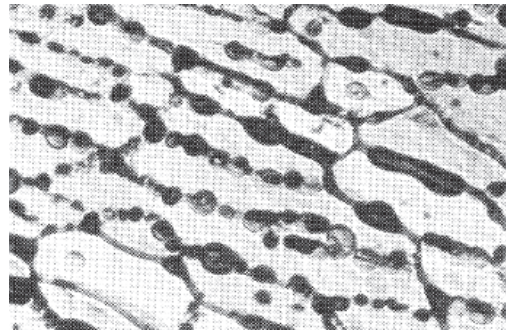
compressed powder



radar absorbing coating



Kusy & Turner
Nature 1971



sea ice

Golden, Ackley, Lytle
Science 1998

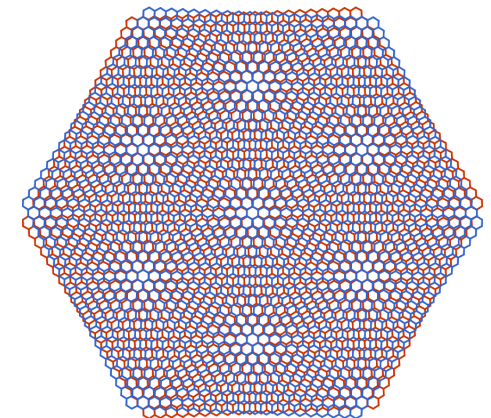
Rule of Fives
fluid flow



human bone

Golden, Murphy, Cherkaev
J. Biomechanics 2011

spectral analysis & RMT



twisted bilayer composites

Morison, Murphy, Cherkaev, Golden
Communications Physics 2022

stealth technology, climate science, medical imaging, twistrionics



*recent losses
in comparison to
the United States*

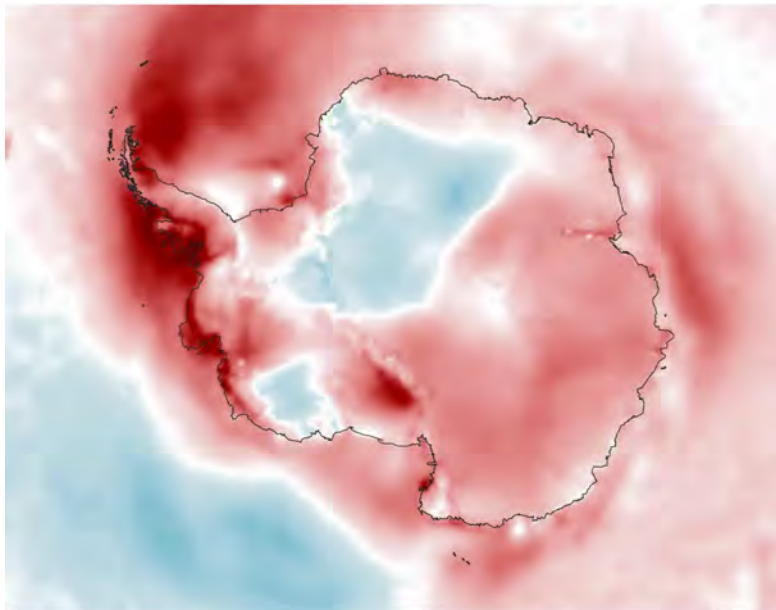


New Record Low for Antarctic Sea Ice

February 13, 2023

**Much of Antarctica
warmer than average**

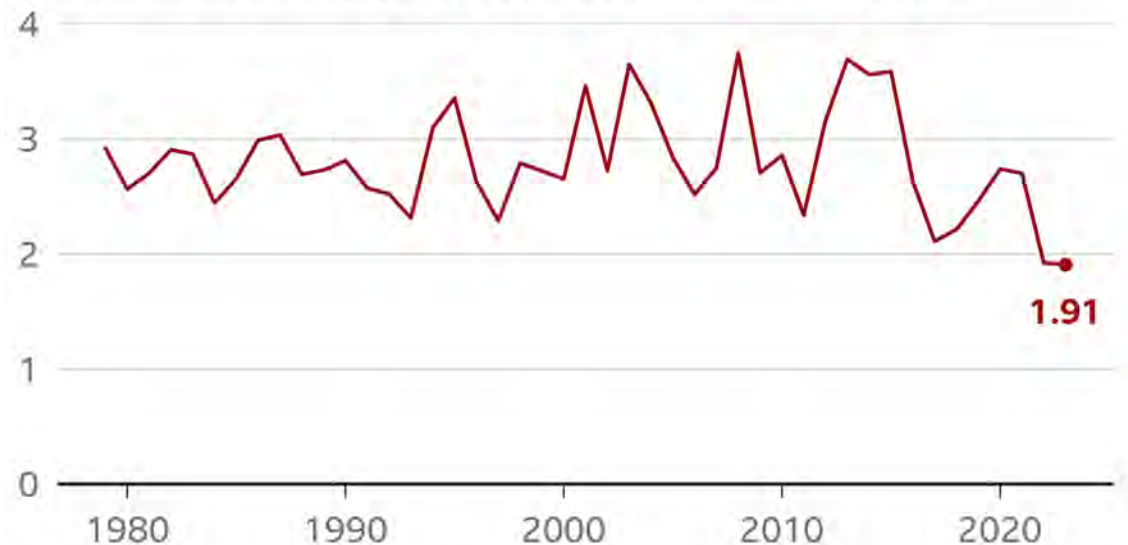
Mean 2022 surface air temp
compared with 1991-2022 ($^{\circ}\text{C}$)



Source: ECMWF ERA5

BBC

**Minimum extent 1979-2023
(million sq km)**



Five-day rolling average of sea-ice extent

Source: National Snow and Ice Data Center (NSIDC)

BBC



sea ice algal communities

D. Thomas 2004

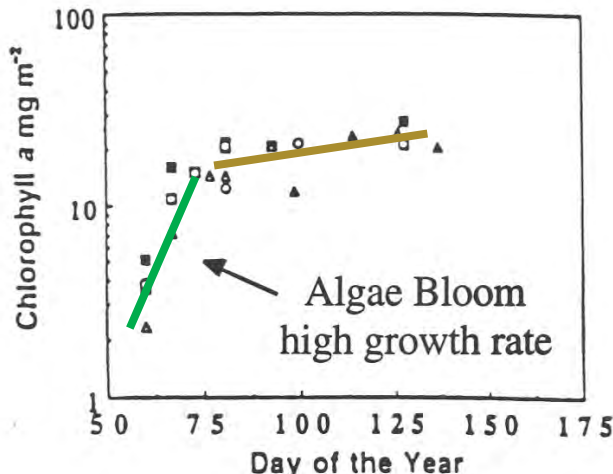
nutrient replenishment
controlled by ice permeability

biological activity turns on
or off according to
rule of fives

Golden, Ackley, Lytle *Science* 1998

Fritsen, Lytle, Ackley, Sullivan *Science* 1994

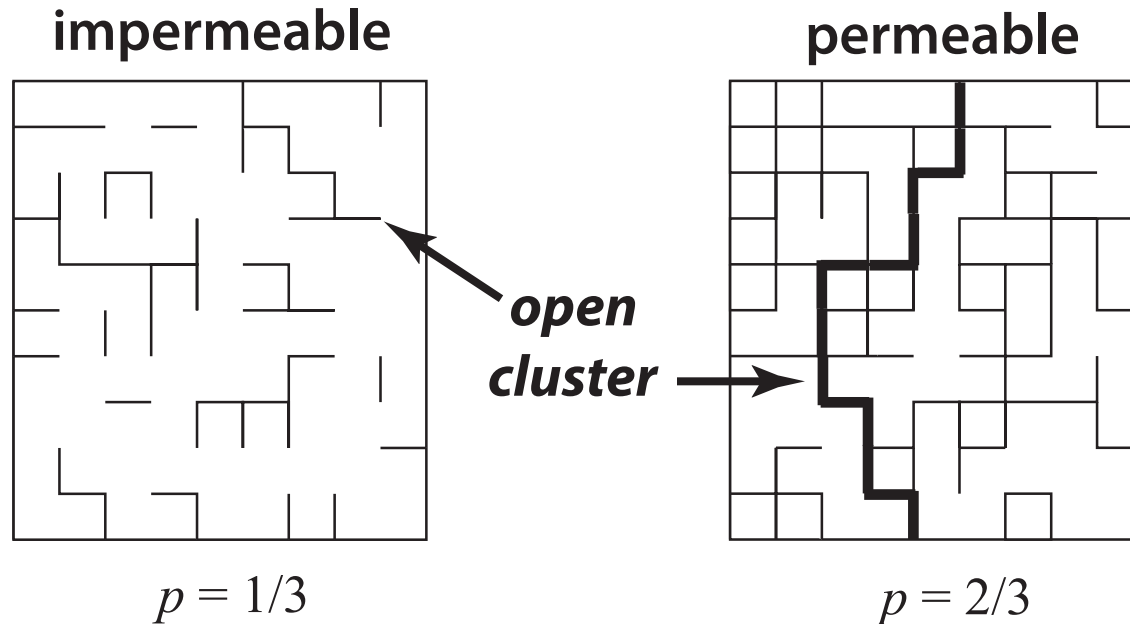
critical behavior of microbial activity



Convection-fueled algae bloom
Ice Station Weddell

percolation theory

probabilistic theory of connectedness



bond \longrightarrow open with probability p
closed with probability $1-p$

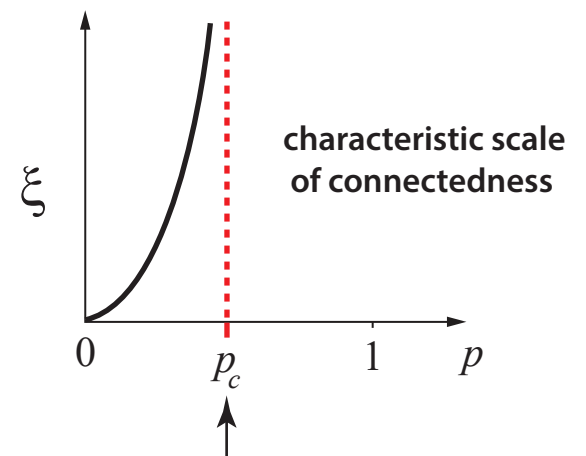
percolation threshold

$$p_c = 1/2 \quad \text{for } d = 2$$

smallest p for which there is an infinite open cluster

correlation length

development of long range order



$$\xi(p) \sim |p - p_c|^{-\nu} \quad p \rightarrow p_c$$

ν universal: depends only on d

p_c depends on type of lattice and d

Critical behavior of fluid transport in sea ice

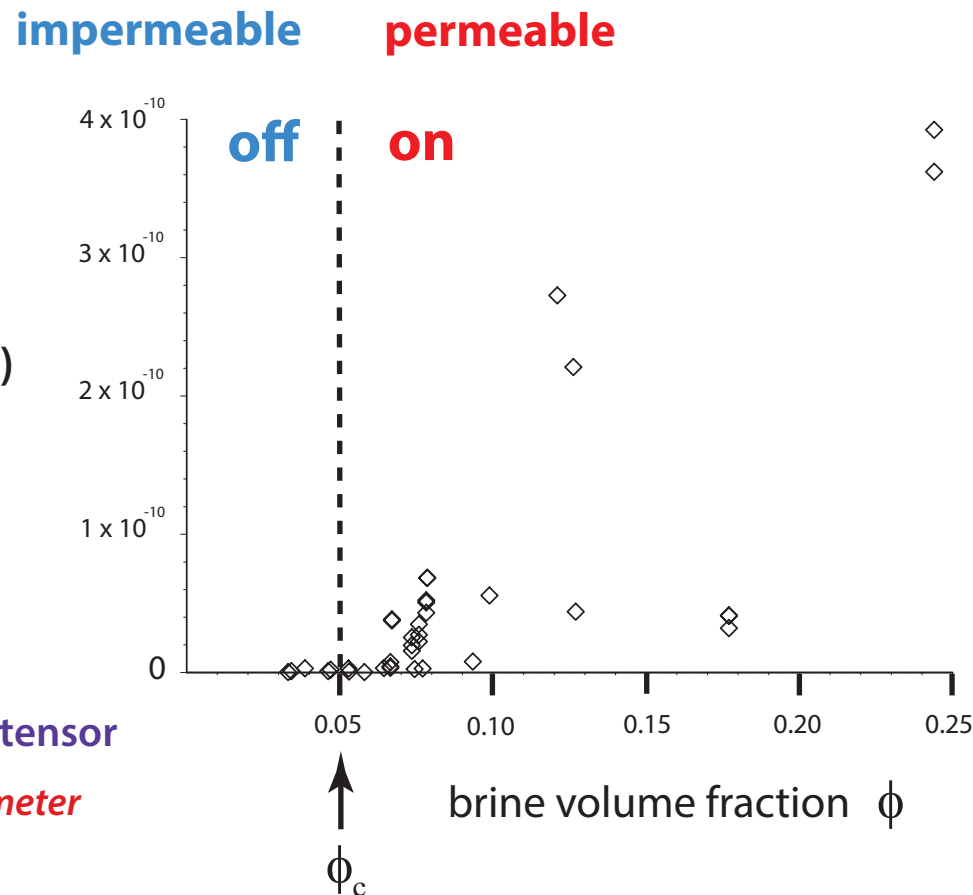
Arctic field data

vertical fluid permeability k (m^2)

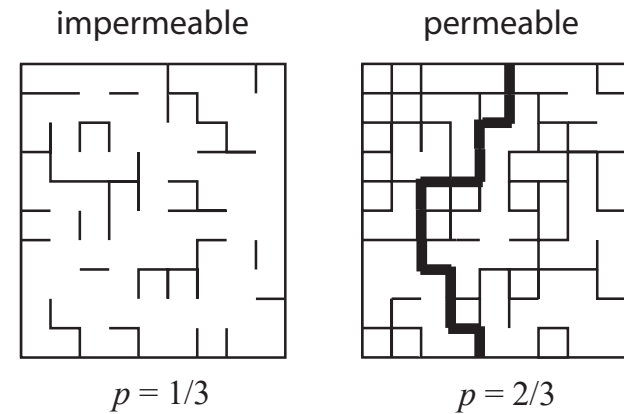
Darcy's Law

$$\mathbf{v} = -\frac{\mathbf{k}}{\eta} \nabla p$$

\mathbf{k} = fluid permeability tensor
homogenized parameter



“on - off” switch
for bulk fluid flow



lattice percolation

FRACTAL
percolation clusters

PERCOLATION THRESHOLD $\phi_c \approx 5\% \longleftrightarrow T_c \approx -5^\circ \text{C}, S \approx 5 \text{ ppt}$

RULE OF FIVES

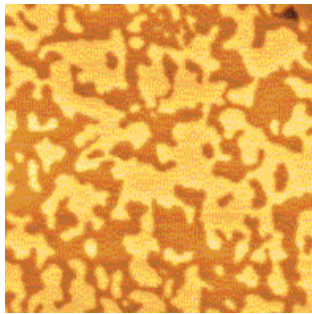
Golden, Ackley, Lytle *Science* 1998

Golden, Eicken, Heaton, Miner, Pringle, Zhu *GRL* 2007

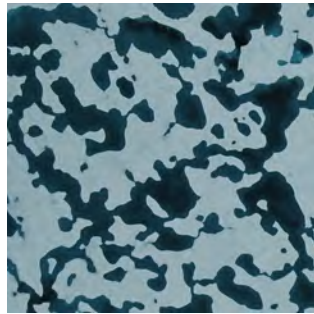
Pringle, Miner, Eicken, Golden *J. Geophys. Res.* 2009

From magnets to melt ponds

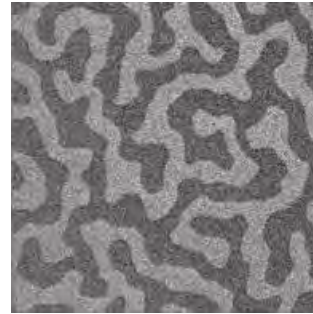
100 year old model for magnetic materials
used to explain melt pond geometry



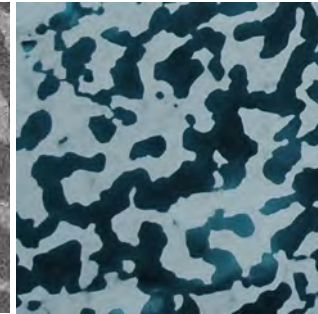
magnetic domains
in cobalt



Arctic melt ponds

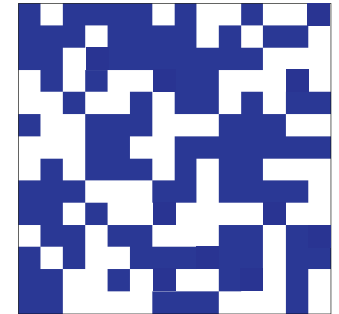
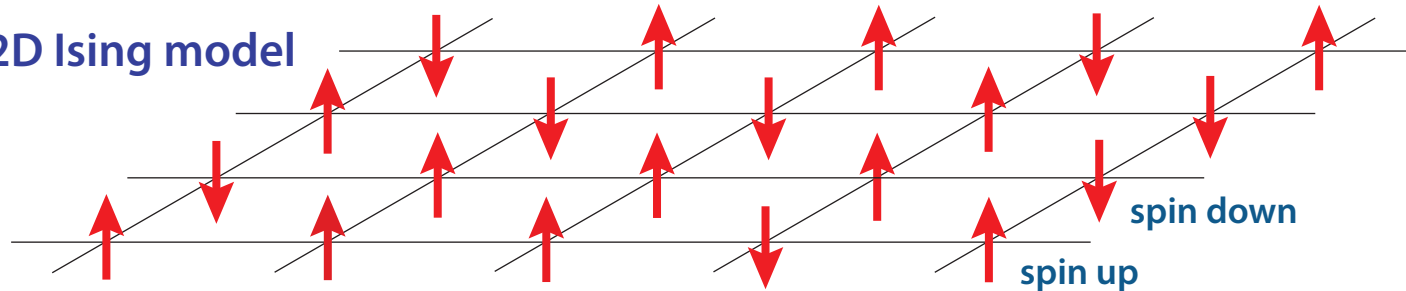


magnetic domains
in cobalt-iron-boron

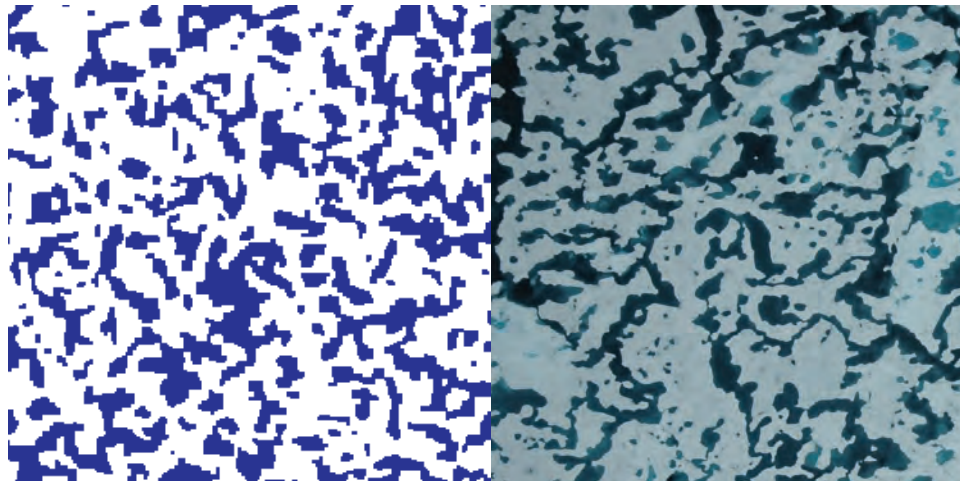


Arctic melt ponds

2D Ising model



model



real ponds
(Perovich)

Ma, Sudakov, Strong,
Golden, *New J. Phys.* 2019

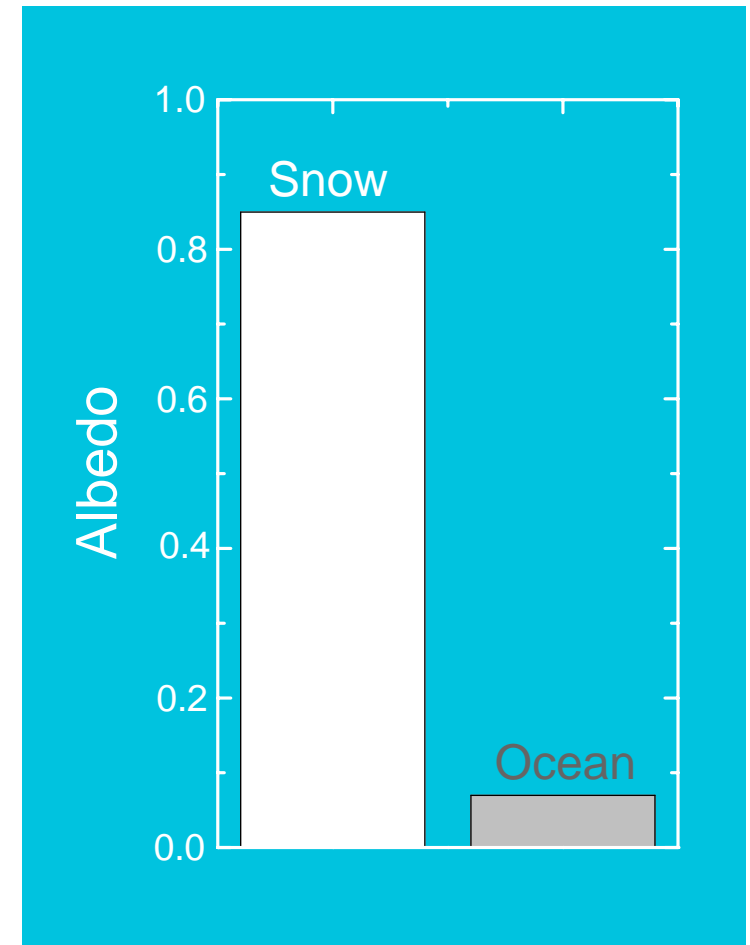
Scientific American,
EOS, PhysicsWorld, ...

Time evolution - William Harrison, Tyler Evans, Ken Golden 2024

polar ice caps critical to global climate in reflecting incoming solar radiation



white snow and ice
reflect

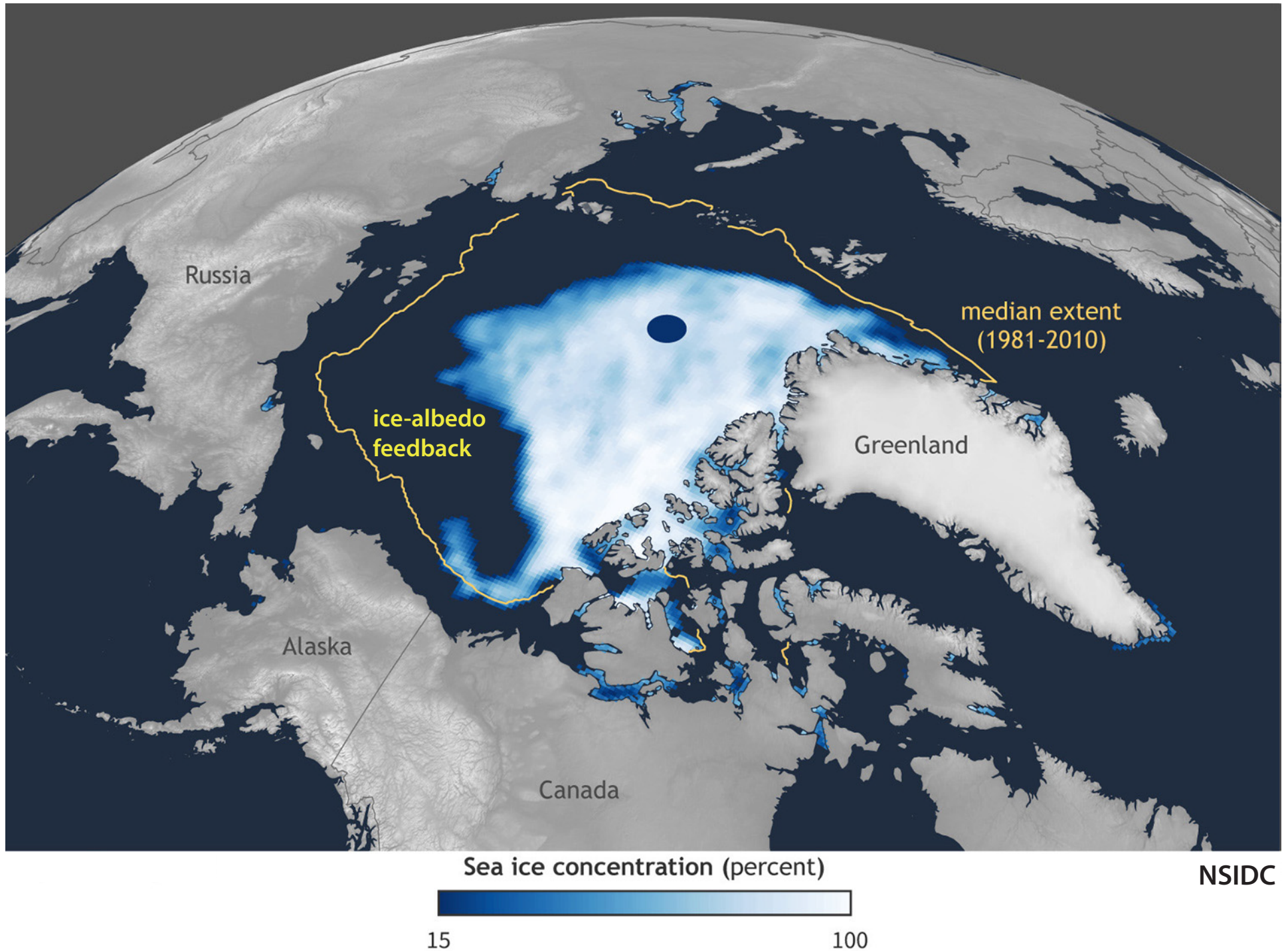


dark water and land
absorb

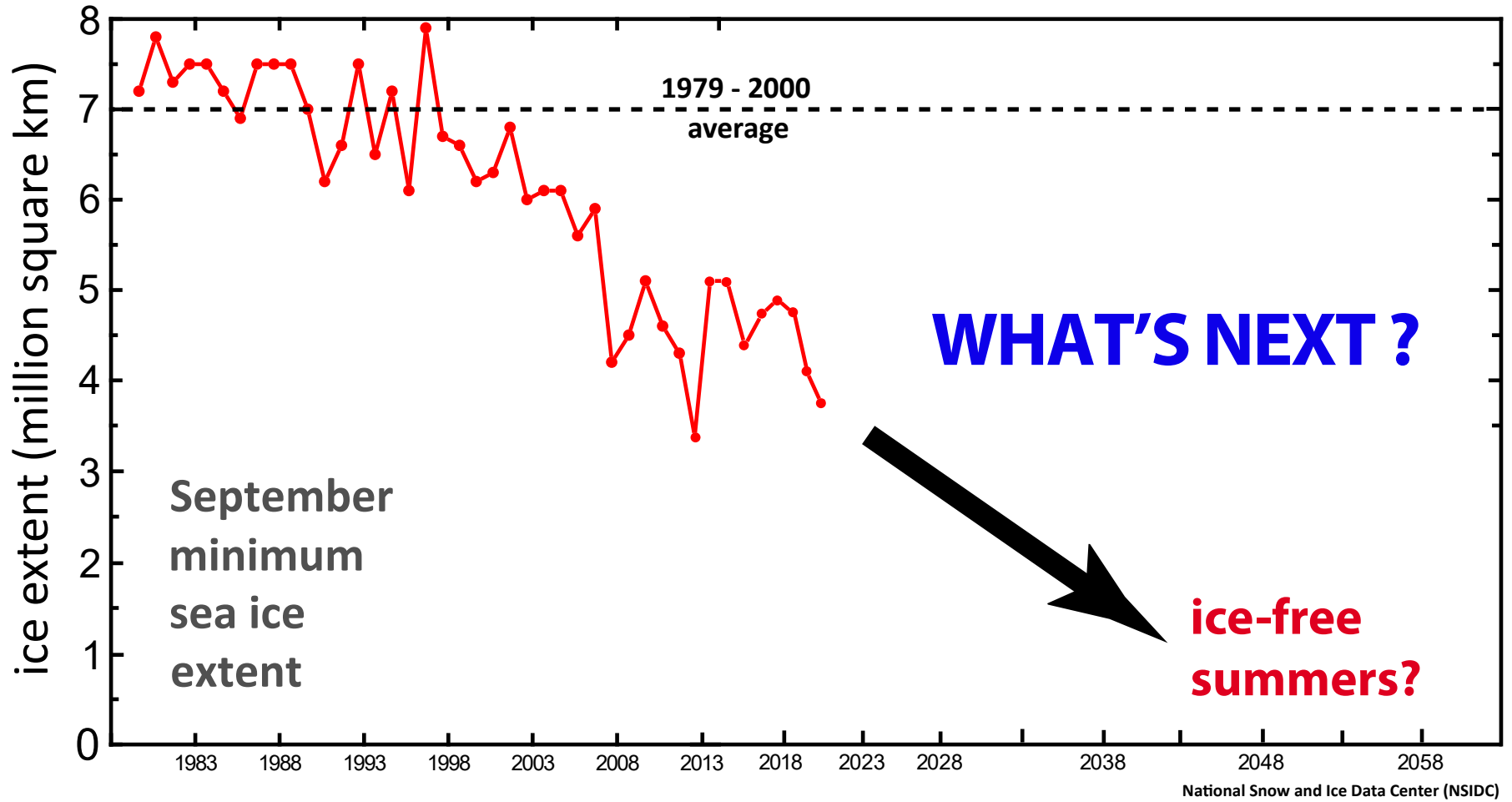
$$\text{albedo } \alpha = \frac{\text{reflected sunlight}}{\text{incident sunlight}}$$

Arctic sea ice extent

September 15, 2020



ARCTIC summer sea ice loss



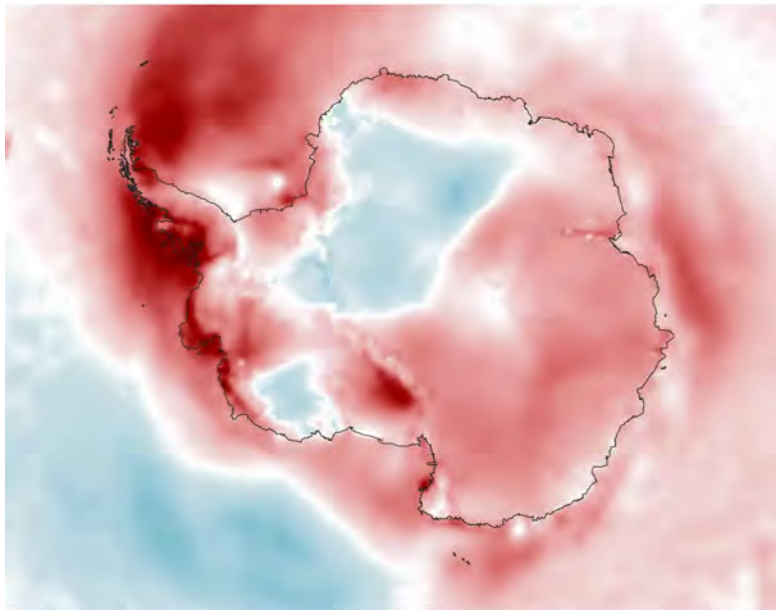
predictions require lots of math modeling

New Record Low for Antarctic Sea Ice

February 13, 2023

**Much of Antarctica
warmer than average**

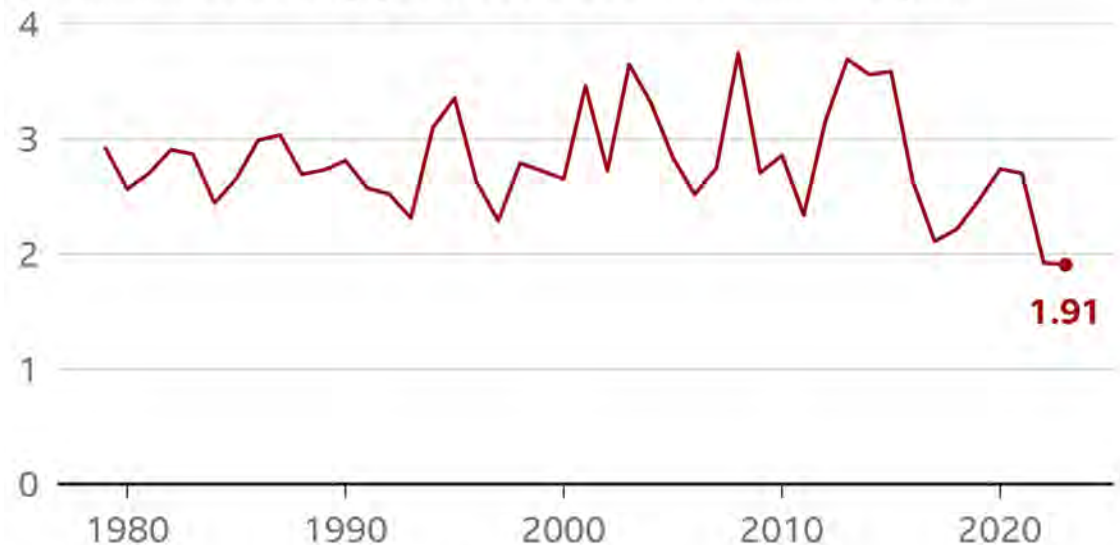
Mean 2022 surface air temp
compared with 1991-2022 ($^{\circ}\text{C}$)



Source: ECMWF ERA5

BBC

**Minimum extent 1979-2023
(million sq km)**



Five-day rolling average of sea-ice extent

Source: National Snow and Ice Data Center (NSIDC)

BBC