Homogenization in the Physics and Biology of Sea Ice

Kenneth M. Golden
Department of Mathematics, University of Utah



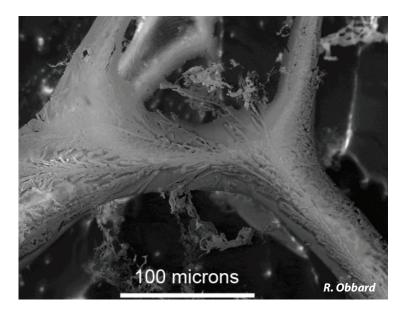




sea ice may appear to be a barren, impermeable cap ...



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)



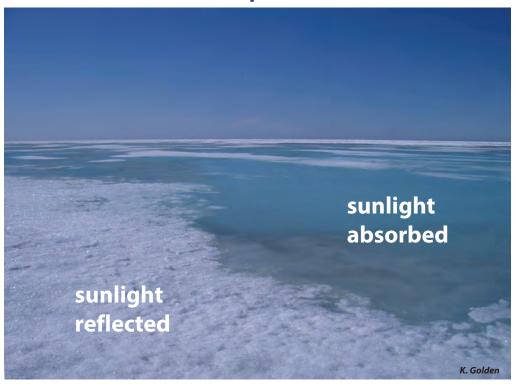
horizontal section



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

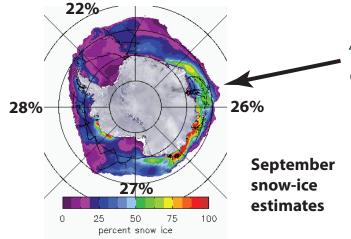


nutrient flux for algal communities









T. Maksym and T. Markus, 2008

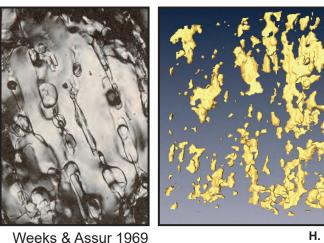
Antarctic surface flooding and snow-ice formation

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

Sea Ice is a Multiscale Composite Material

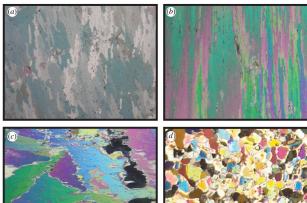
microscale

brine inclusions



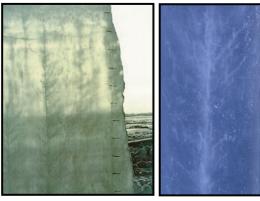
H. Eicken Golden et al. GRL 2007

polycrystals



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

brine channels



D. Cole K. Golden

millimeters

centimeters

macroscale

mesoscale

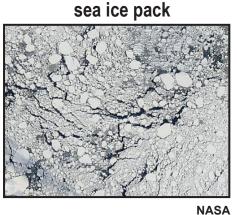
Arctic melt ponds

Antarctic pressure ridges



sea ice floes



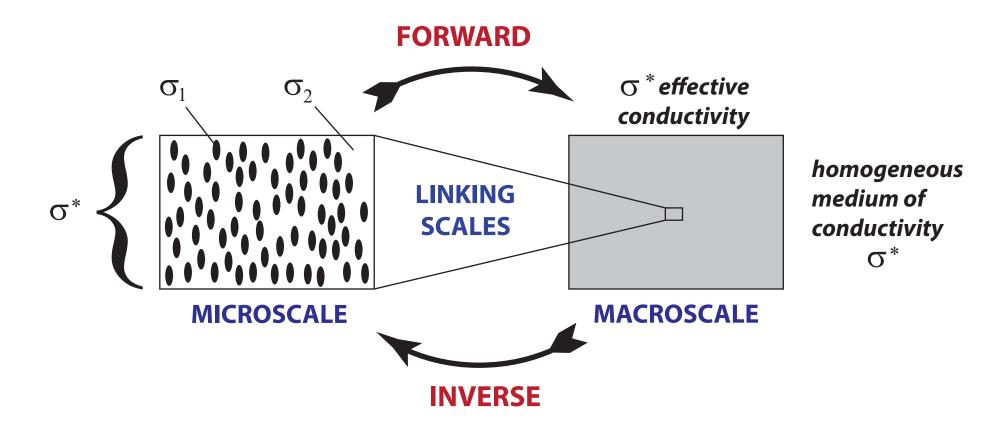


meters

K. Frey

kilometers

HOMOGENIZATION for Composite Materials



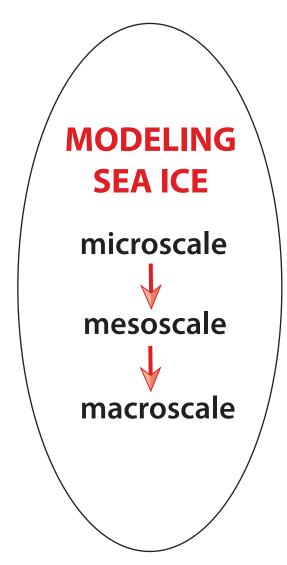
Maxwell 1873: effective conductivity of a dilute suspension of spheres Einstein 1906: effective viscosity of a dilute suspension of rigid spheres in a fluid

Wiener 1912: arithmetic and harmonic mean bounds on effective conductivity Hashin and Shtrikman 1962: variational bounds on effective conductivity

widespread use of composites in late 20th century due in large part to advances in mathematically predicting their effective properties

What is this talk about?

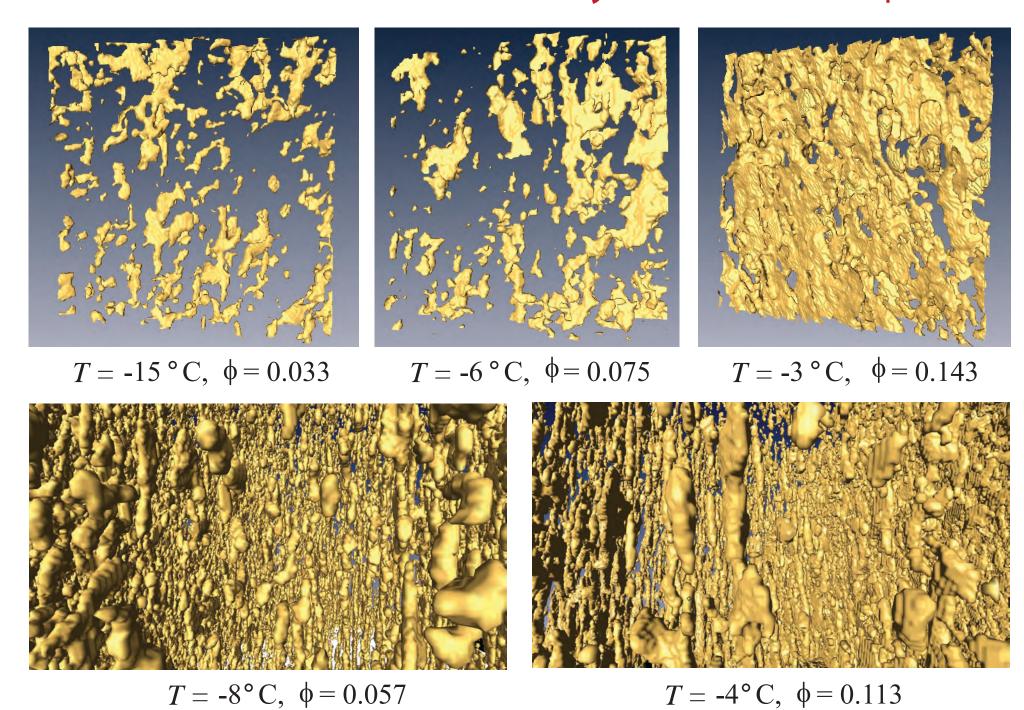
Using methods of homogenization and statistical physics to model sea ice effective behavior and advance representation of sea ice in climate models, process studies, ...



A tour of key sea ice processes on micro, meso, and macro scales.

microscale

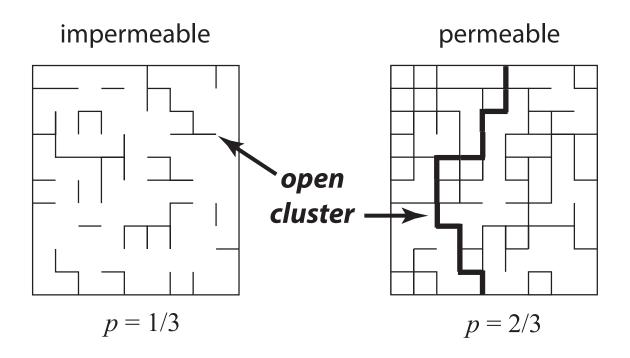
brine volume fraction and *connectivity* increase with temperature



X-ray tomography for brine in sea iceGolden et al., Geophysical Research Letters, 2007

percolation theory

probabilistic theory of connectedness



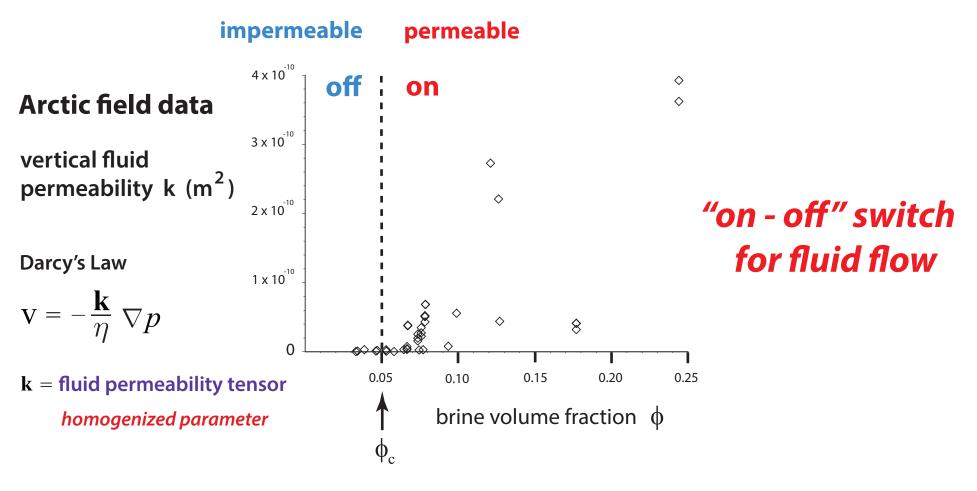
bond
$$\longrightarrow$$
 open with probability p closed with probability 1-p

percolation threshold

$$p_c = 1/2$$
 for $d = 2$

smallest p for which there is an infinite open cluster

Critical behavior of fluid transport in sea ice



critical brine volume fraction $\phi_c \approx 5\%$ \longrightarrow $T_c \approx -5^{\circ} \text{C}$, $S \approx 5 \text{ ppt}$

RULE OF FIVES

Golden, Ackley, Lytle Science 1998 Golden, Eicken, Heaton, Miner, Pringle, Zhu GRL 2007 Pringle, Miner, Eicken, Golden J. Geophys. Res. 2009

sea ice ~ compressed powder in stealthy composites





sea ice algal communities

D. Thomas 2004

nutrient replenishment controlled by ice permeability

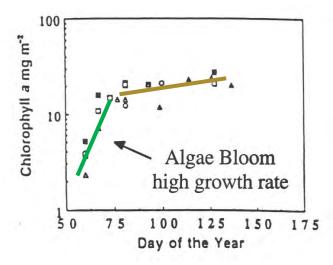
biological activity turns on or off according to rule of fives

Golden, Ackley, Lytle

Science 1998

Fritsen, Lytle, Ackley, Sullivan Science 1994

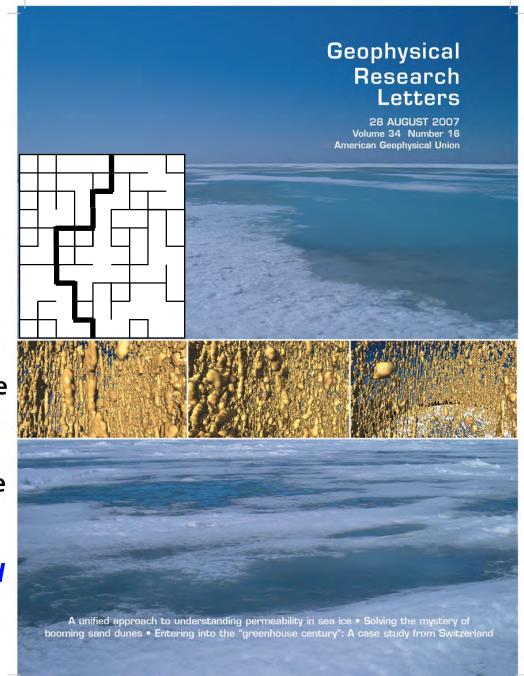
critical behavior of microbial activity



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

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

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

theories agree closely with field data

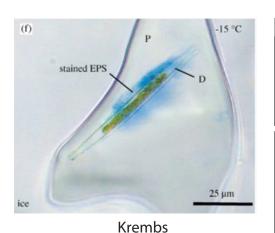
microscale governs

mesoscale processes

melt pond evolution

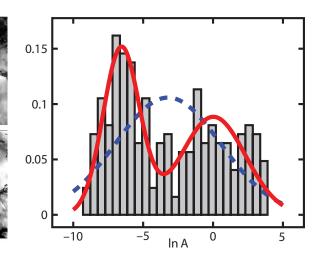
Sea ice algae secrete extracellular polymeric substances (EPS) affecting evolution of brine microstructure.

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

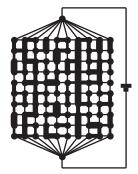


without EPS with EPS

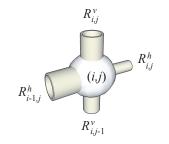
Krembs, Eicken, Deming, PNAS 2011



RANDOM PIPE MODEL



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

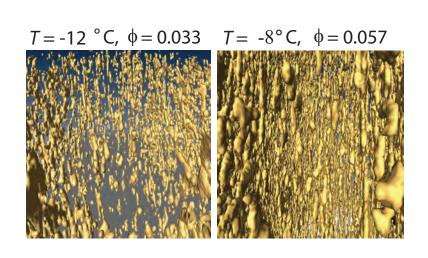


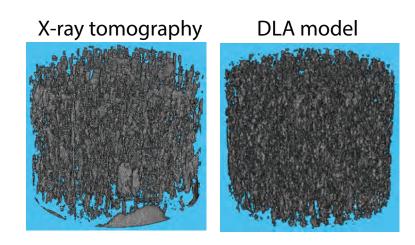
Zhu, Jabini, Golden, Eicken, Morris *Ann. Glac.* 2006

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

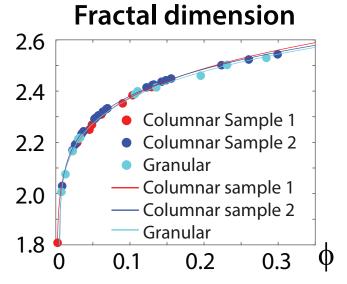
Thermal evolution of the fractal geometry of the brine microstructure in sea ice

N. Ward, D. Hallman, J. Reimer, H. Eicken, M. Oggier and K. M. Golden, 2022









brine volume fraction (porosity)

theory of porosity as a function of fractal dimension

invert

excellent correspondence with data

Katz and Thompson, PRL, 1985

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



Notices

of the American Mathematical Society

Climate Change and

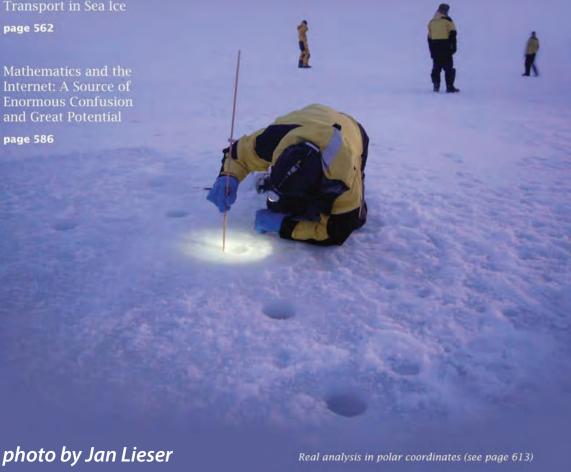
the Mathematics of

page 562

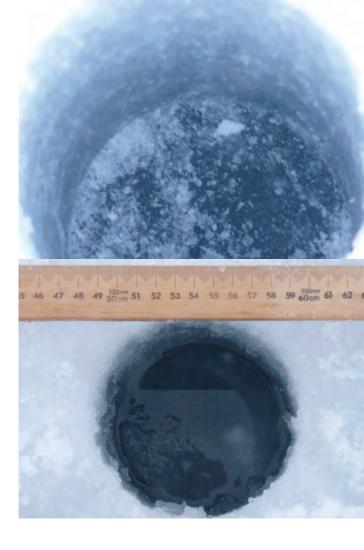
May 2009

Mathematics and the **Enormous Confusion** and Great Potential

page 586



Volume 56, Number 5



measuring fluid permeability of Antarctic sea ice

SIPEX 2007

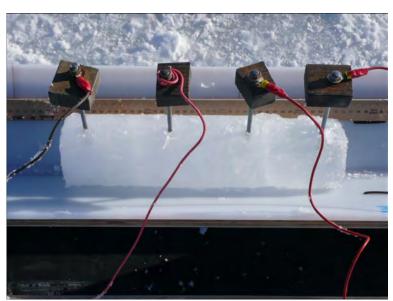
electrical measurements



Wenner array





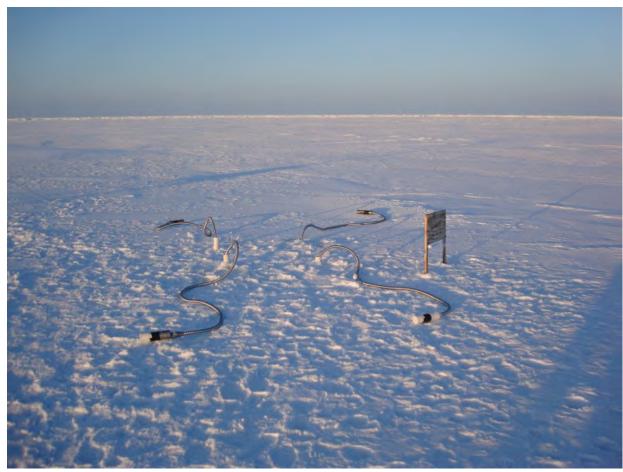


vertical conductivity

Zhu, Golden, Gully, Sampson *Physica B* 2010 Sampson, Golden, Gully, Worby *Deep Sea Research* 2011

cross borehole tomography





Measuring sea ice thickness











Remote sensing of sea ice











sea ice thickness ice concentration

INVERSE PROBLEM

Recover sea ice properties from electromagnetic (EM) data

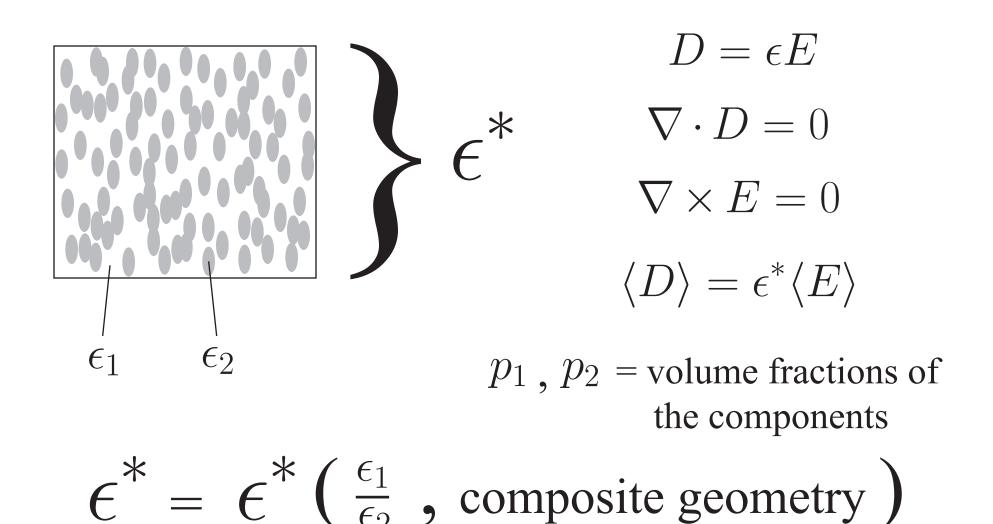
8*3

effective complex permittivity (dielectric constant, conductivity)



brine volume fraction brine inclusion connectivity

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



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 and Papanicolaou (1983), Theory of Composites, Milton (2002)

Stieltjes integral representation for homogenized parameter

separates geometry from parameters

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

$$\mu = \begin{cases} \bullet \text{ spectral measure of self adjoint operator } \Gamma \chi \\ \bullet \text{ mass} = p_1 \\ \bullet \text{ higher moments depend} \end{cases}$$

$$\bullet$$
 mass = p_1

on *n*-point correlations

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

 $\chi = \text{characteristic function}$ of the brine phase

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

$| \ \ \ \rangle \chi$: microscale \rightarrow macroscale

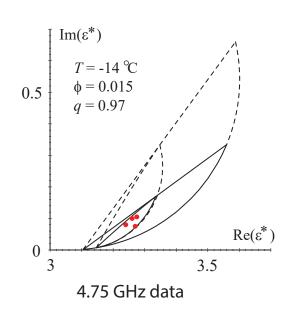
$\Gamma \chi$ links scales

Golden and Papanicolaou, Comm. Math. Phys. 1983

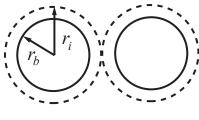
This representation distills the complexities of mixture geometry into the spectral properties of an operator like the Hamiltonian in physics.

forward and inverse bounds on the complex permittivity of sea ice

forward bounds



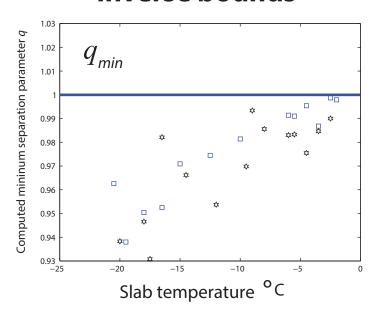
matrix particle



$$q = r_b / r_i$$

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)



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

SEA ICE

HUMAN BONE

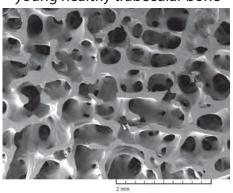


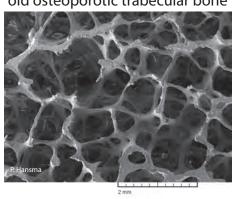


spectral characterization of porous microstructures in human bone

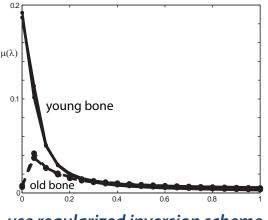
young healthy trabecular bone

old osteoporotic trabecular bone





reconstruct spectral measures from complex permittivity data



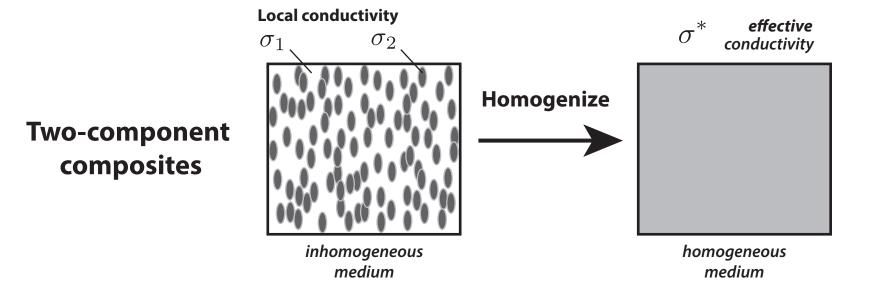
use regularized inversion scheme

apply spectral measure analysis of brine connectivity and spectral inversion to electromagnetic monitoring of osteoporosis

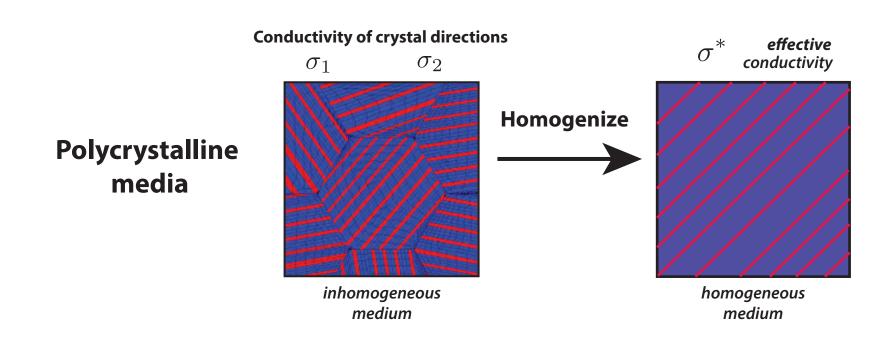
Golden, Murphy, Cherkaev, J. Biomechanics 2011

the math doesn't care if it's sea ice or bone!

Homogenization for polycrystalline materials



Find the homogeneous medium which behaves macroscopically the same as the inhomogeneous medium



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





Proc. Roy. Soc. A 8 Feb 2015

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PROCEEDINGS A



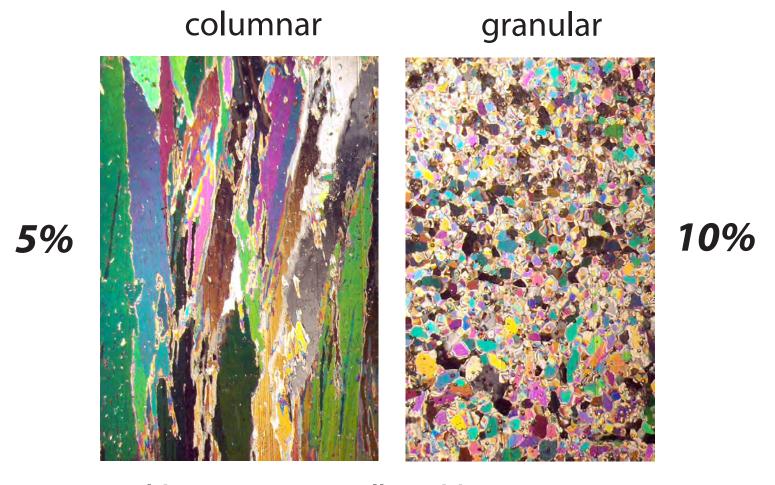
An invited review commemorating 350 years of scientific publishing at the Royal Society A method to distinguish between different types of sea ice using remote sensing techniques A computer model to determine how a human should walk so as to expend the least energy



higher threshold for fluid flow in granular sea ice

microscale details impact "mesoscale" processes

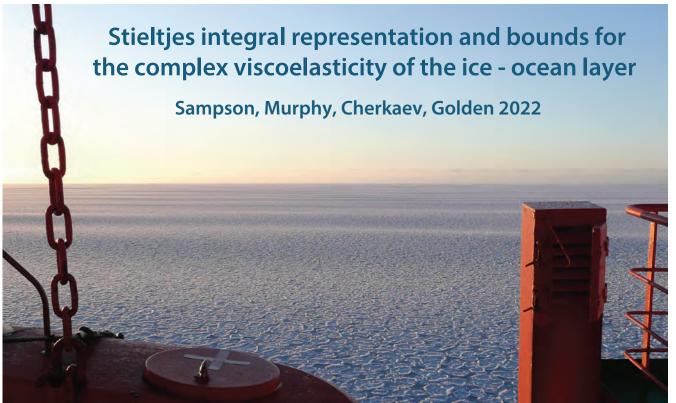
nutrient fluxes for microbes melt pond drainage snow-ice formation



Golden, Sampson, Gully, Lubbers, Tison 2022

electromagnetically distinguishing ice types Kitsel Lusted, Elena Cherkaev, Ken Golden

wave propagation in the marginal ice zone (MIZ)



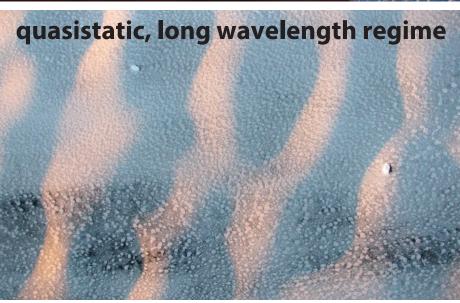
first theory of key parameter in wave-ice interactions only fitted to wave data before

Keller, 1998 Mosig, Montiel, Squire, 2015 Wang, Shen, 2012

Analytic Continuation Method

Bergman (78) - Milton (79) integral representation for ϵ^* Golden and Papanicolaou (83)

Milton, Theory of Composites (02)



homogenized parameter depends on sea ice concentration and ice floe geometry

like EM waves



direct calculation of spectral measures

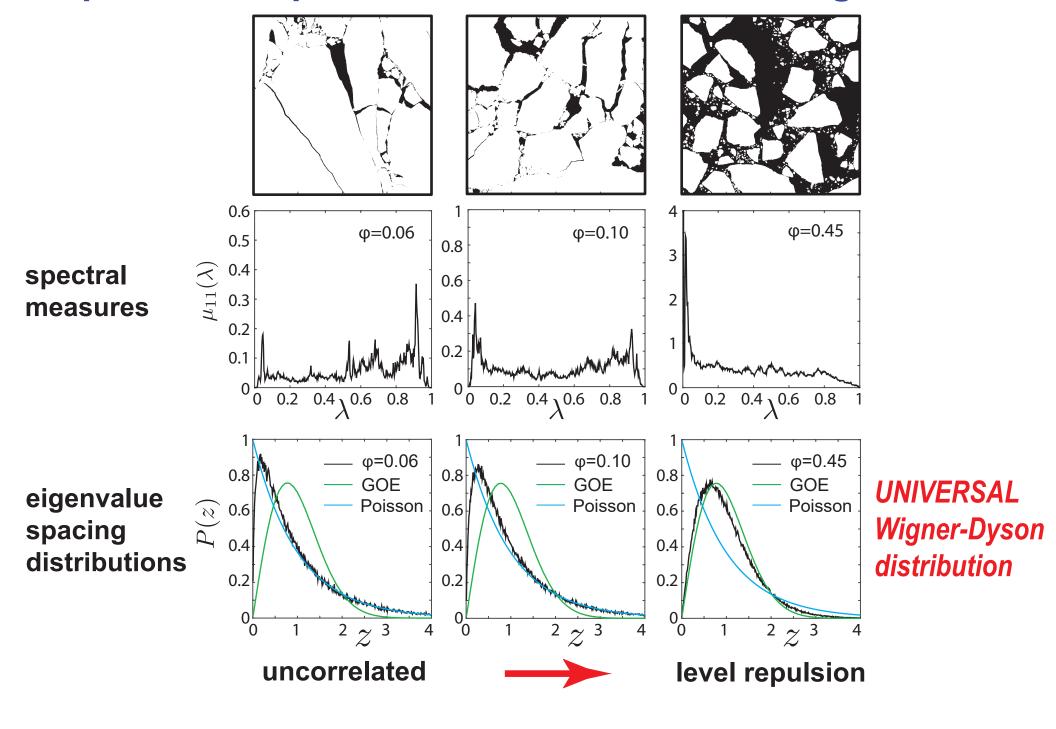
Murphy, Hohenegger, Cherkaev, Golden, Comm. Math. Sci. 2015

- depends only on the composite geometry
- discretization of microstructural image gives binary network
- fundamental operator becomes a random matrix
- spectral measure computed from eigenvalues and eigenvectors

once we have the spectral measure μ it can be used in Stieltjes integrals for other transport coefficients:

electrical and thermal conductivity, complex permittivity, magnetic permeability, diffusion, fluid flow properties

Spectral computations for sea ice floe configurations



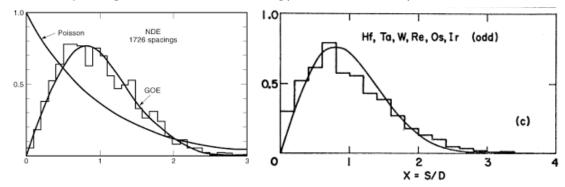
Eigenvalue Statistics of Random Matrix Theory

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

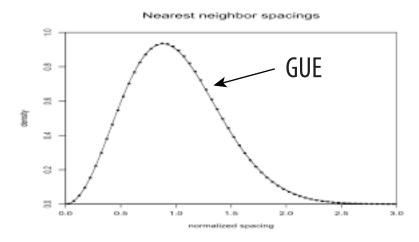
$$[N]_{ij} \sim N(0,1),$$
 $A = (N+N^T)/2$ Gaussian orthogonal ensemble (GOE) $[N]_{ij} \sim N(0,1) + iN(0,1),$ $A = (N+N^T)/2$ Gaussian unitary ensemble (GUE)

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

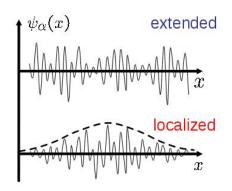
Spacing distributions of energy levels for heavy atomic nuclei



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



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



electronic transport in semiconductors

metal / insulator transition localization

Anderson 1958 Mott 1949 Shklovshii et al 1993 Evangelou 1992

Anderson transition in wave physics: quantum, optics, acoustics, water waves, ...

from analysis of spectral measures for brine, melt ponds, ice floes

we find percolation-driven

Anderson transition for classical transport in composites

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

PERCOLATION TRANSITION



universal eigenvalue statistics (GOE) extended states, mobility edges

-- but with NO wave interference or scattering effects! --

local conductivity in 1D inhomogeneous material

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

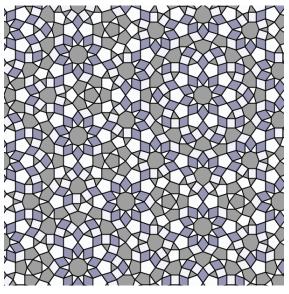
effective conductivity

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

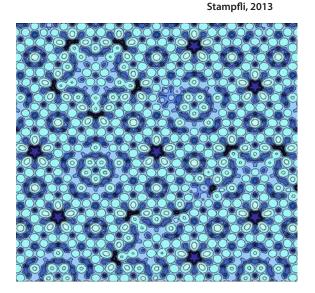
Golden, Goldstein, Lebowitz, Phys. Rev. Lett. 1985

Order to Disorder in Quasiperiodic Composites

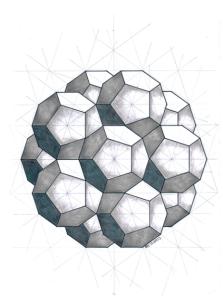
D. Morison (Physics), N. B. Murphy, E. Cherkaev, K. M. Golden, Communications Physics 2022



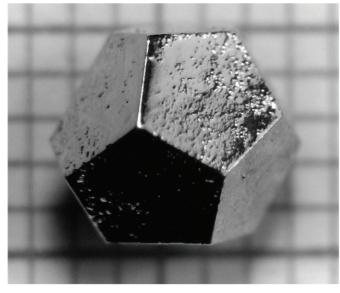
quasiperiodic checkerboard



energy surface Al-Pd-Mn quasicrystal



dense packing of dodecahedra
3D Penrose tiling Tripkovic, 2019



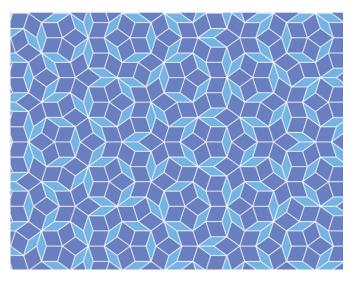
Holmium-magnesium-zinc quasicrystal

quasiperiodic crystal quasicrystal

ordered but aperiodic

lacks translational symmetry

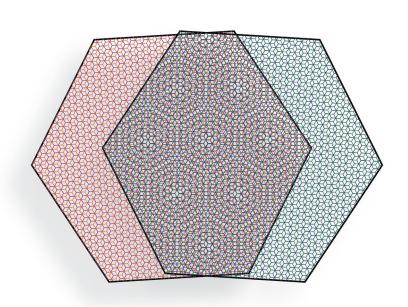
Schechtman et al., 1984 Levine & Steinhardt, 1984

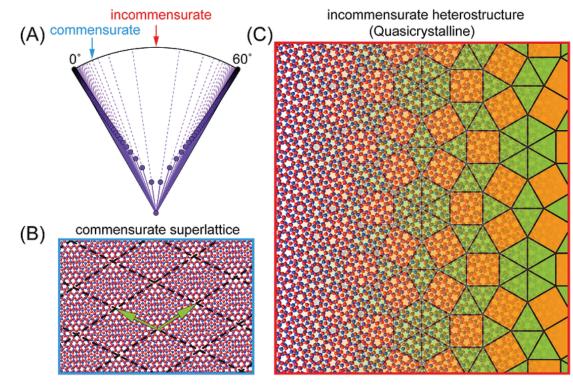


aperiodic tiling of the plane - R. Penrose 1970s

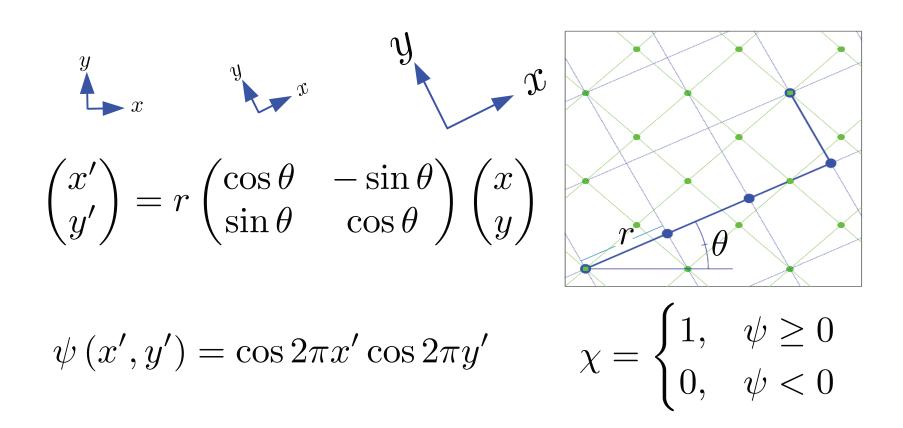
graphene 4° graphene

twisted bilayer graphene





Moiré patterns generate two component composites



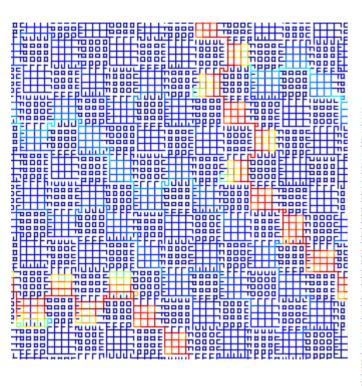
rotation and dilation

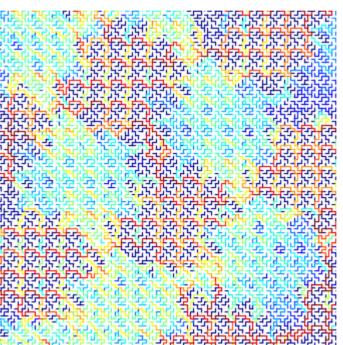
Small Difference in Moiré Parameters

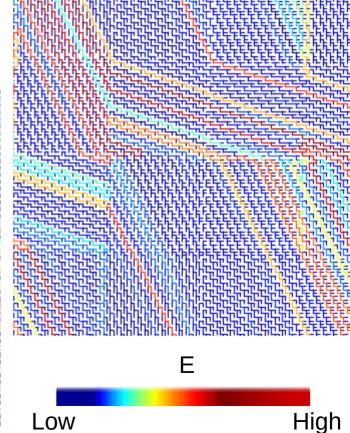


Big Difference in Material Properties

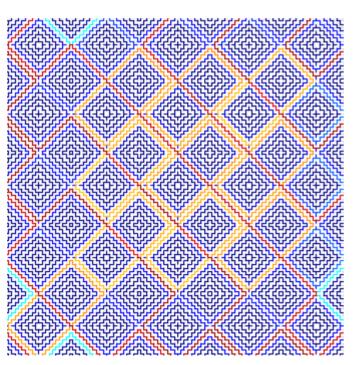
Wide Variety of Microgeometries

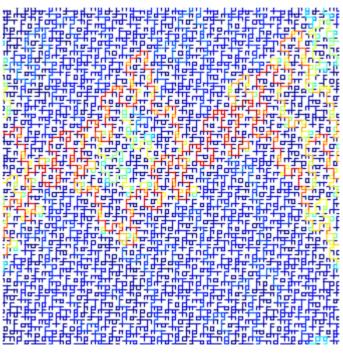


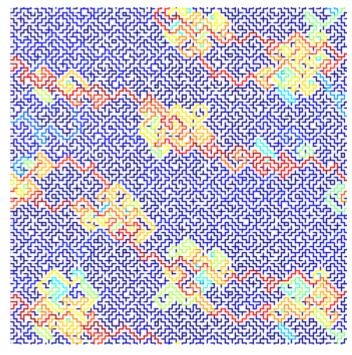




Wide Variety of Microgeometries

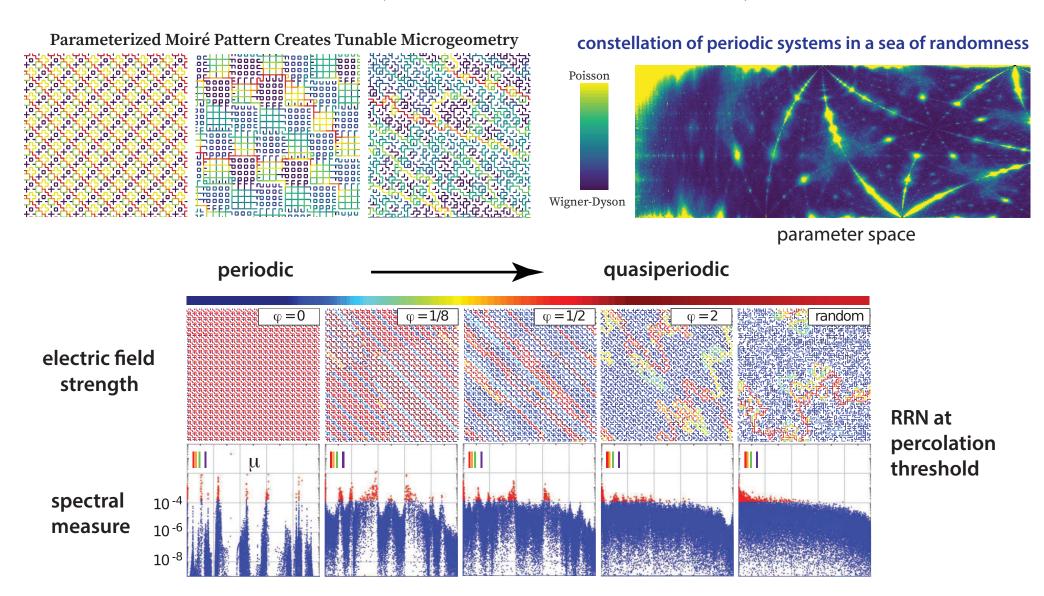






Order to disorder in quasiperiodic composites

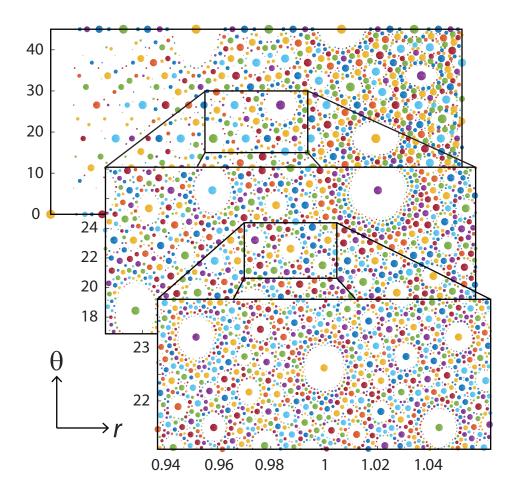
Morison, Murphy, Cherkaev, Golden, Commun. Phys. 2022



we bring the framework of solid state physics of electronic transport and band gaps in semiconductors to classical transport in periodic and quasiperiodic composites

photonic crystals and quasicrystals

Fractal arrangement of periodic systems



Sequential insets zooming into smaller regions of parameter space.

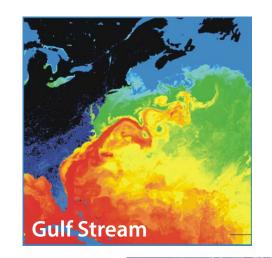
size of the dots ~ length of period

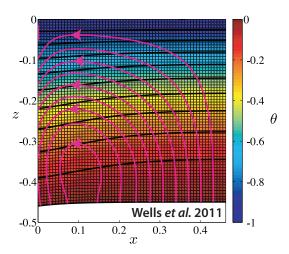
(large dot ~ small period; small dot ~ large period; white space ~ "infinite" period)

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





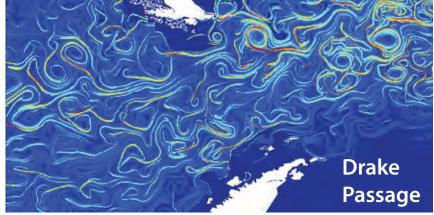
advection diffusion equation with a velocity field $ec{u}$

 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









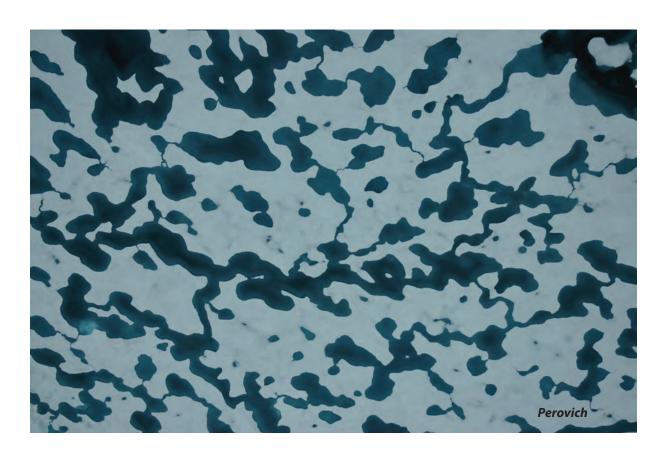
melt pond formation and albedo evolution:

- 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

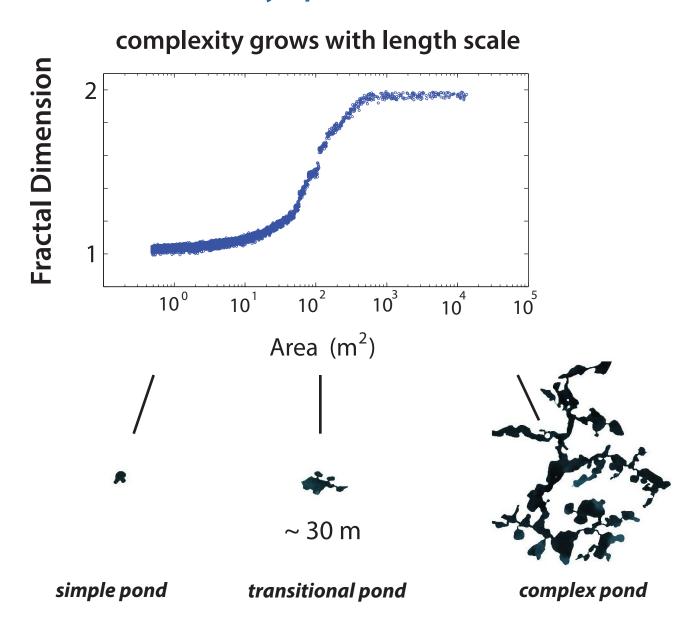


Are there universal features of the evolution similar to phase transitions in statistical physics?

Transition in the fractal geometry of Arctic melt ponds

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

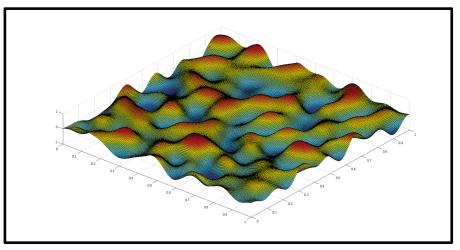
The Cryosphere, 2012

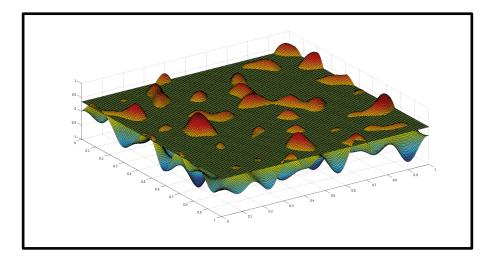


Continuum percolation model for melt pond evolution

level sets of random surfaces

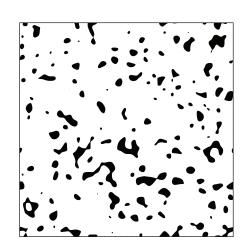
Brady Bowen, Court Strong, Ken Golden, J. Fractal Geometry 2018

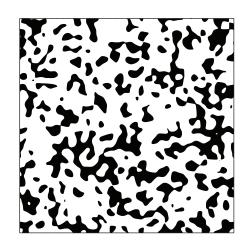


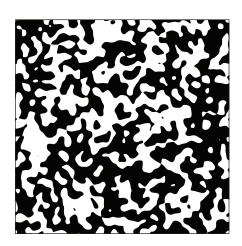


random Fourier series representation of surface topography

intersections of a plane with the surface define melt ponds



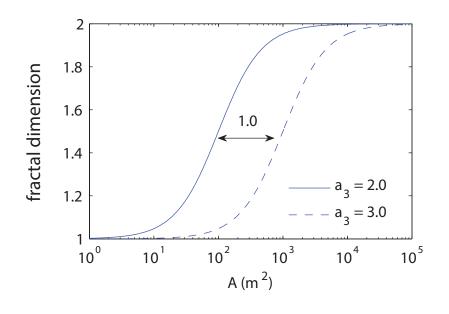


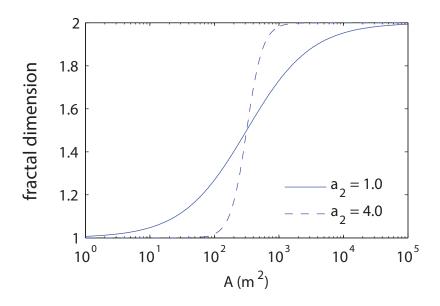


electronic transport in disordered media

diffusion in turbulent plasmas

fractal dimension curves depend on statistical parameters defining random surface





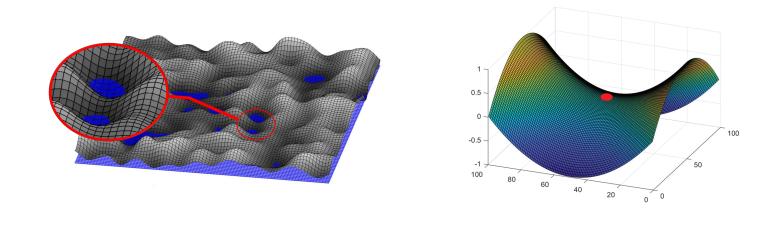
Topology of the sea ice surface and the fractal geometry of Arctic melt ponds

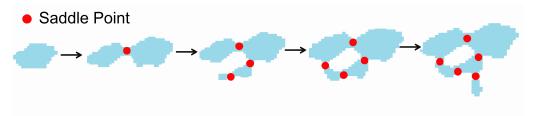
Physical Review Research (invited, under revision)

Ryleigh Moore, Jacob Jones, Dane Gollero, Court Strong, Ken Golden

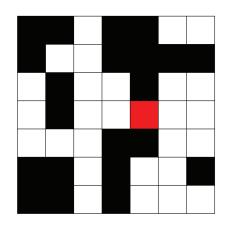
Several models replicate the transition in fractal dimension, but none explain how it arises.

We use Morse theory applied to the random surface model to show that saddle points play the critical role in the fractal transition.

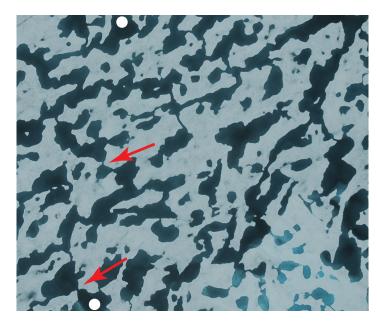




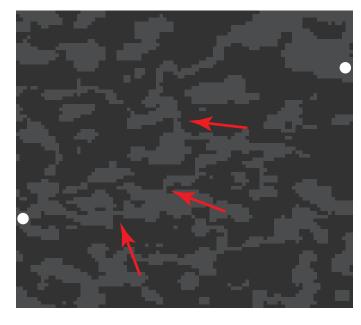
ponds coalesce (change topology) and complexify at saddle points



- Ponds connect through saddle points (Morse Theory).
- Red bonds in lattice percolation theory ~ saddle points.



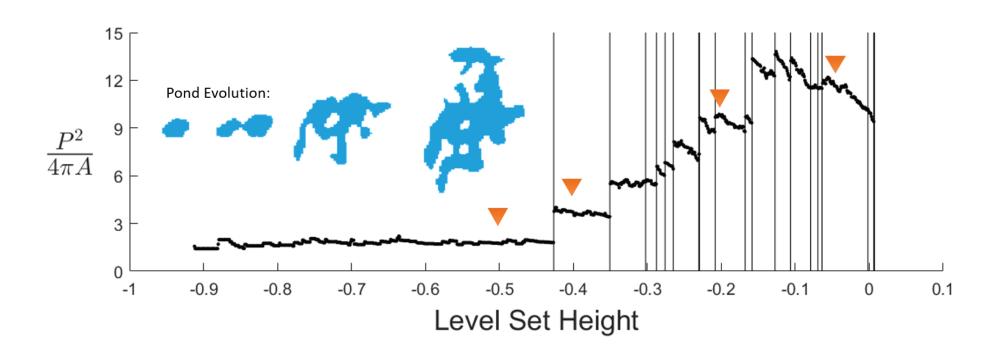
saddles



"red squares"

Main results

Isoperimetric quotient - as a proxy for fractal dimension - increases in discrete jumps when ponds coalesce at saddle points.



Horizontal fluid permeability "controlled" by saddles ~ electronic transport in 2D random potential.

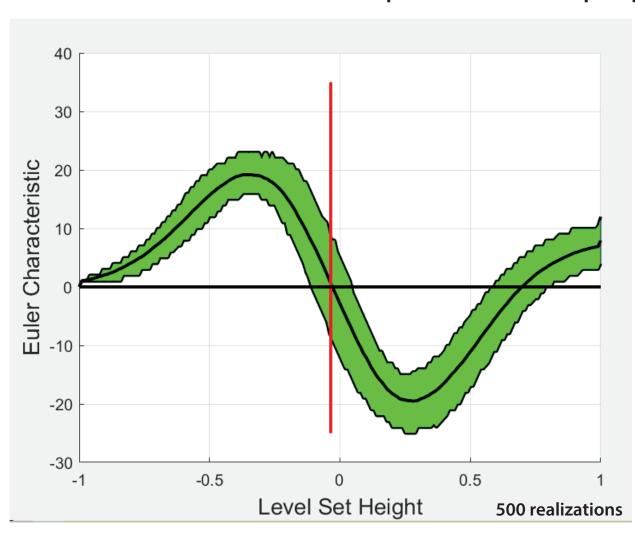
drainage processes, seal holes

Topological Data Analysis

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

persistent homology

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

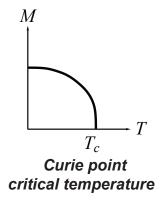
Vogel, 2002 GRF

porous media cosmology brain activity

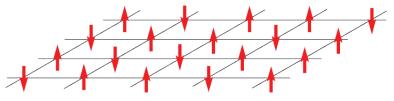
melt pond donuts







Ising Model for a Ferromagnet



$$S_i = \begin{cases} +1 & \text{spin up} \\ -1 & \text{spin down} \end{cases}$$

blue white

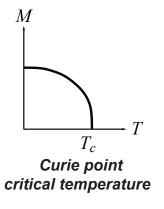
applied magnetic
$$H$$

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

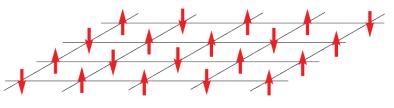
nearest neighbor Ising Hamiltonian

$$M(T, H) = \lim_{N \to \infty} \frac{1}{N} \left\langle \sum_{j} s_{j} \right\rangle$$

effective magnetization



Ising Model for a Ferromagnet



$$S_i = \begin{cases} +1 & \text{spin up} \\ -1 & \text{spin down} \end{cases}$$

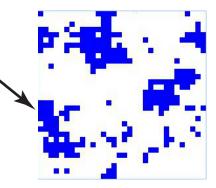
applied magnetic
$$H$$

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

blue

white

islands of like spins

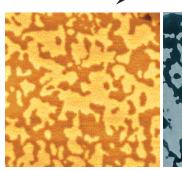


nearest neighbor Ising Hamiltonian

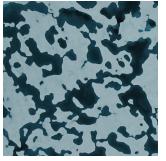
$$M(T, H) = \lim_{N \to \infty} \frac{1}{N} \left\langle \sum_{j} s_{j} \right\rangle$$

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

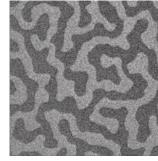
effective magnetization



magnetic domains in cobalt



melt ponds (Perovich)



magnetic domains in cobalt-iron-boron



melt ponds (Perovich)

Ising model for ferromagnets ----- Ising model for melt ponds

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

$$\mathcal{H} = -\sum_{i}^{N} H_{i} \, s_{i} - J \sum_{\langle i,j \rangle}^{N} s_{i} s_{j} \qquad s_{i} = \left\{ \begin{array}{ccc} \uparrow & \text{+1 water (spin up)} \\ \downarrow & -1 & \text{ice (spin down)} \end{array} \right. \quad \text{random magnetic field} \quad \text{represents snow topography}$$

 $\begin{array}{ll} \text{magnetization} & M & \text{pond area fraction} \\ & & \text{\sim albedo} \end{array} \quad F = \frac{(M+1)}{2} \quad \begin{array}{ll} \text{only nearest neighbor} \\ \text{patches interact} \end{array}$

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 for ferromagnets ----- Ising model for melt ponds

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

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

random magnetic field represents snow topography

magnetization M

model

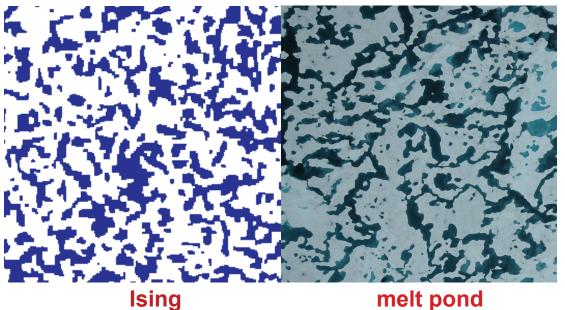
pond area fraction $F = \frac{(M+1)}{2}$

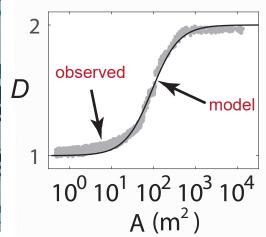
$$F = \frac{(M+1)}{2}$$

only nearest neighbor patches interact

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

Order from Disorder





pond size distribution exponent

observed -1.5

(Perovich, et al. 2002)

-1.58 model

EOS, PhysicsWorld, ...

Scientific American photo (Perovich)

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



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

WINDOWS

Have we crossed into a new ecological regime?

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

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

no bloom bloom massive under-ice algal bloom

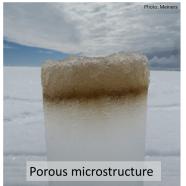
Arrigo et al., Science 2012

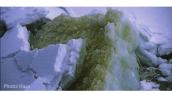
The effect of melt pond geometry on the distribution of solar energy under first year sea ice

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

(2015 AMS MRC)

SEA ICE ALGAE

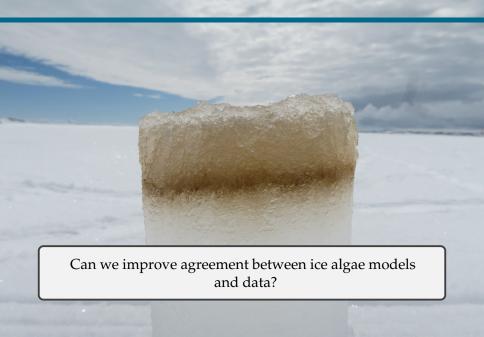






80% of polar bear diet can be traced to ice algae*.

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



ALGAL BLOOM MODEL*

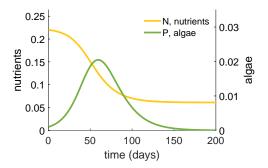
nutrients:
$$\frac{dN}{dt} = \underbrace{\alpha}_{\text{input}} - \underbrace{\beta NP}_{\text{uptake}} - \underbrace{\eta N}_{\text{loss}}$$

$$\text{algae:} \qquad \frac{dP}{dt} = \underbrace{\gamma \beta NP}_{\text{growth}} - \underbrace{\delta P}_{\text{death}},$$

$$N(0) = n_0, \qquad P(0) = p_0$$

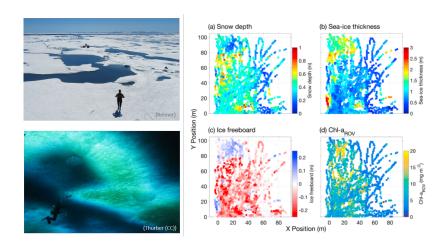
^{*}Huppert, A., et al. (2002). American Naturalist, 159(2), 156-171

ALGAL BLOOM MODEL



- poor agreement with data
- poor agreement between models

HETEROGENEITY



HETEROGENEITY IN INITIAL CONDITIONS

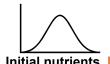
At each location within a larger region, we could consider

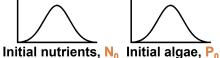
$$\frac{dN}{dt} = \alpha - BNP - \eta N$$

$$\frac{dP}{dt} = \gamma BNP - \delta P$$

$$N(0) = N_0, \qquad P(0) = P_0$$

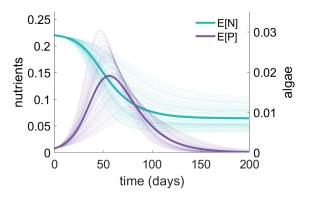






HOW DO WE ANALYZE THIS MODEL?

Monte Carlo simulations?



Too slow! Full algae model takes **8 hours** (cloud computing).

Uncertainty quantification and ecological dynamics in a model of a sea ice algae bloom, in prep. 2022

Jody Reimer, Fred Adler, Ken Golden, and Akil Narayan

POLYNOMIAL CHAOS EXPANSIONS

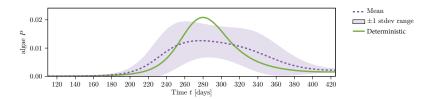
$$N(t; B, P_0, N_0) \approx N_V(t; B, P_0, N_0) := \sum_{j=1}^n \widetilde{N}_j(t) \phi_j(B, P_0, N_0),$$

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

where

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

ECOLOGICAL INSIGHTS



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

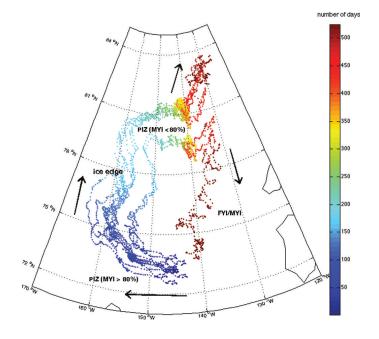
macroscale

Anomalous diffusion in sea ice dynamics

Ice floe diffusion in winds and currents

observations from GPS data:

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



- On short time scales floes observed (buoy data) to exhibit Brownian-like behavior, but they are also being advected by winds and currents.
- Effective behavior is purely diffusive, sub-diffusive or super-diffusive depending on ice pack and advective conditions Hurst exponent.

modeling:

Huy Dinh, Ben Murphy, Elena Cherkaev, Court Strong, Ken Golden 2022 floe scale model to analyze transport regimes in terms of ice pack crowding, advective conditions

Delaney Mosier, Jennifer Hutchings, Jennifer Lukovich, Marta D'Elia, George Karniadakis, Ken Golden 2022

learning fractional PDE governing diffusion from data

Floe Scale Model of Anomalous Diffusion in Sea Ice Dynamics

Huy Dinh, Ben Murphy, Elena Cherkaev, Court Strong, Ken Golden 2022

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

 $\alpha = \text{Hurst exponent}$

diffusive $\alpha = 1$

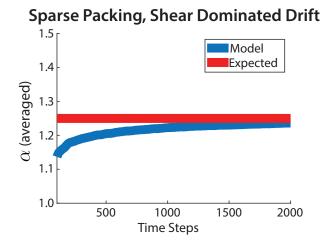
sub-diffusive $\alpha < 1$

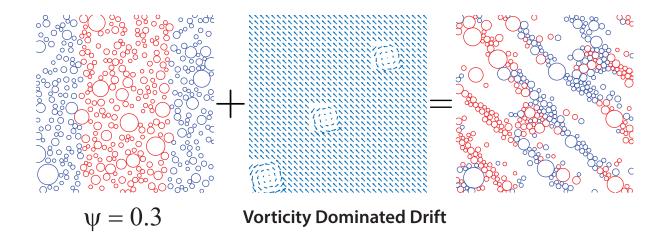
super-diffusive $\alpha>1$

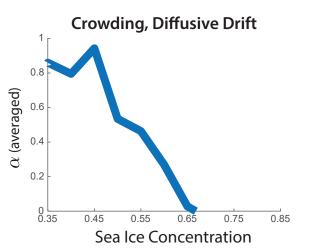
Model Approximations

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



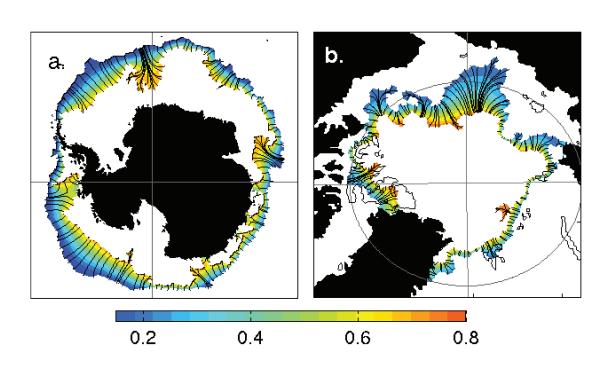




Marginal Ice Zone

MIZ

- biologically active region
- intense ocean-sea ice-atmosphere interactions
- region of significant wave-ice interactions



transitional region between dense interior pack (c > 80%) sparse outer fringes (c < 15%)

MIZ WIDTH

fundamental length scale of ecological and climate dynamics

Strong, *Climate Dynamics* 2012 Strong and Rigor, *GRL* 2013 How to objectively measure the "width" of this complex, non-convex region?

Objective method for measuring MIZ width motivated by medical imaging and diagnostics

Strong, *Climate Dynamics* 2012 Strong and Rigor, *GRL* 2013 39% widening 1979 - 2012

streamlines of a solution to Laplace's equation

"average" lengths of streamlines

MIZ pack ice

0.7 0.6 0.5 0.4 0.3 0.2 Length 4×10^{-3} 3×10^{-3} 2×10^{-3} 1×10^{-3} 0

Arctic Marginal Ice Zone

crossection of the cerebral cortex of a rodent brain

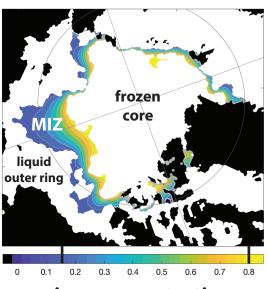
analysis of different MIZ WIDTH definitions

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

Strong and Golden
Society for Industrial and Applied Mathematics News, April 2017

Model larger scale effective behavior with partial differential equations that homogenize complex local structure and dynamics.

Arctic MIZ



sea ice concentration ψ

Predict MIZ width and location with basin-scale phase change model.

dynamic transitional region - mushy layer - separating two "pure" phases

seasonal and long term trends

C. Strong, E. Cherkaev, and K. M. Golden, Annual cycle of Arctic marginal ice zone location and width explained by phase change front model, 2022

Learning the velocity field in an advection diffusion model for sea ice concentration

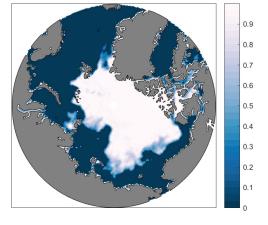
Eric Brown, Delaney Mosier, Bao Wang, Ken Golden, 2022

Goal: Develop PDE model to describe evolution of sea ice concentration field.

advection diffusion model for sea ice concentration:

$$\frac{\partial \psi}{\partial t} = -\mathbf{v} \cdot \nabla \psi + k \Delta \psi$$

Use two-layer neural network to infer advective fields based on satellite imagery



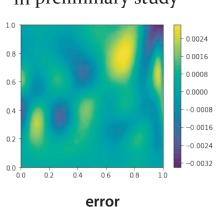
National Snow and Ice Data Center

initital test concentation predicted concentation

discretized satellite concentration data

Figure 1. Arctic sea ice concentration in early August 2012.

2.5% absolute error in preliminary study

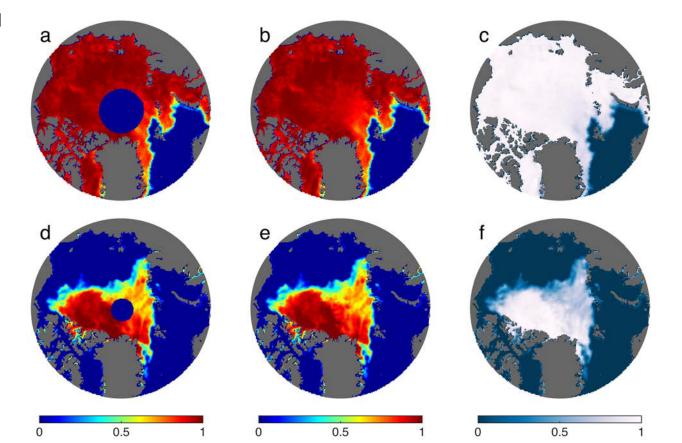


Filling the polar data gap with partial differential equations

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



fill = harmonic function with learned stochastic term

Strong and Golden, *Remote Sensing* 2016 Strong and Golden, *SIAM News* 2017 NOAA/NSIDC Sea Ice Concentration CDR product update will use our PDE method.

Conclusions

- 1. Sea ice is a fascinating multiscale composite with structure similar to many other natural and man-made materials.
- 2. Mathematical methods developed for sea ice advance theories of composites and inverse problems in science and engineering.
- 3. Homogenization and statistical physics help *link scales in sea ice* and composites; provide rigorous methods for finding effective behavior; advance sea ice representations in climate models.
- 4. Inverse problems of many types arise naturally in studying sea ice and the impact of climate change in Earth's polar regions.
- 5. Field experiments are essential to developing relevant mathematics.
- 6. Our research is helping to improve projections of climate change, the fate of Earth's sea ice packs, and the ecosystems they support.

University of Utah Sea Ice Modeling Group (2017-2021)

Senior Personnel: Ken Golden, Distinguished Professor of Mathematics

Elena Cherkaev, Professor of Mathematics

Court Strong, Associate Professor of Atmospheric Sciences

Ben Murphy, Adjunct Assistant Professor of Mathematics

Postdoctoral Researchers: Noa Kraitzman (now at ANU), Jody Reimer

Graduate Students: Kyle Steffen (now at UT Austin with Clint Dawson)

Christian Sampson (now at UNC Chapel Hill with Chris Jones)

Huy Dinh (now a sea ice MURI Postdoc at NYU/Courant)

Rebecca Hardenbrook

David Morison (Physics Department)

Ryleigh Moore

Delaney Mosier

Daniel Hallman

Undergraduate Students: Kenzie McLean, Jacqueline Cinella Rich,

Dane Gollero, Samir Suthar, Anna Hyde,

Kitsel Lusted, Ruby Bowers, Kimball Johnston,

Jerry Zhang, Nash Ward, David Gluckman

High School Students: Jeremiah Chapman, Titus Quah, Dylan Webb

Sea Ice Ecology Group

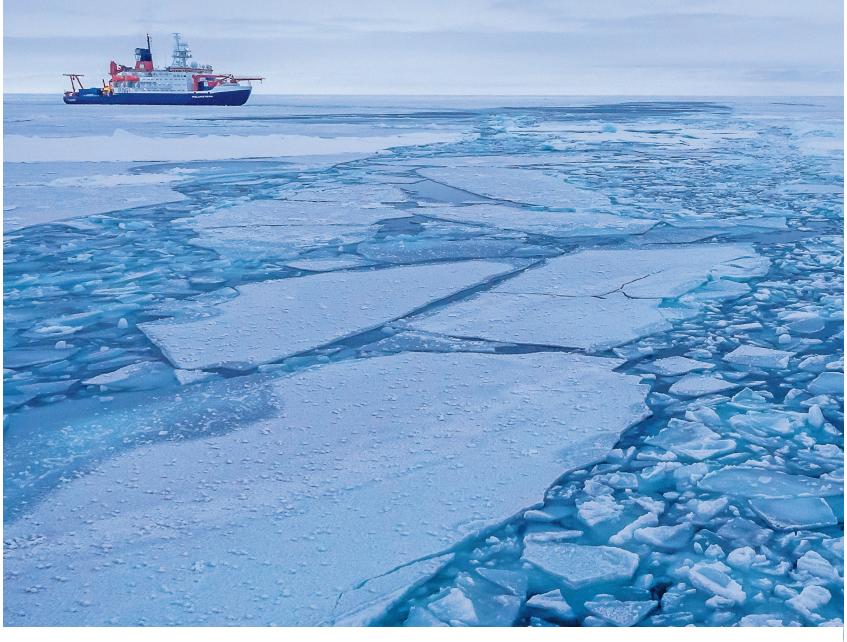
Postdoc Jody Reimer, Grad Student Julie Sherman, Undergraduates Kayla Stewart, Nicole Forrester

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National Science Foundation

Division of Mathematical Sciences

Division of Polar Programs

















