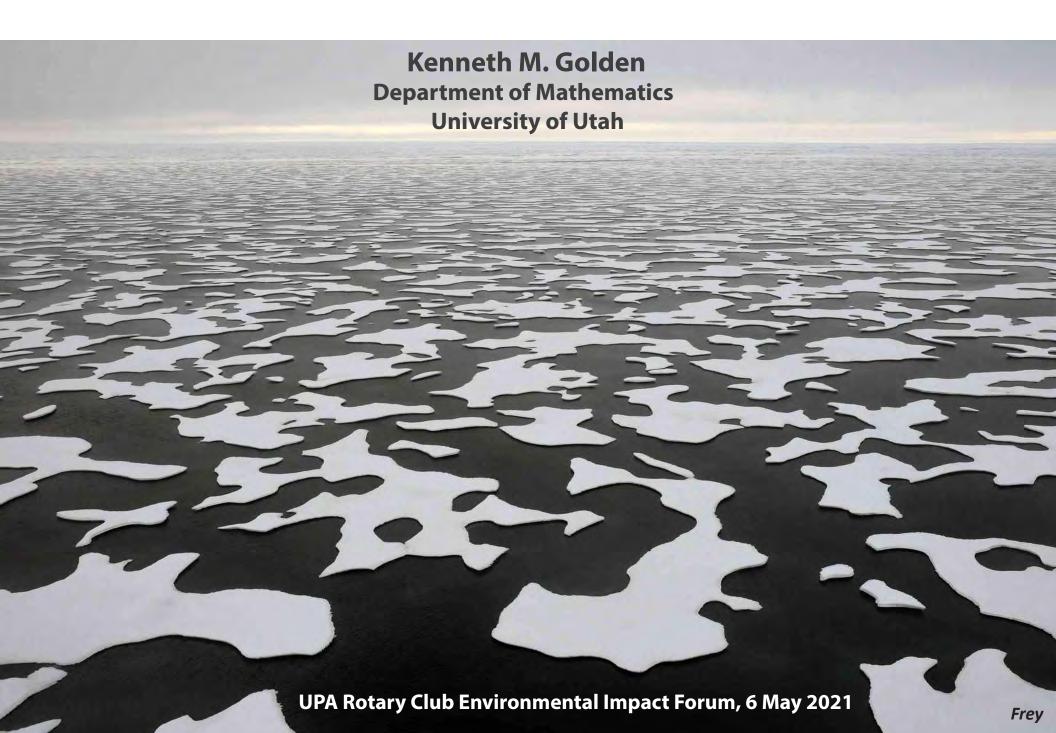
On Thinning Ice: Modeling Sea Ice in a Warming Climate

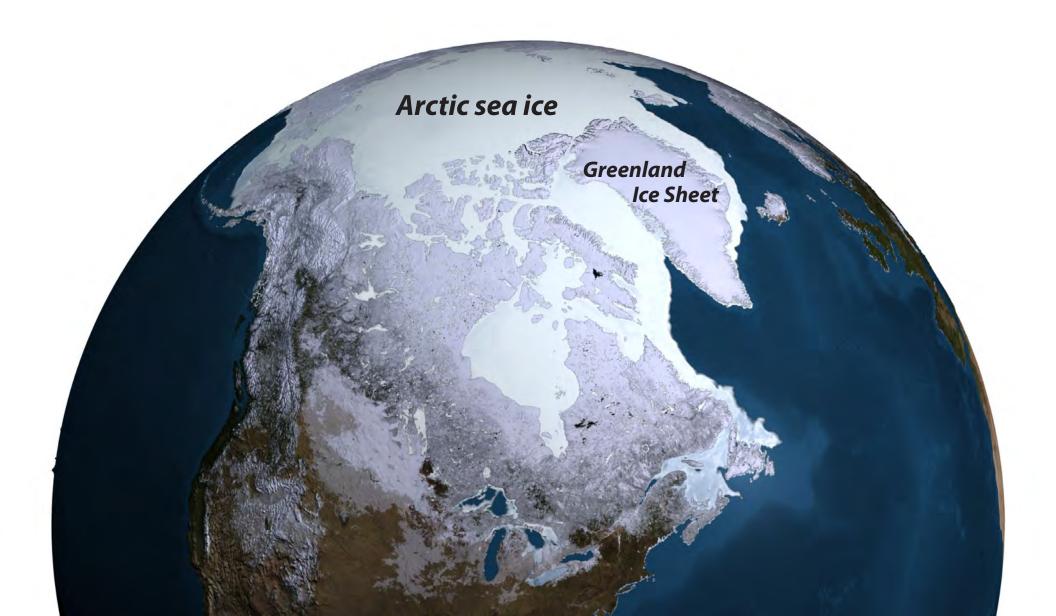


ANTARCTICA

southern cryosphere



northern cryosphere

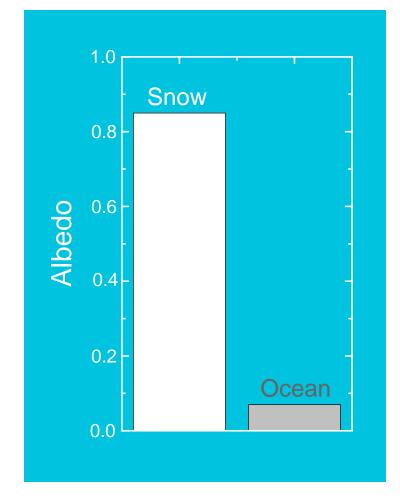




polar ice caps critical to global climate in reflecting incoming solar radiation

white snow and ice reflect



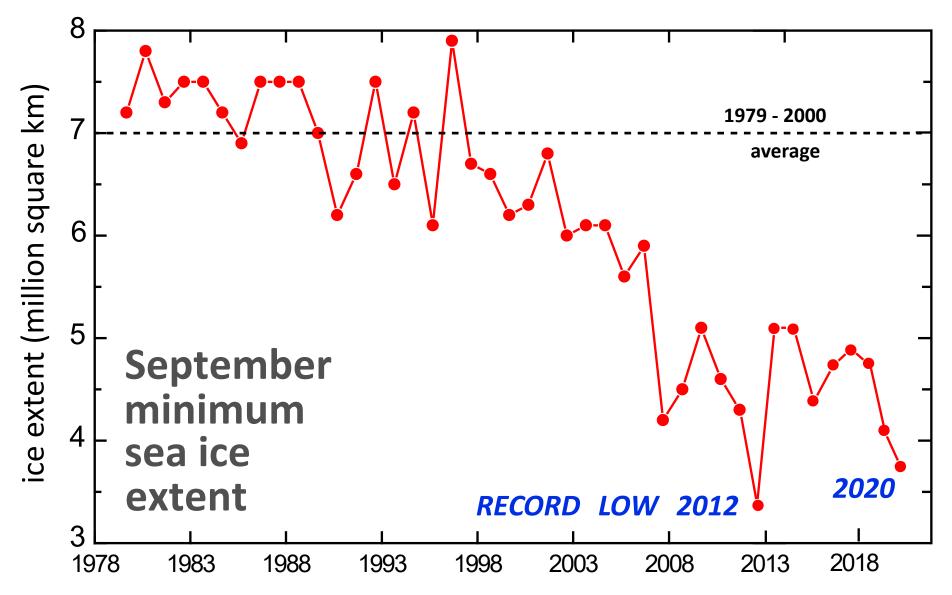




dark water and land absorb

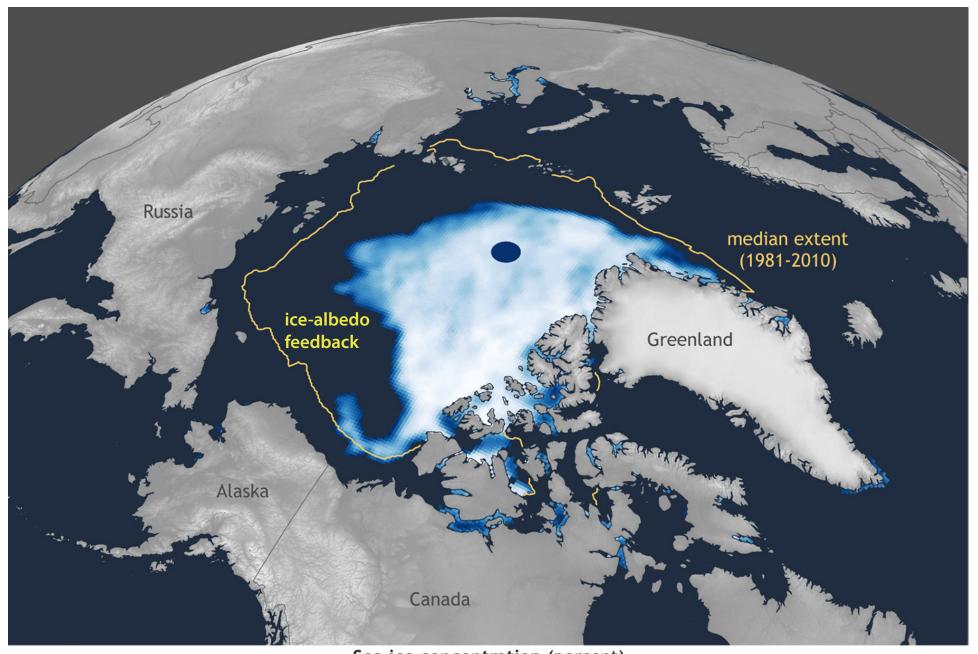
albedo
$$\alpha = \frac{\text{reflected sunlight}}{\text{incident sunlight}}$$

the summer Arctic sea ice pack is melting



Arctic sea ice extent

September 15, 2020



Sea ice concentration (percent)

NSIDC

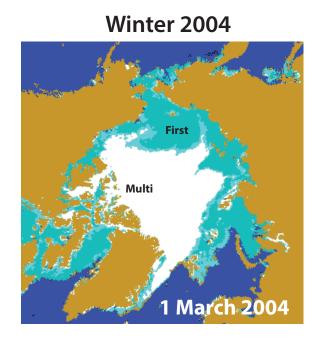
15 100



recent losses in comparison to the United States

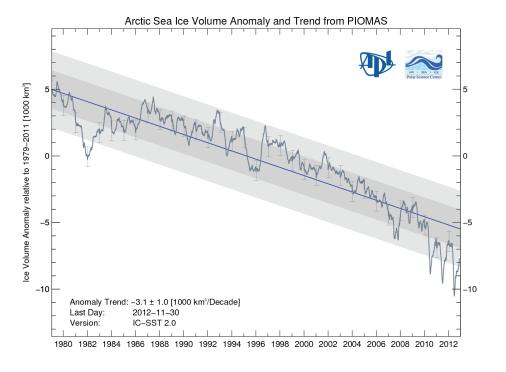


thicker multiyear ice being replaced by thinner first year ice



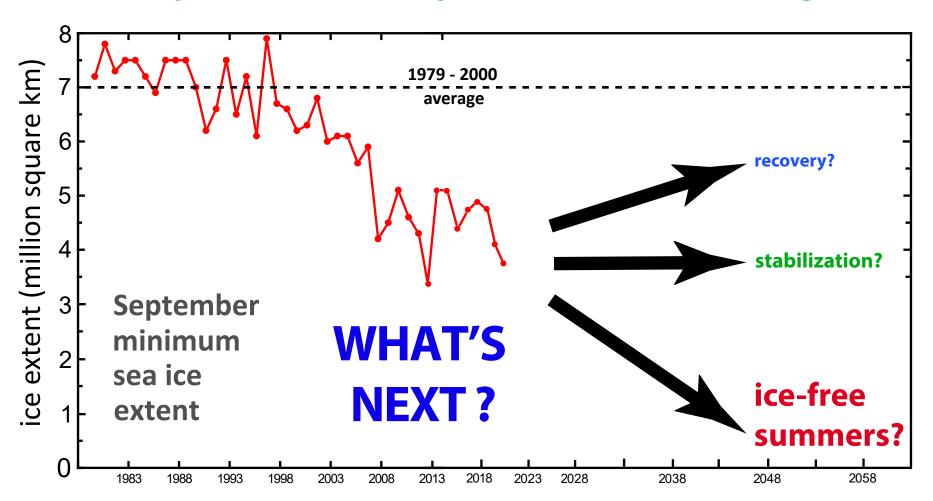


Son Nghiem



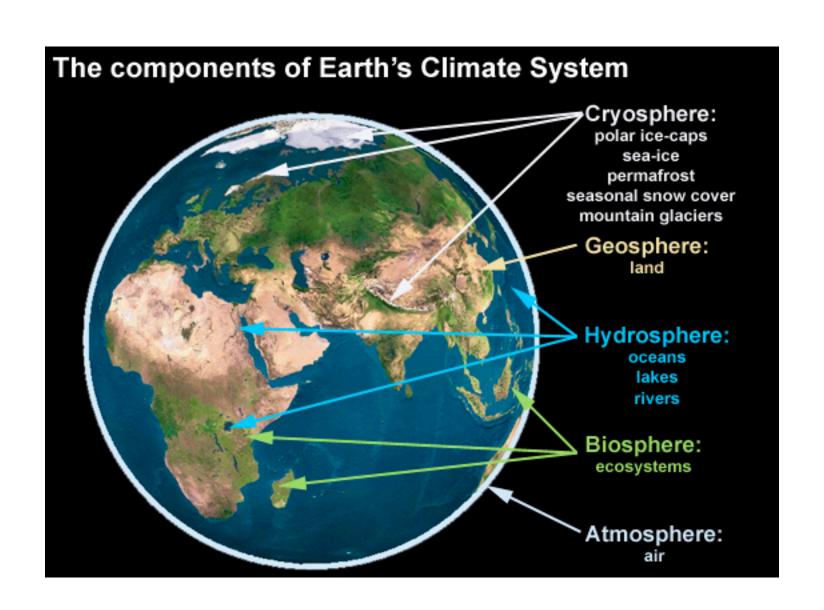
... and sea ice volume is declining

Predicting what may come next requires lots of math modeling.



Basics of climate modeling and planetary warming

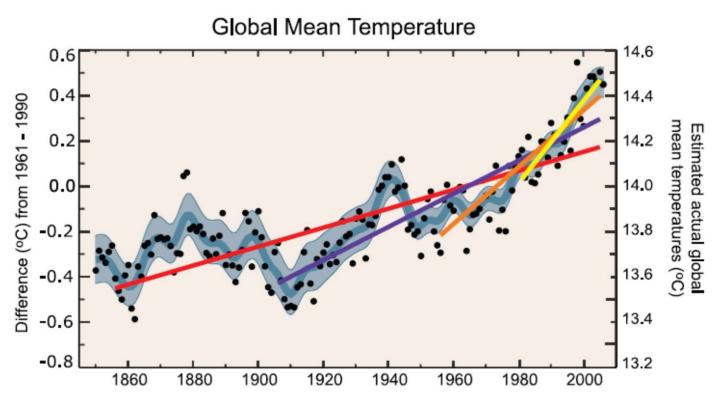






Evidence of a Changing Climate

Intergovernmental Panel on Climate Change (IPCC): Warming is "unequivocal"



Dots: yearly average

Curve: decadal average Blue: uncertainty interval



IPCC: Warming is "unequivocal"

Global mean surface temp

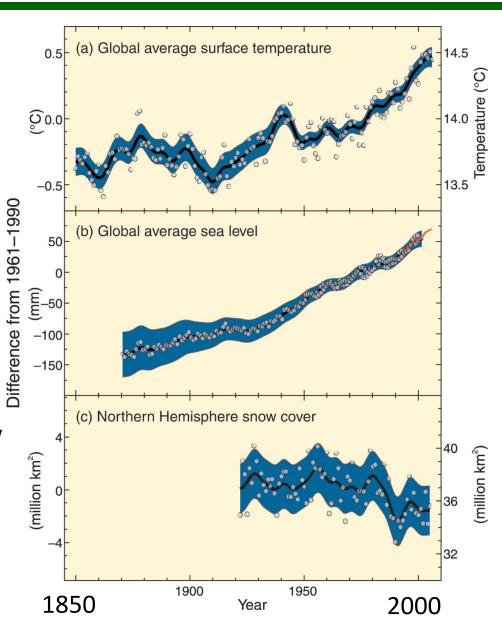
Global mean sea level

Northern Hemisphere snow cover (March-April)

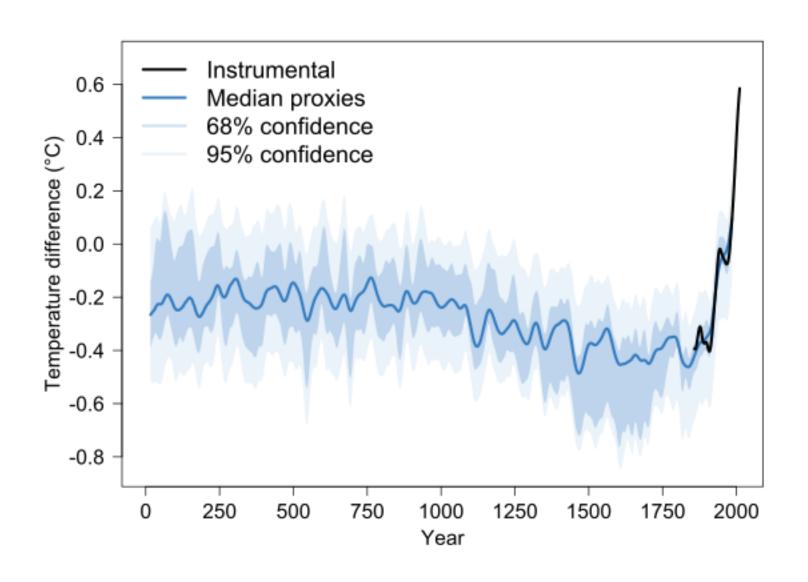
Dots: yearly average

Curve: decadal average

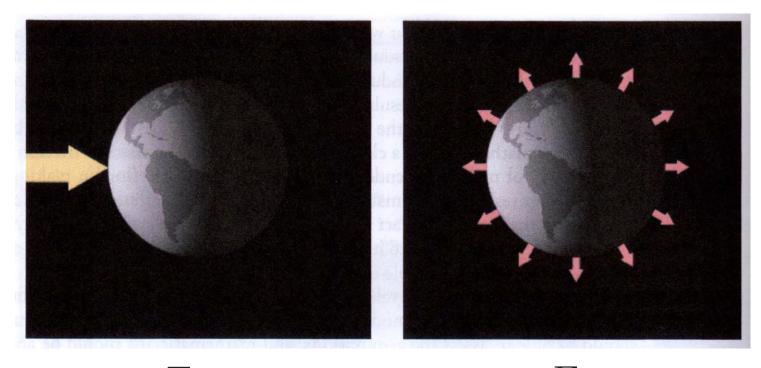
Blue: uncertainty interval



Mean Global Temperature over the past 2000 years



Earth's energy balance



 $E_{in} \\ \\ \text{incoming shortwave radiation} \\ \\ \text{sunlight} \\$

 $E_{out} \\ \\ \text{outgoing longwave radiation} \\ \\ \text{heat} \\$

if
$$E_{out}$$
 > E_{in} planet cools if E_{out} < E_{in} planet warms

albedo of Earth's surface

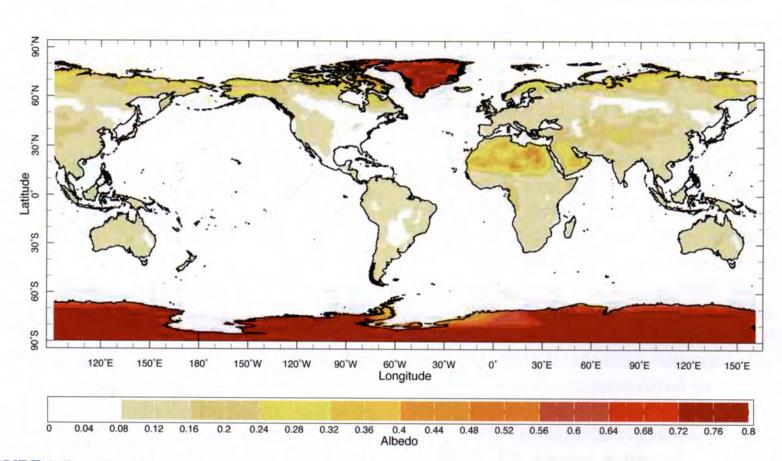


FIGURE 2.5. The albedo of the Earth's surface. Over the ocean the albedo is small (2–10%). It is larger over the land (typically 35–45% over desert regions) and is particularly high over snow and ice (\sim 80%) (see Table 2.2).

average albedo ~ 0.3

Energy Balance Model

$$C\frac{dT}{dt} = E_{in} - E_{out}$$



rate of change with time of mean global temperature

C = heat capacity = energy needed to raise temperature by one Kelvin

$$E_{in} = ?$$

$$E_{out} = ?$$

Basics of global warming date back to the 1800's



HEAT EQUATION FOURIER SERIES

1. Jean Baptiste Joseph Fourier (1768-1830), French mathematician and natural philosopher, did groundbreaking work in mathematics and the theory of heat. He was the first to propose that the Earth's atmosphere acts to raise the planet's temperature.

"As a dam built across a river causes a local deepening of the stream, so our atmosphere, thrown as a barrier across the terrestrial rays, produces a local heightening of the temperature at the Earth's surface."

atmosphere traps heat escaping from Earth - acts like a greenhouse

Fourier, 1827

2. 1861 John Tyndall discovers in his laboratory that certain gases - water vapor and CO2 are opaque to heat rays. He understood that such gases high in the air help keep our planet warm by interfering with escaping radiation.

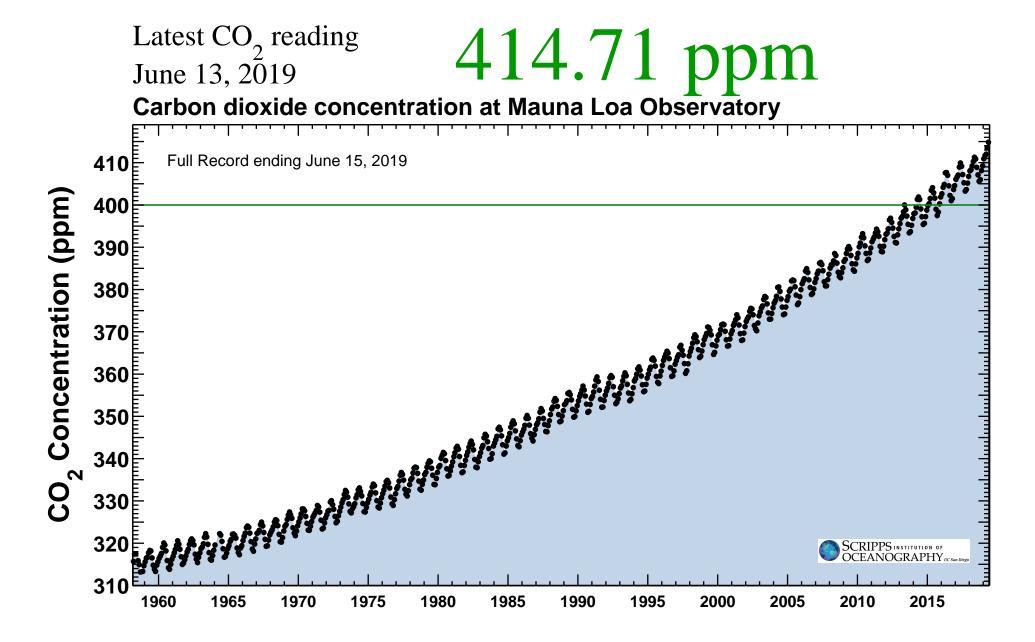
3. 1896 Svante Arrhenius (1903 Nobel Prize in Chemistry) proposed: relationship between atmospheric CO2 concentrations and temperature;

global warming may result from fossil fuel combustion (burning coal).

He and Thomas Chamberlin calculated that human activities could warm the earth by adding carbon dioxide to the atmosphere.

In a nutshell:

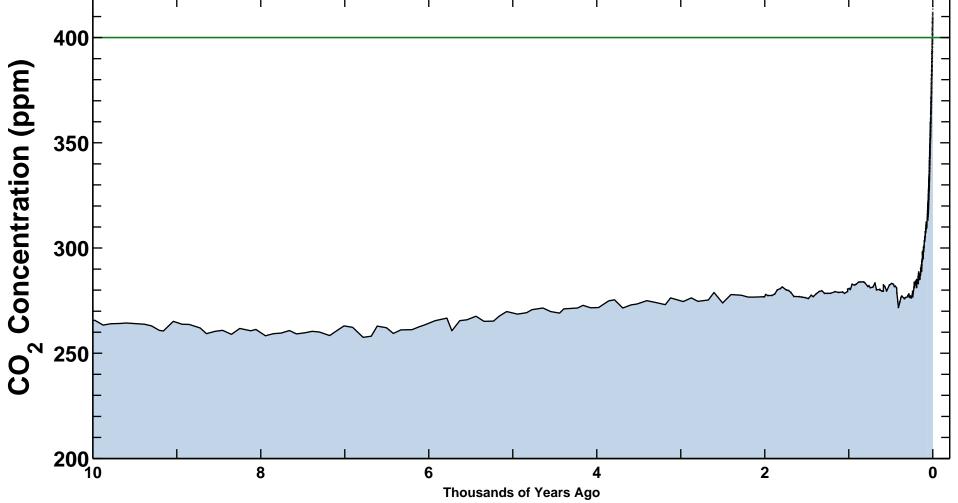
Scientific basis of CO2 greenhouse effect was given by Tyndall (1861); while the first extensive calculations of its magnitude were made by Arrhenius (1896).



Latest CO₂ reading June 13, 2019

414.71 ppm

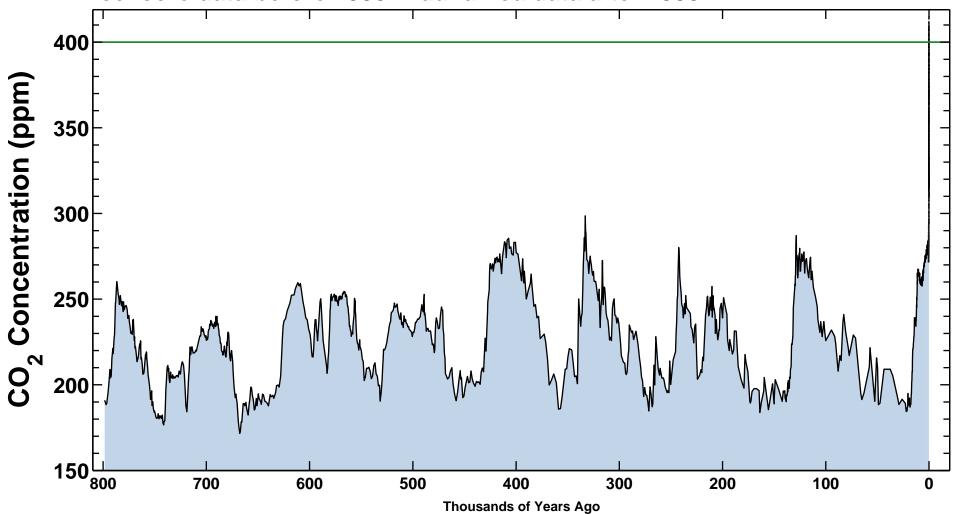
Ice-core data before 1958. Mauna Loa data after 1958.

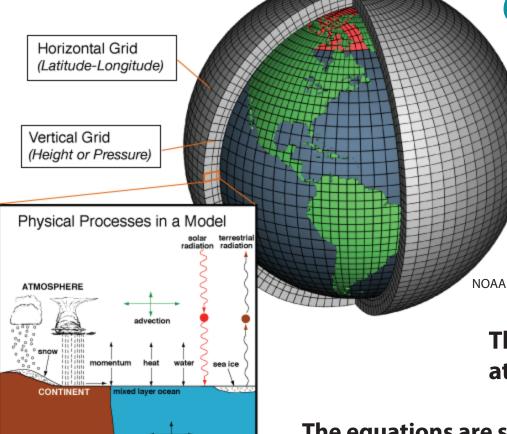


Latest CO₂ reading June 13, 2019

414.71 ppm

Ice-core data before 1958. Mauna Loa data after 1958.





Global Climate Models

climate fueled by the nonuniform spatial distribution of incoming solar radiation.

Stute et al., PNAS 2001

Climate models are systems of partial differential equations (PDE) derived from the basic laws of physics, chemistry, and fluid motion.

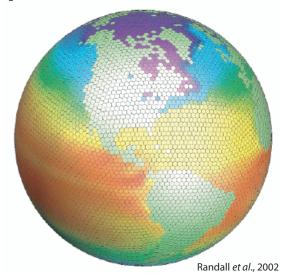
They describe the state of the ocean, land, ice atmosphere, biosphere, and their interactions.

The equations are solved on 3-dimensional grids of the air-ice-ocean-land system (with horizontal grid size ~ 100 km), using very powerful computers.

key challenge:

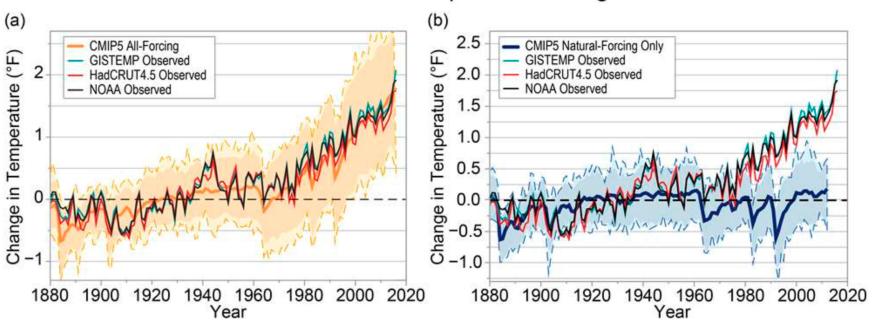
incorporating sub - grid scale processes

linking scales



Human influence dominant

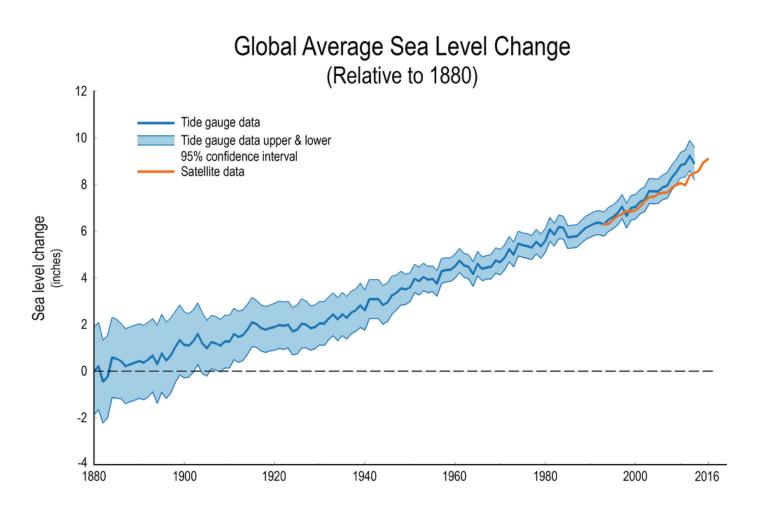
Global Mean Temperature Change



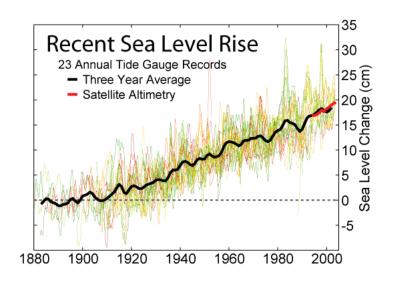
- We cannot explain observed warming without including effects of anthropogenic greenhouse gas emissions
- Observed temperature curve reproduced reasonably well only when taking into consideration all forcing factors

Why is sea level rising?

(melting sea ice does not directly impact rising sea level)



As Earth's climate warms, why does sea level rise?





- melting land ice: Antarctica, Greenland, mountain glaciers (if all melted: 70 m or ~230 ft of sea level rise)
- thermal expansion of warming ocean

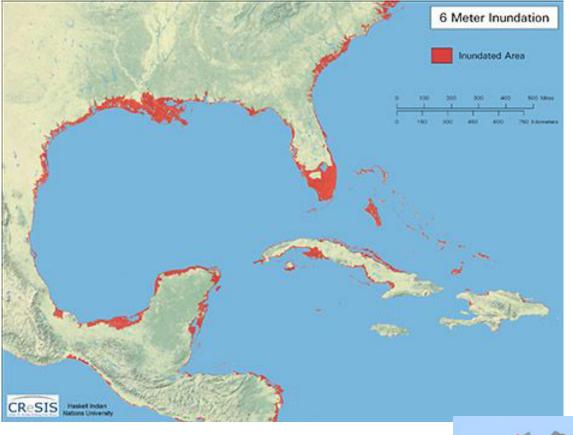
 accounts for about 25% of rise in last half of 20th century, rate ~ tripled in 21st century
- continental rebound

rise of land masses that were depressed by the huge weight of ice sheets



The interaction of warm waters with the periphery of the large ice sheets represents one of the most significant possibilities for abrupt change in the climate sysytem.

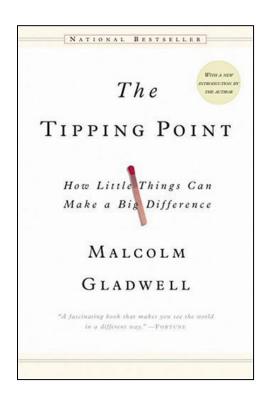
no coupling yet of ice sheets and ocean in climate models - no feedback effects





tipping points in the mainstream

Increasing emphasis in recent years on idea of climate tipping points, with September Arctic sea ice cover receiving much of the attention.







Melting of the Greenland ice sheet

Melting of the West Antarctic ice sheet

Permafrost and tundra loss, leading to the release of methane

Formation of Atlantic deep water near the Arctic ocean

•••

opposite "pole" from GCM's

active area of mathematical research on sea ice:

Has Arctic sea ice loss passed through a "tipping point"?

an irreversible downward slide to ice-free Arctic summers, driven by ice-albedo feedback

Eisenman, Wettlaufer, PNAS 2009:

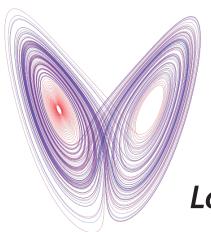
analyze a single nonlinear differential equation for the energy in the upper ocean

look for "bifurcations" in solutions

- unlikely in current loss of summer ice
- more likely in further loss of winter ice

Abbot, Silber, Pierrehumbert, JGR 2011:

bifurcations when include clouds and ice loss



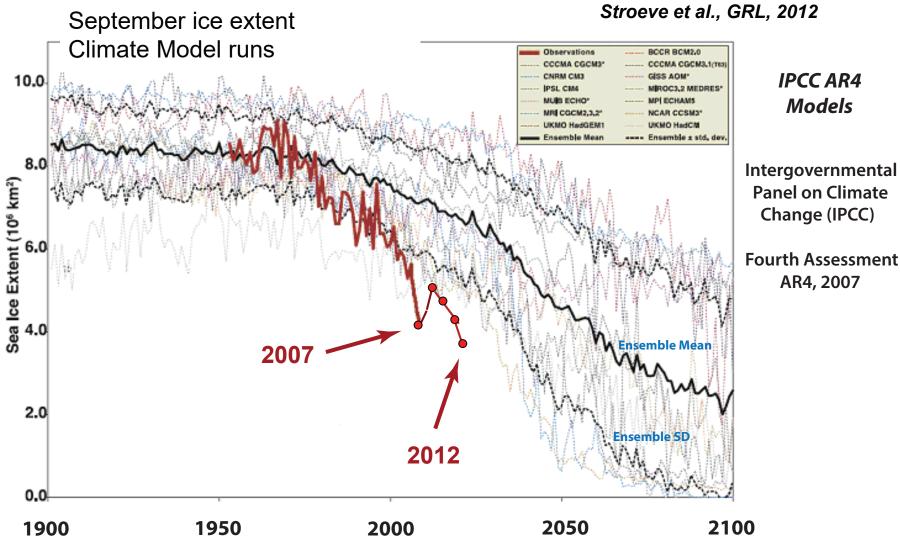
low order (toy) model of Arctic climate change

Lorenz butterfly

dynamical systems

Arctic sea ice decline: faster than predicted by climate models

Stroeve et al., GRL, 2007 Stroeve et al., GRL, 2012

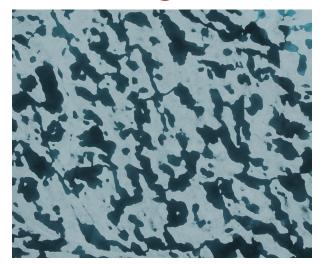


challenge:

Represent sea ice more realistically in climate models to improve projections.



How do patterns of dark and light evolve?



Account for key processes

e.g. melt pond evolution

Including PONDS in simulations LOWERS predicted sea ice volume over time by 40%.

Flocco, Schroeder, Feltham, Hunke, JGR Oceans 2012

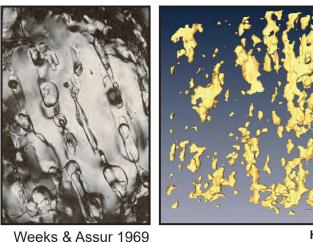
... and other sub-grid scale structures and processes.

linkage of scales

Sea Ice is a Multiscale Composite Material

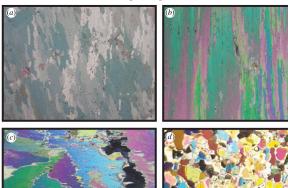
microscale

brine inclusions



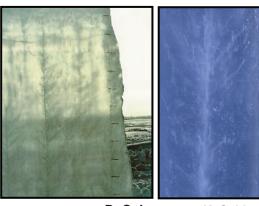
H. Eicken Golden et al. GRL 2007

polycrystals



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

brine channels



D. Cole K. Golden

millimeters

centimeters

mesoscale

Arctic melt ponds

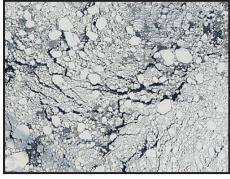


Antarctic pressure ridges





sea ice floes



sea ice pack

J. Weller

NASA

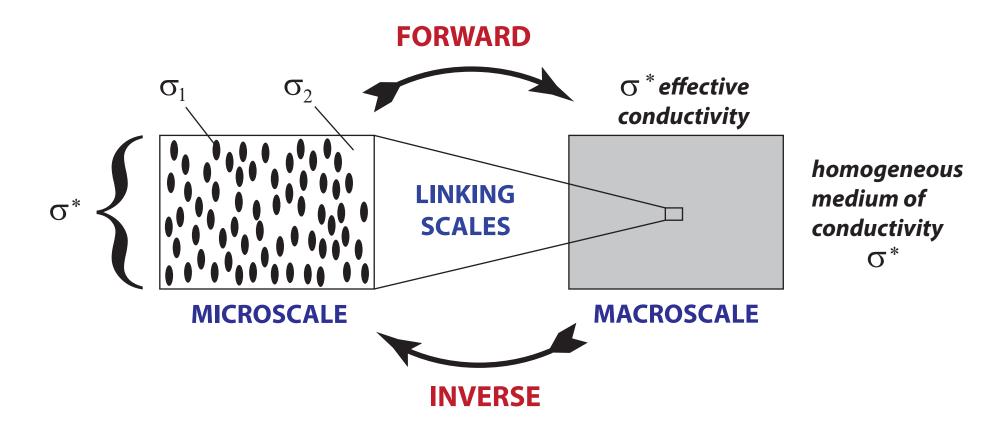
K. Golden

meters

kilometers

macroscale

HOMOGENIZATION for Composite Materials



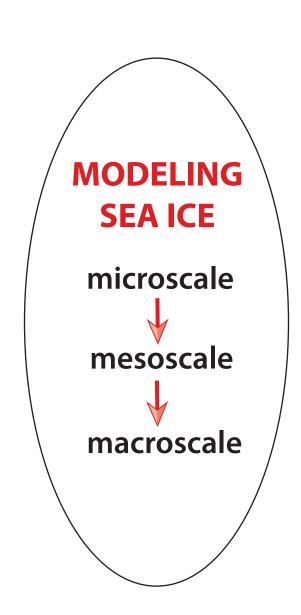
Maxwell 1873: effective conductivity of a dilute suspension of spheres Einstein 1906: effective viscosity of a dilute suspension of rigid spheres in a fluid

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

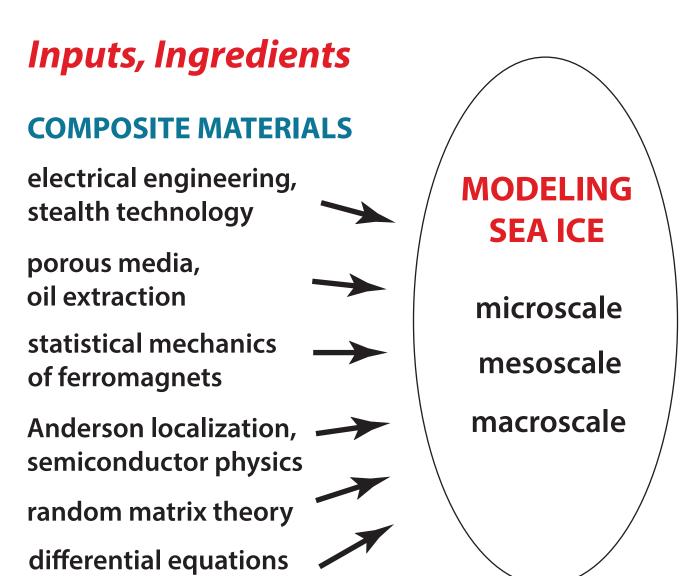
What is our research about?

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



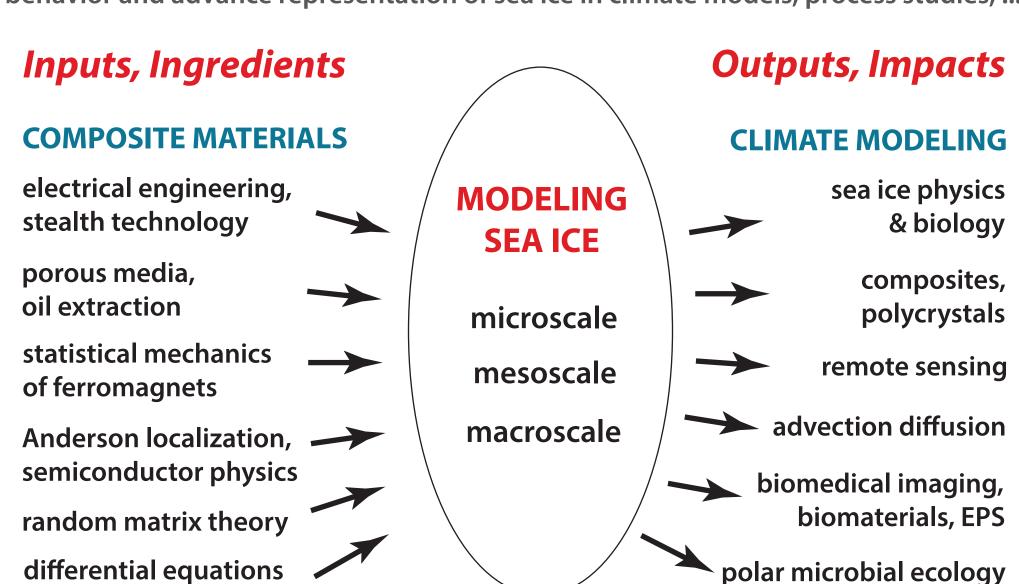
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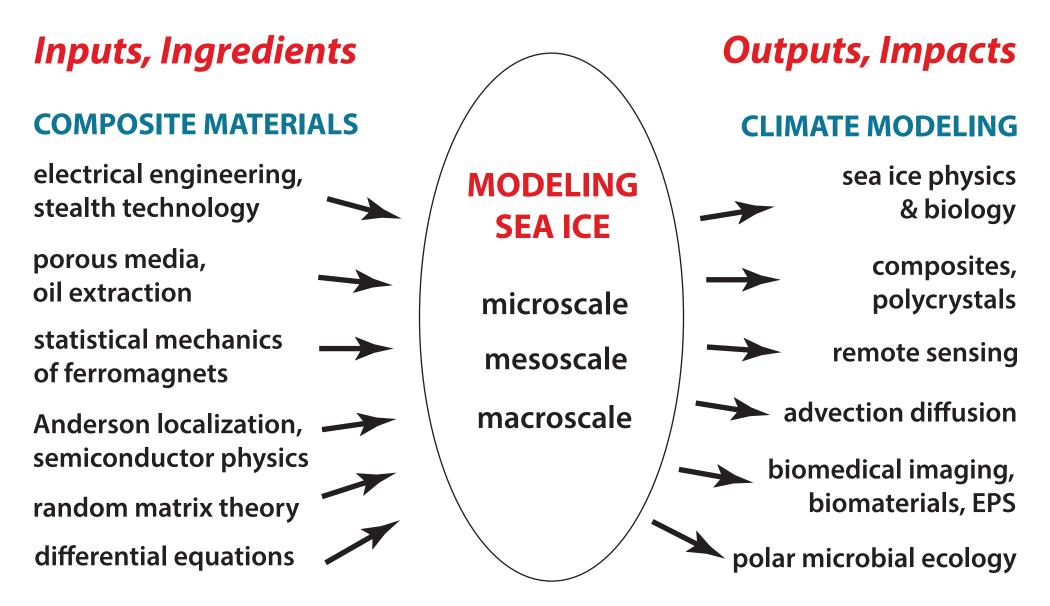
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What is our research about?

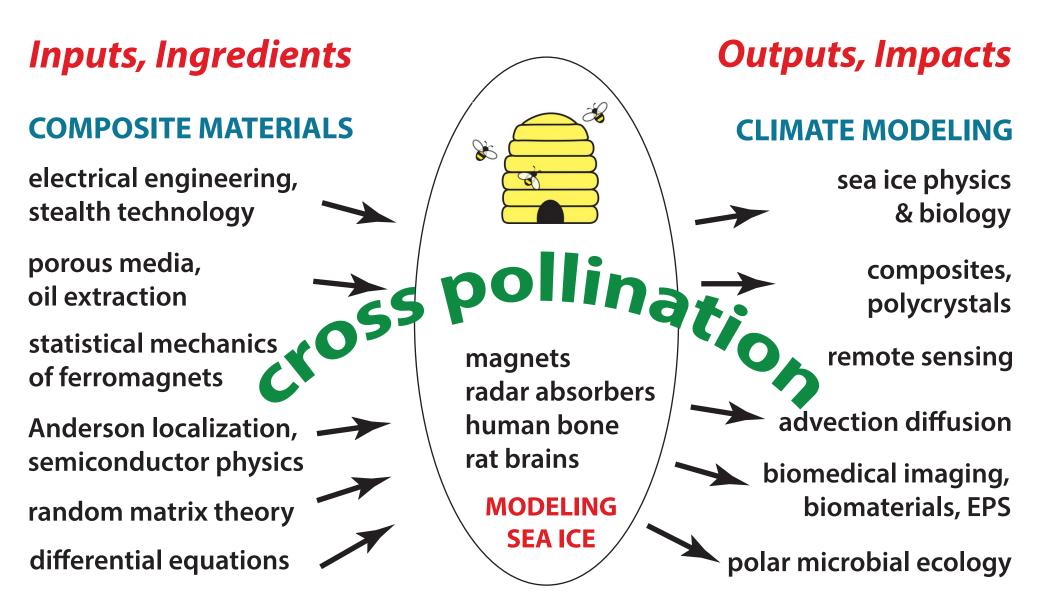
Using methods of homogenization and statistical physics to model sea ice effective behavior and advance representation of sea ice in climate models, process studies, ...



Physics of sea ice drives advances in many areas of science and engineering.

What is our research 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, ...



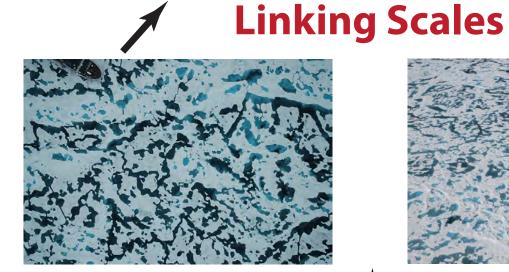
Physics of sea ice drives advances in many areas of science and engineering.

How do scales interact in the sea ice system?

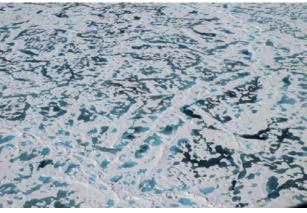


basin scale grid scale albedo

km scale melt ponds



Linking



Perovich

mm scale brine

inclusions



Scales



meter scale snow topography

sea ice formation









sea ice dynamics plate tectonics on a fast time scale





leads



heat flows directly from ocean to atmosphere

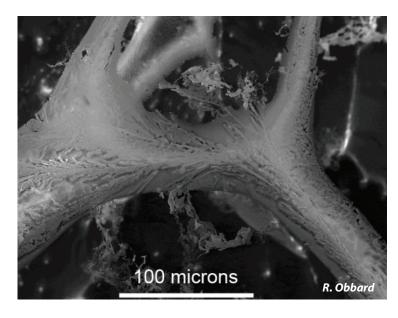
sea ice microphysics

fluid transport





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

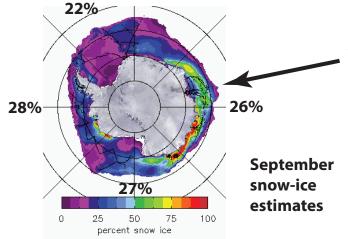


nutrient flux for algal communities









T. Maksym and T. Markus, 2008

Antarctic surface flooding and snow-ice formation

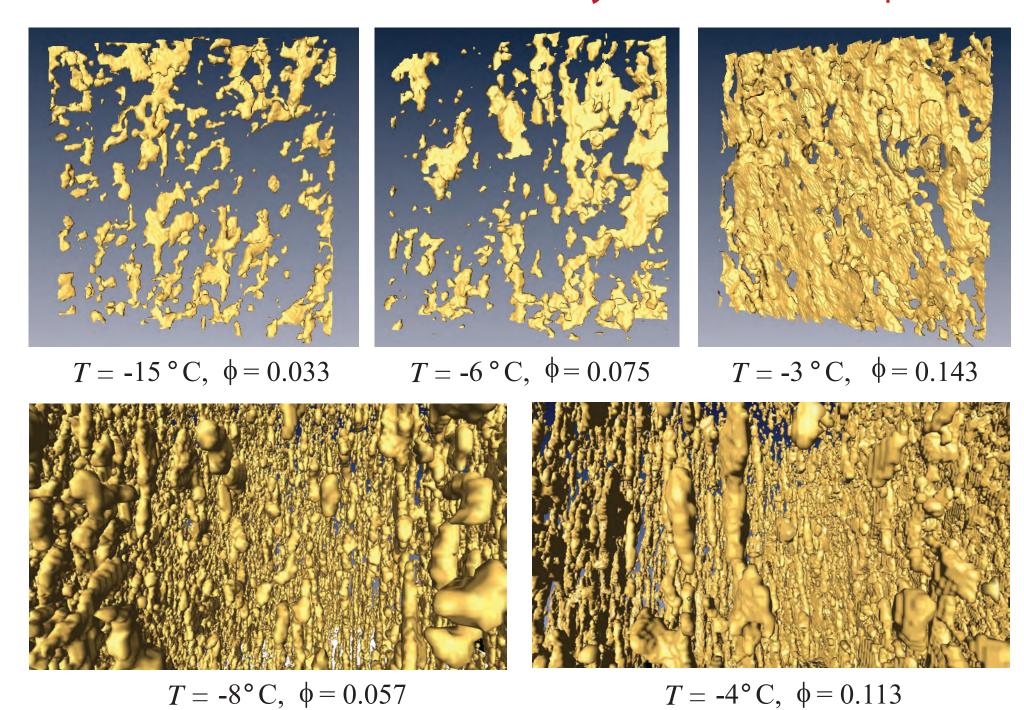
- evolution of salinity profiles
- ocean-ice-air exchanges of heat, CO₂

sea ice ecosystem



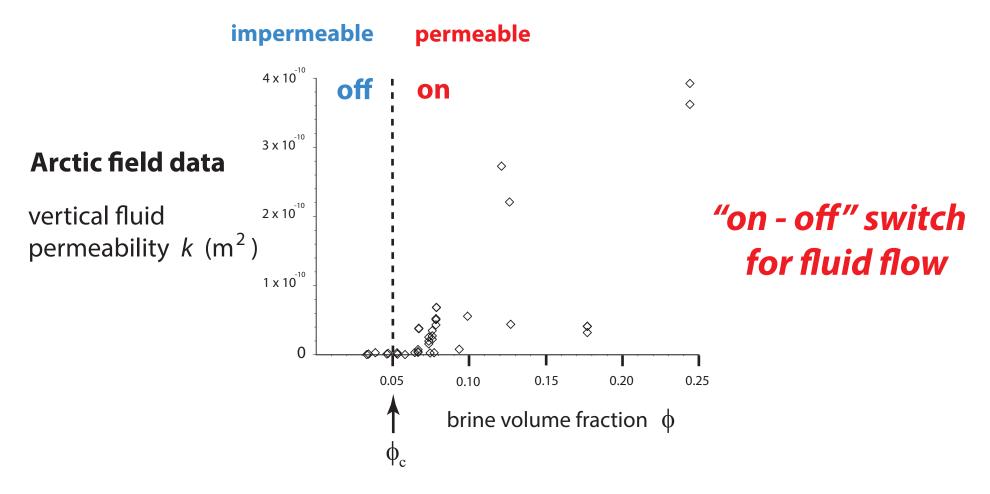
sea ice algae support life in the polar oceans

brine volume fraction and *connectivity* increase with temperature



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

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 algal communities

D. Thomas 2004

nutrient replenishment controlled by ice permeability

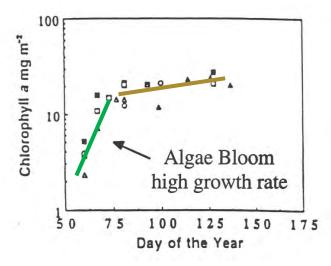
biological activity turns on or off according to rule of fives

Golden, Ackley, Lytle

Science 1998

Fritsen, Lytle, Ackley, Sullivan Science 1994

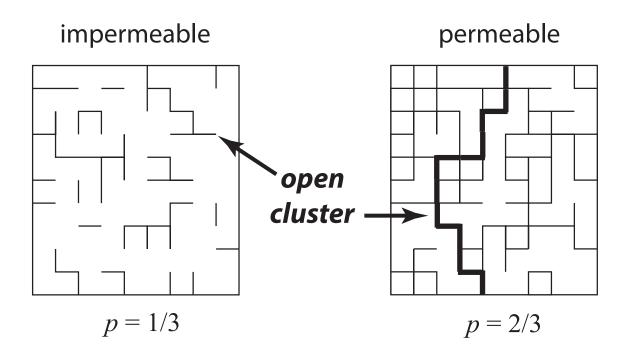
critical behavior of microbial activity



Convection-fueled algae bloom Ice Station Weddell

percolation theory

probabilistic theory of connectedness



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

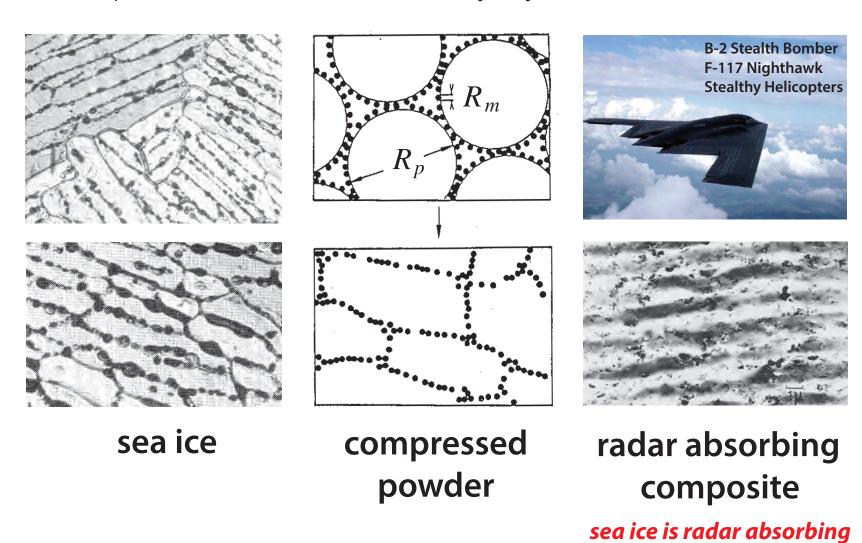
percolation threshold

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

smallest p for which there is an infinite open cluster

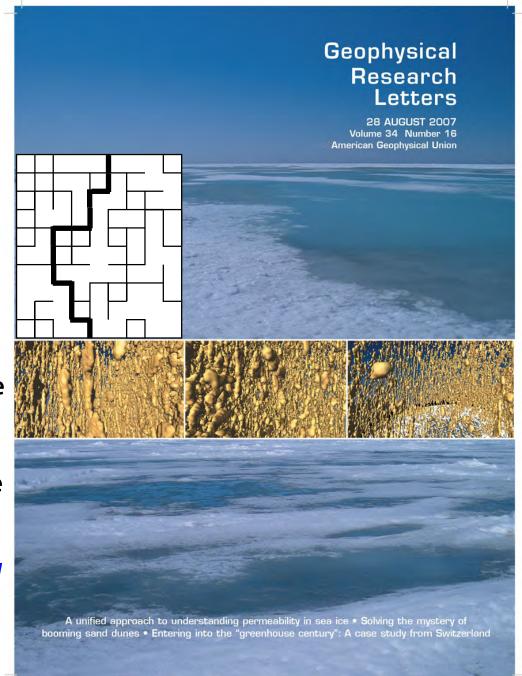
Continuum percolation model for stealthy materials applied to sea ice microstructure explains Rule of Fives and Antarctic data on ice production and algal growth

 $\phi_c \approx 5 \%$ Golden, Ackley, Lytle, *Science*, 1998



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

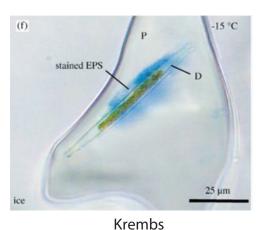
microscale governs

mesoscale processes

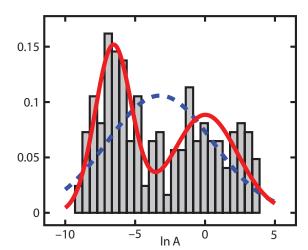
melt pond evolution

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

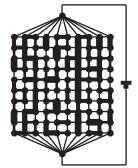
How does EPS affect fluid transport? How does the biology affect the physics?



without EPS with EPS with EPS

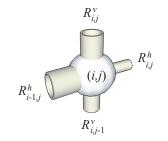


RANDOM PIPE MODEL



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

Krembs, Eicken, Deming, PNAS 2011



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

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

Notices

of the American Mathematical Society

Climate Change and the Mathematics of

page 562

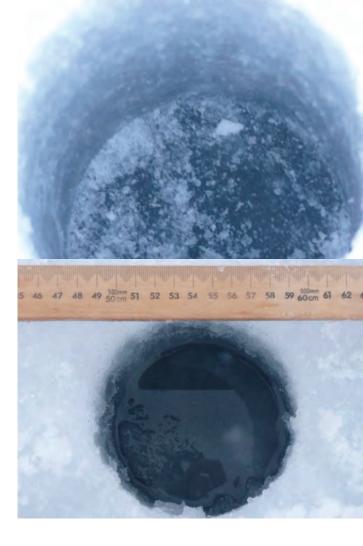
May 2009

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

page 586



Volume 56, Number 5



measuring fluid permeability of Antarctic sea ice

SIPEX 2007

tracers flowing through inverted sea ice blocks









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

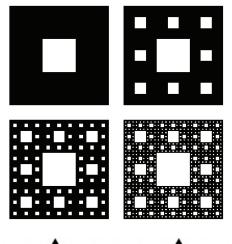
2012 Antarctic SIPEX II

2013 Arctic Barrow AK

2014 Arctic Chukchi Sea



mesoscale



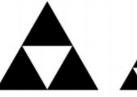


fractals

self-similar structure

non-integer dimension

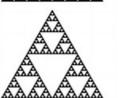


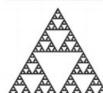












$$D = \frac{\log 3}{\log 2} = 1.585...$$





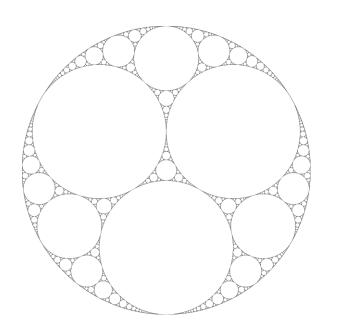


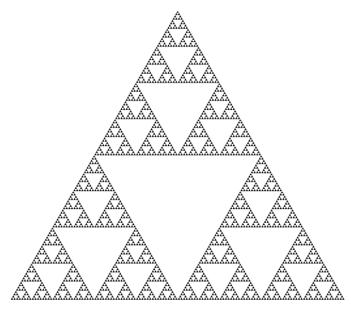
the sea ice pack is a fractal

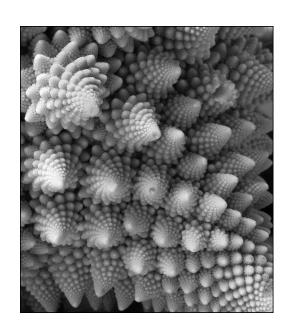
displaying self-similar structure on many scales

floe size distribution important in dynamics (fracture), thermodynamics (melting)

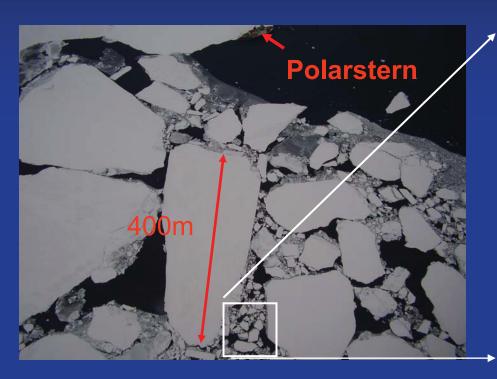
bigger floes easier to break, smaller floes easier to melt

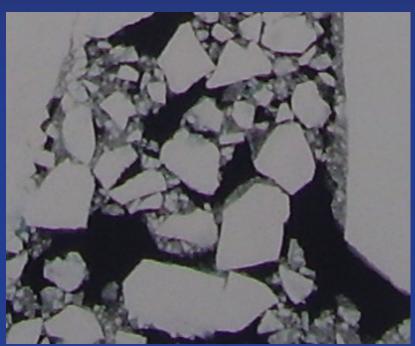






Self-similarity of sea ice floes





Weddell Sea, Antarctica 2006

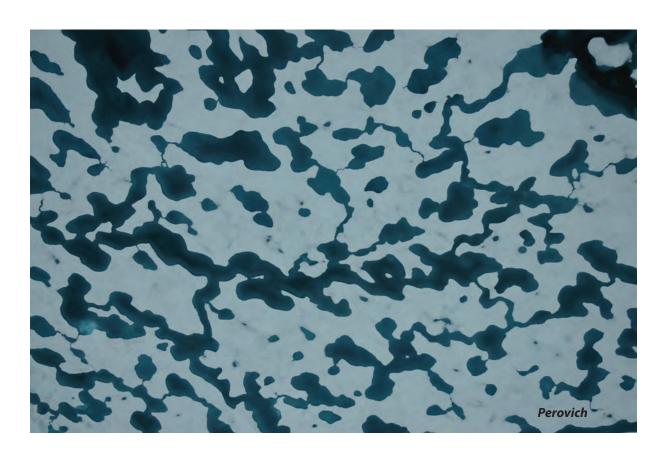
melt pond formation and albedo evolution:

- 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

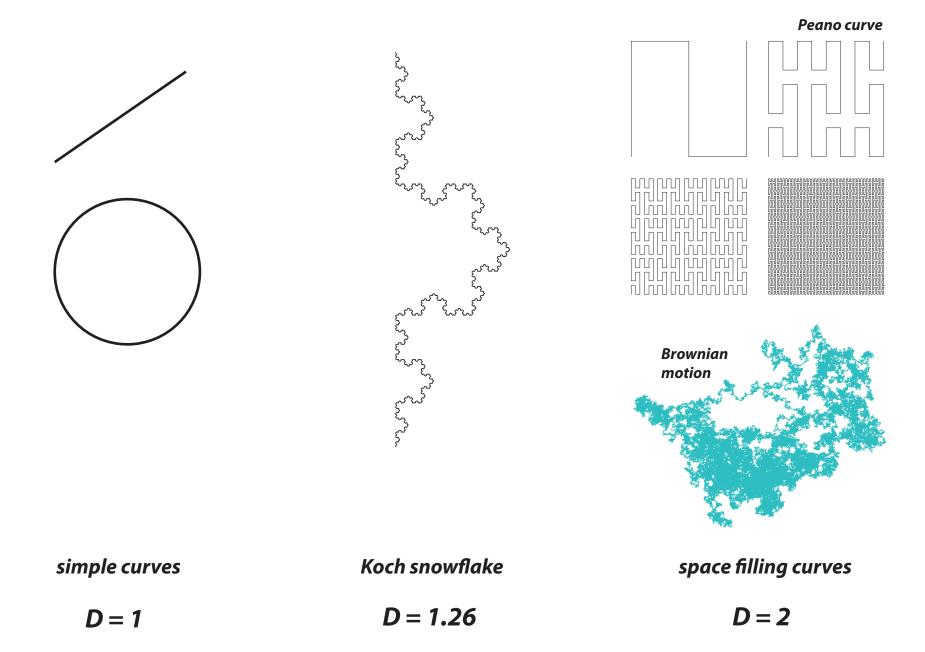
Skyllingstad, Paulson, Perovich 2009 Flocco, Feltham, Hunke 2012



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

fractal curves in the plane

they wiggle so much that their dimension is >1

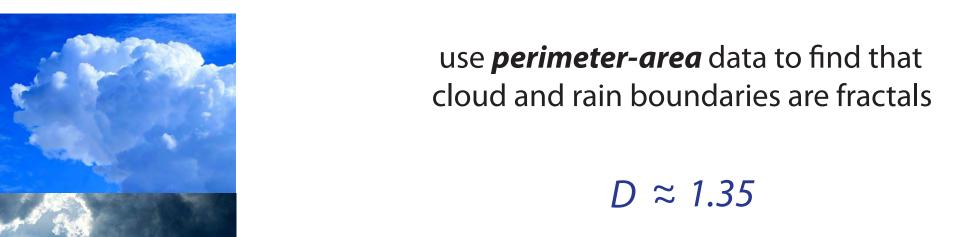




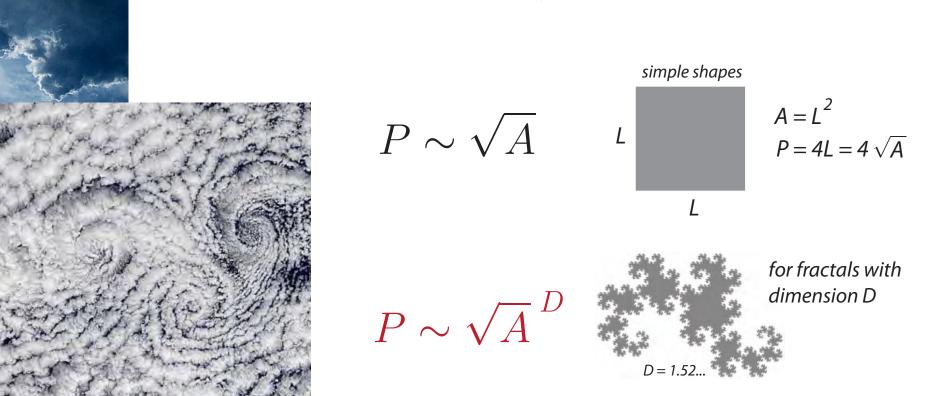
30th Congressional District, Texas, 1991-1996



clouds exhibit fractal behavior from 1 to 1000 km



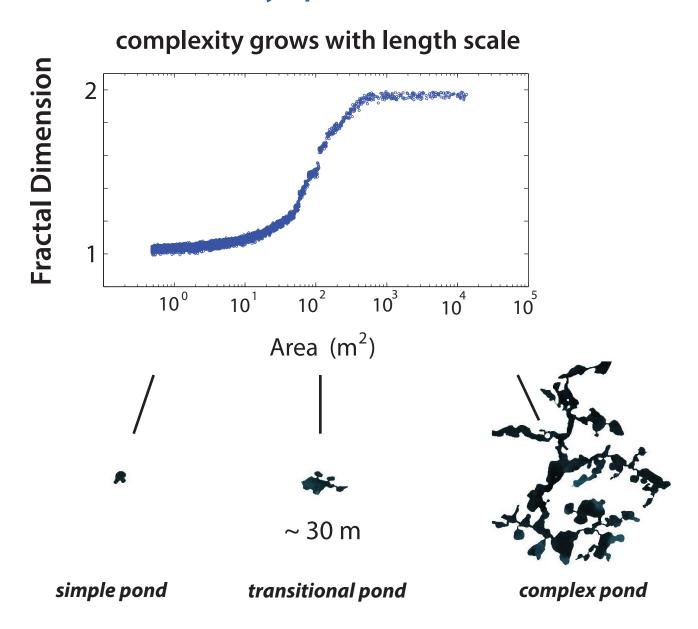
S. Lovejoy, Science, 1982



Transition in the fractal geometry of Arctic melt ponds

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

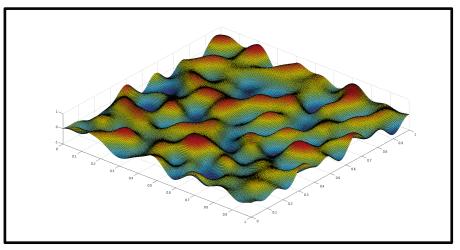
The Cryosphere, 2012

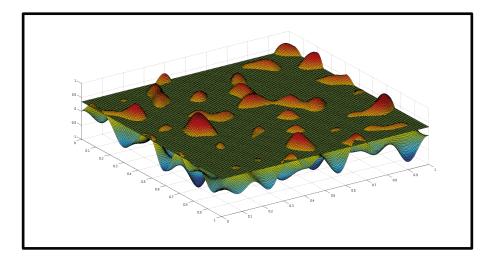


Continuum percolation model for melt pond evolution

level sets of random surfaces

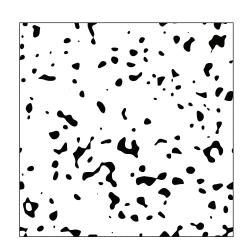
Brady Bowen, Court Strong, Ken Golden, J. Fractal Geometry 2018

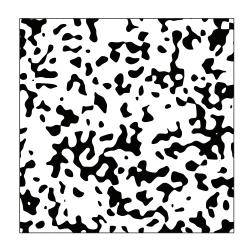


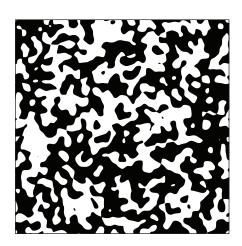


random Fourier series representation of surface topography

intersections of a plane with the surface define melt ponds





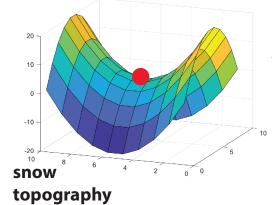


electronic transport in disordered media

diffusion in turbulent plasmas

Saddle Points, Morse Theory and the Fractal Geometry of Melt Ponds

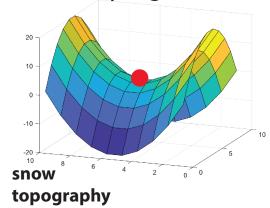
Ryleigh Moore, Jacob Jones, Dane Gollero, Court Strong, Ken Golden 2021



As ponds coalesce at saddle points, fractal dimension proxy isoperimetric quotient $P^2/4\pi A$ jumps, driving the transition.

Saddle Points, Morse Theory and the Fractal Geometry of Melt Ponds

Ryleigh Moore, Jacob Jones, Dane Gollero, Court Strong, Ken Golden 2021



As ponds coalesce at saddle points, fractal dimension proxy isoperimetric quotient $P^2/4\pi A$ jumps, driving the transition.

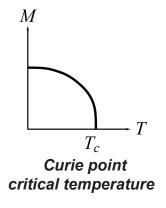


Ryleigh Moore
Department of Mathematics
University of Utah

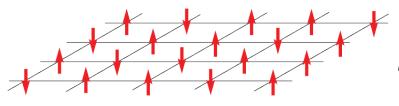
Multidisciplinary drifting Observatory for the Study of Arctic Climate (MOSAiC)

MOSAiC School aboard the icebreaker *RV Akademik Federov*

20 grad students from around the world (3 from U.S., 1 mathematician)



Ising Model for a Ferromagnet



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

blue white

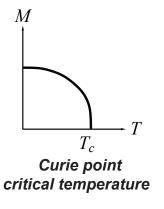
$$\begin{array}{c|c} \text{applied} & \\ \text{magnetic} & \\ \text{field} & \end{array}$$

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

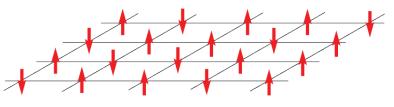
nearest neighbor Ising Hamiltonian

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

effective magnetization



Ising Model for a Ferromagnet



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

blue white

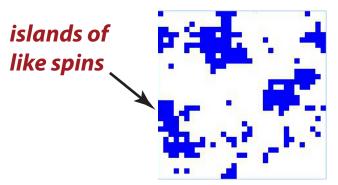
applied magnetic
$$H$$

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

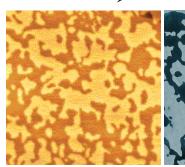
nearest neighbor Ising Hamiltonian

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

effective magnetization



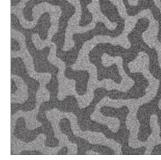
energy is lowered when nearby spins align with each other, forming magnetic domains



magnetic domains in cobalt



melt ponds (Perovich)



magnetic domains in cobalt-iron-boron



melt ponds (Perovich)

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

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

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

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

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

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

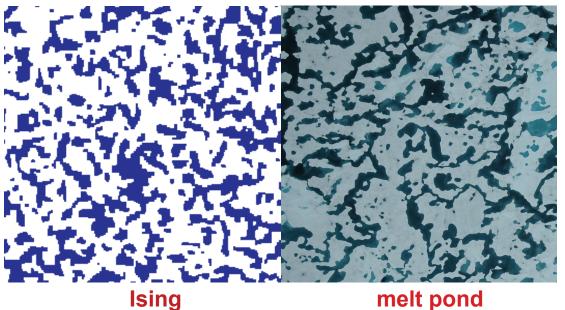
pond area fraction $F = \frac{(M+1)}{2}$

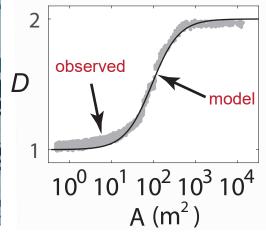
$$F = \frac{(M+1)}{2}$$

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

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)

no bloom bloom massive under-ice algal bloom

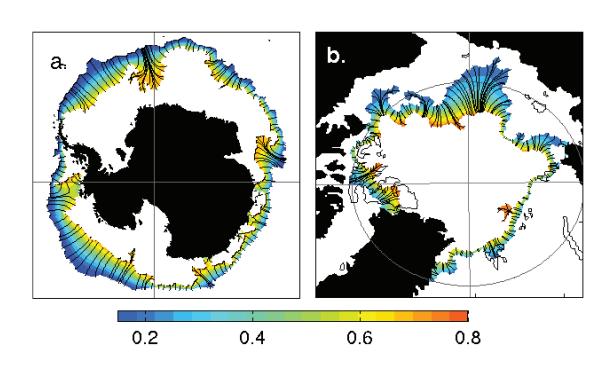
Arrigo et al., Science 2012

macroscale

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?

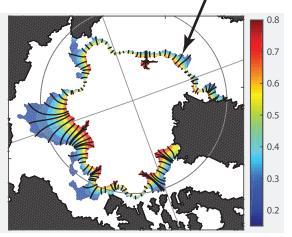
Objective method for measuring MIZ width motivated by medical imaging and diagnostics

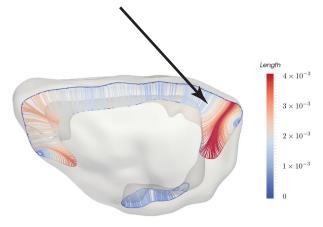
Strong, *Climate Dynamics* 2012 Strong and Rigor, *GRL* 2013 39% widening 1979 - 2012

streamlines of a solution to Laplace's equation

"average" lengths of streamlines







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

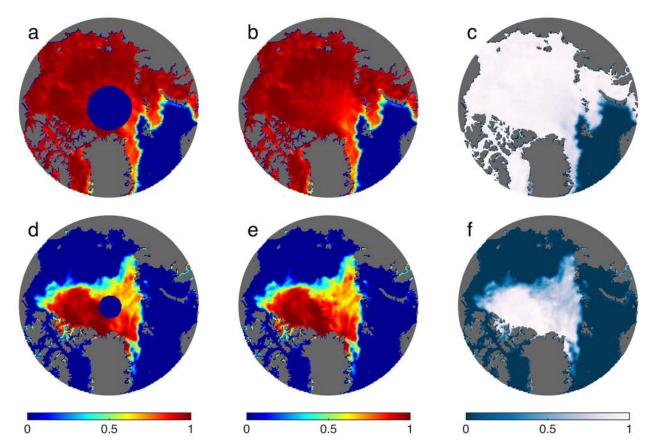
Society for Industrial and Applied Mathematics News, April 2017

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 with harmonic function satisfying satellite BC's plus 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.





Who cares if Arctic sea ice disappears?







- The Arctic
 holds 25% of
 the world's
 undiscovered oil
 gas reserves
- Sea ice is both a hazard and a supporting feature for hydrocarbon exploration & production

oil companies care about Arctic sea ice loss



Orsolini et al., 2011

Sea-ice loss: impacts beyond the Arctic

changes in precipitation and temperature patterns, storm tracks, ...

 One climate model projects reduced precipitation in American West (Sewall & Sloan, 2005)

Utah - greatest snow on Earth?

- Analysis of 2007 ice minimum suggests above normal snow deposition in NW North America (Orsolini et al., 2011)
- Colder weather in SE Asia, possibly in Eastern US (Hondo et al., 2009)

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 the theory of composites and other areas of 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. Fluid flow through sea ice mediates melt pond evolution and many processes important to climate change and polar ecosystems.
- 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

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







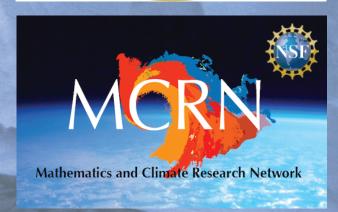












Fire endangers Hobart's ice ship

BY DAVID CARRIGG

AN engine-room fire has left the Hobart-based Antarctic research ship Aurora Australia without power in dangerous sea ice off the Antarctic coast.

None of the 79 people on board was injured in the blaze, which broke out early yesterday morning while the ship was in deep water 185km off the coast.

The extent of the damage is not known.

Australian Antarctic Division director Rex Moncur said the fire was extinguished by flooding the engine room with an inert gas.

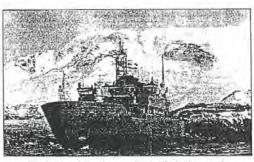
The gas had to be cleared before crew wearing breathing apparatus could enter and assess the situation.

He said it could be some time before the extent of damage was

The 25 crew and 54 expeditioners, mostly from Hobart, would wear thermal clothing and stay below decks to keep

"There is always a risk of becoming ice-bound in these waters at this time of the year rut at this stage we don't expect to launch a rescue mission from Hobart," Mr Moncur said.

The ship was in regular radio contact with the Antarctic Div-



A file photo of the Aurora Australis in Antarctica.

ision's Hobart office.

He expected the expeditioners and crew to abandon the pioneering winter voyage and return the ship to Hobart for repairs in about a week.

The Antarctic Division, which hires the ship from P&O Australia, would not be hiring another vessel for the expedition.

"It's a pretty specialist vessel so you couldn't get the sort of research capability that this ship has got readily available," Mr Moncur said.

"We hope the next voyage can still proceed on schedule, which is early September."

The Aurora Australis is owned by P&O Australia and charted by the Antarctic Division for about \$11 million

Australia managing director Richard Hein said yesterday the company was assessing the situation and a number of rescue options were being

It was too early to say whether P&O would be liable for the cost of the aborted

The vessel left Hobart last Wednesday for a seven-week voyage mainly to study a polyn-ya, an area where savage winds break up the sea ice and cause heavy, salt-laden water to sink to the bottom.

The ship was nearing the polynya when the fire broke out.

Australia Hobart Casev Antarctica

Oceanographers believe a closer study of the phenomenon will lead to a better understanding of climate change.

CSIRO Marine Research oceanographer Steve Rintoul said the dense bottom water, created only in a few places in Antarctica and to a lesser extent in the North Atlantic, was critical to the chemistry and biology of the world's oceans.

2:45 am July 22, 1998

"Please don't be alarmed but we have an uncontrolled fire in the engine room"

about 10 minutes later ...

"Please don't be alarmed but we're lowering the lifeboats"

Fire strands Antarctic ship in sea ice

AN engine more fire has Australian Anteretic Div- arctic continent and return disabled the leabreaker Ausora Australia in sea ico, deep in Antarotic waters

There were no injuries and the ship was not in danger after Tuesday night's fire,

ision director Mr Rex to Hobart for repairs. Moncur said. But Mr Moncur said he expected it would have to abandon its

The cause of the fire was not known but the engines would have to abandon its have been turned off, with pioneering mid-winter voy- the ship 100 nautical miles age to the edge of the Ant- from the Antaretic coast.

THE CANBERRA TIMES Thursday 23 July 1998 Page 4

Antarctic voyage stopped

by fire HOBART: An engine room fire has disabled the Austra: lian icebreaker Aurora Australis in sea ice, deep in Antarctic

Australian Antarctic Division director Rex Moneur said there were no injuries and the ship was not in danger after Tuesday night's fire.

But Mr Moncur said he expected Aurora Australis would have to abandon its ploneering mid-winter voyage to the edge of the Antarctic continent to return to Hobart for repairs.

The fire had been extinguished and the engines were turned off, leaving the ship in sea ice about 100 nautical miles from the Antarctic coast, he said. The weather was good.

Crew had to wear breathing apparatus to enter the engine room and it was likely to be 24 hours before the damage could be fully assessed.

The Aurora, with 54 expeditioners and 25 crew, left Hobart last Wednesday for a seven-week voyage which was to have focused on a polynya, an area where savage winds break up the sea ice and cause beavy, salt-laden water to sink to the bottom.

Mr Moncur said, the cause of the fire was not yet known.



Sydney Morning Herald 23 July, 1998

ICEBREAKER BURNS

A ploneering 2 million as Australian scientific voyage to the mid-winter Antarous package is expected to be scrapped following an engine-grow fire on the Aurora Australis yesterday. The 54 people on board were locked on decicin me

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Notices

of the American Mathematical Society

November 2020 Volume 67, Number 10





Modeling Sea Ice



Kenneth M. Golden, Luke G. Bennetts, Elena Cherkaev, Ian Eisenman, Daniel Feltham, Christopher Horvat, Elizabeth Hunke, Christopher Jones, Donald K. Perovich, Pedro Ponte-Castañeda, Courtenay Strong, Deborah Sulsky, and Andrew J. Wells

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Pedro Ponte-Castañeda is a Raymond S. Markowitz Faculty Fellow and professor of mechanical engineering and applied mechanics and of mathematics at the University of Pennsylvania. His email address is ponte@seas.upenn.edu. Courtenay Strong is an associate professor of atmospheric sciences at the University of Utah. His email address is court.strong@utah.edu.

Deborah Sulsky is a professor of mathematics and statistics and of mechanical engineering at the University of New Mexico. Her email address is sulsky @math.unm.edu.

Andrew J. Wells is an associate professor of physical climate science at the University of Oxford. His email address is Andrew.Wells@physics.ox.ac.uk. Communicated by Notices Associate Editor Reza Malek-Madani.

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Volume 53/ Issue 9 November 2020

Special Issue on the Mathematics of Planet Earth

Read about the application of mathematics and computational science to issues concerning invasive populations, Arctic sea ice, insect flight, and more in this Planet Earth **special issue!**

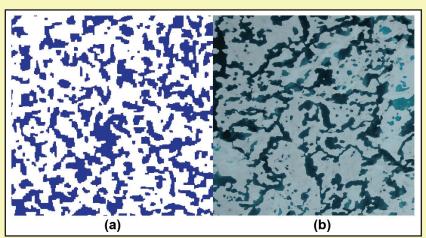


Figure 3. Comparison of real Arctic melt ponds with metastable equilibria in our melt pond Ising model. **3a.** Ising model simulation. **3b.** Real melt pond photo. Figure 3a courtesy of Yiping Ma, 3b courtesy of Donald Perovich.

Vast labyrinthine ponds on the surface of melting Arctic sea ice are key players in the polar climate system and upper ocean ecology. Researchers have adapted the Ising model, which was originally developed to understand magnetic materials, to study the geometry of meltwater's distribution over the sea ice surface. In an article on page 5, Kenneth Golden, Yiping Ma, Courtenay Strong, and Ivan Sudakov explore model predictions.

Controlling Invasive Populations in Rivers

By Yu Jin and Suzanne Lenhart

 $\Gamma^{
m low}$ regimes can change significantly over time and space and strongly impact all levels of river biodiversity, from the individual to the ecosystem. Invasive species in rivers-such as bighead and silver carp, as well as quagga and zebra mussels—continue to cause damage. Management of these species may include targeted adjustment of flow rates in rivers, based on recent research that examines the effects of river morphology and water flow on rivers' ecological statuses. While many previous methodologies rely on habitat suitability models or oversimplification of the hydrodynamics, few studies have focused on the integration of ecological dynamics into water flow assessments.

Earlier work yielded a hybrid modeling approach that directly links river hydrology with stream population models [3]. The hybrid model's hydrodynamic component is based on the water depth in a gradually varying river structure. The model derives the steady advective flow from this structure and relates it to flow features like water discharge, depth, velocity, cross-

sectional area, bottom roughness, bottom slope, and gravitational acceleration. This approach facilitates both theoretical understanding and the generation of quantitative predictions, thus providing a way for scientists to analyze the effects of river fluctuations on population processes.

When a population spreads longitudinally in a one-dimensional (1D) river with spatial heterogeneities in habitat and temporal fluctuations in discharge, the resulting hydrodynamic population model is

$$\begin{split} N_t &= -A_t(x,t) \frac{N}{A(x,t)} + \\ &\frac{1}{A(x,t)} \Big(D(x,t) A(x,t) N_x \Big)_x - \\ &\frac{Q(t)}{A(x,t)} N_x + r N \bigg(1 - \frac{N}{K} \bigg) \\ N(0,t) &= 0 & \text{on } (0,T), x = 0, \\ N_x(L,t) &= 0 & \text{on } (0,T), x = L, \\ N(x,0) &= N_0(x) & \text{on } (0,L), t = 0 \end{split}$$

See Invasive Populations on page 4

Modeling Resource Demands and Constraints for COVID-19 Intervention Strategies

By Erin C.S. Acquesta, Walt Beyeler, Pat Finley, Katherine Klise, Monear Makvandi, and Emma Stanislawski

As the world desperately attempts to control the spread of COVID-19, the need for a model that accounts for realistic trade-offs between time, resources, and corresponding epidemiological implications is apparent. Some early mathematical models of the outbreak compared trade-offs for non-pharmaceutical interventions [3], while others derived the necessary level of test coverage for case-based interventions [4] and demonstrated the value of prioritized testing for close contacts [7].

Isolated analyses provide valuable insights, but real-world intervention strategies are interconnected. Contact tracing is the lynchpin of infection control [6] and forms the basis of prioritized testing. Therefore, quantifying the effectiveness of contact tracing is crucial to understanding the real-life implications of disease control strategies.

Contact Tracing Demands

Contact tracers are skilled, culturally competent interviewers who apply their knowledge of disease and risk factors when notifying people who have come into contact with COVID-19-infected individuals. They also continue to monitor the situation after case investigations [1].

Case investigation consists of four steps:

- Identify and notify cases
- 2. Interview cases
- 3. Locate and notify contacts
- 4. Monitor contacts.

Most health departments are implementing case investigation, contact identification, and quarantine to disrupt COVID-19 transmission. The timeliness of contact tracing is constrained by the length of the infectious period, the turn-around time for testing and result reporting, and the ability to successfully reach and interview patients and their contacts. The European Centre for Disease Prevention and Control approximates that contact tracers spend one to two hours conducting an interview [2]. Estimates regarding the timelines of other steps are limited to subject matter expert elicitation and can vary based on cases' access to phone service or willingness to participate in interviews.

Bounded Exponential

The fundamental structure of our model follows traditional susceptible-exposed-infected-recovered (SEIR) compartmental modeling [5]. We add an asymptomatic population A, a hospitalized population H, and disease-related deaths D, as well as corresponding quarantine states. We define the states $\{S_i, E_i, A_i, I_i, H, R, D\}_{i=0,1}$ for our compartments, such that i=0 and i=1

correspond to unquarantined and quarantined respectively. Rather than focus on the dynamics that are associated with the state transition diagram in Figure 1, we introduce a formulation for the real-time demands on contact tracers' time as a function of infection prevalence, while also respecting constraints on resources.

When the work that is required to investigate new cases and monitor existing contacts exceeds available resources, a backlog develops. To simulate this backlog, we introduce a new compartment C for tracking the dynamic states of cases:

$$\frac{dC}{dt} = [flow_{in}] - [flow_{out}].$$

Flow into the backlog compartment, represented by $[flow_{in}]$, reflects case identification that is associated with the following transitions in the model:

- $\begin{array}{llll} & & \text{The} & \text{rate} & \text{of} & \text{random} & \text{testing:} \\ q_{rA}(t)A_0(t) & \rightarrow A_1(t) & \text{and} & q_{rI}(t)I_0(t) & \rightarrow I_1(t) \\ & & \text{Testing triggered by contact tracing:} \\ q_{tA}(t)A_0(t) & \rightarrow A_1(t), & q_{tI}(t)I_0(t) & \rightarrow I_1(t), \\ \text{and} & q_{tE}(t)E_1(t) & \rightarrow \{A_1(t), I_1(t)\} \end{array}$
- The population that was missed by the non-pharmaceutical interventions that require hospitalization: $\tau_{IH}(t)I_0(t) \rightarrow H(t)$.

Here, $q_{x*}(t)$ defines the time-dependent rate of random testing, $q_{t*}(t)$ signifies the time-dependent rate of testing that is triggered by contact tracing, and $\tau_{\rm IH}$ is the inverse of the expected amount of time for which an infected individual is symptomatic before hospitalization. These terms collectively provide the simulated number of newly-identified positive COVID-19 cases. However, we also need the average number of contacts per case. We thus define function $\mathcal{K}(\kappa, T_{_S}, \phi_{_\kappa})$ that depends on the average number of contacts a day (κ) , the average number of days for which an individual is infectious before going into isolation (T_s) , and the likelihood that the individual

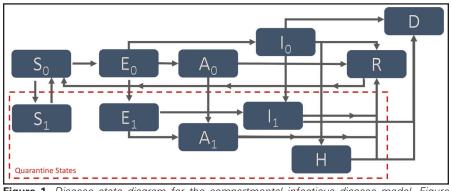


Figure 1. Disease state diagram for the compartmental infectious disease model. Figure

SOCIETY for INDUSTRIAL and APPLIED MATHEMATICS 3600 Market Street, 6th Floor Philadelphia, PA 19104-2688 USA