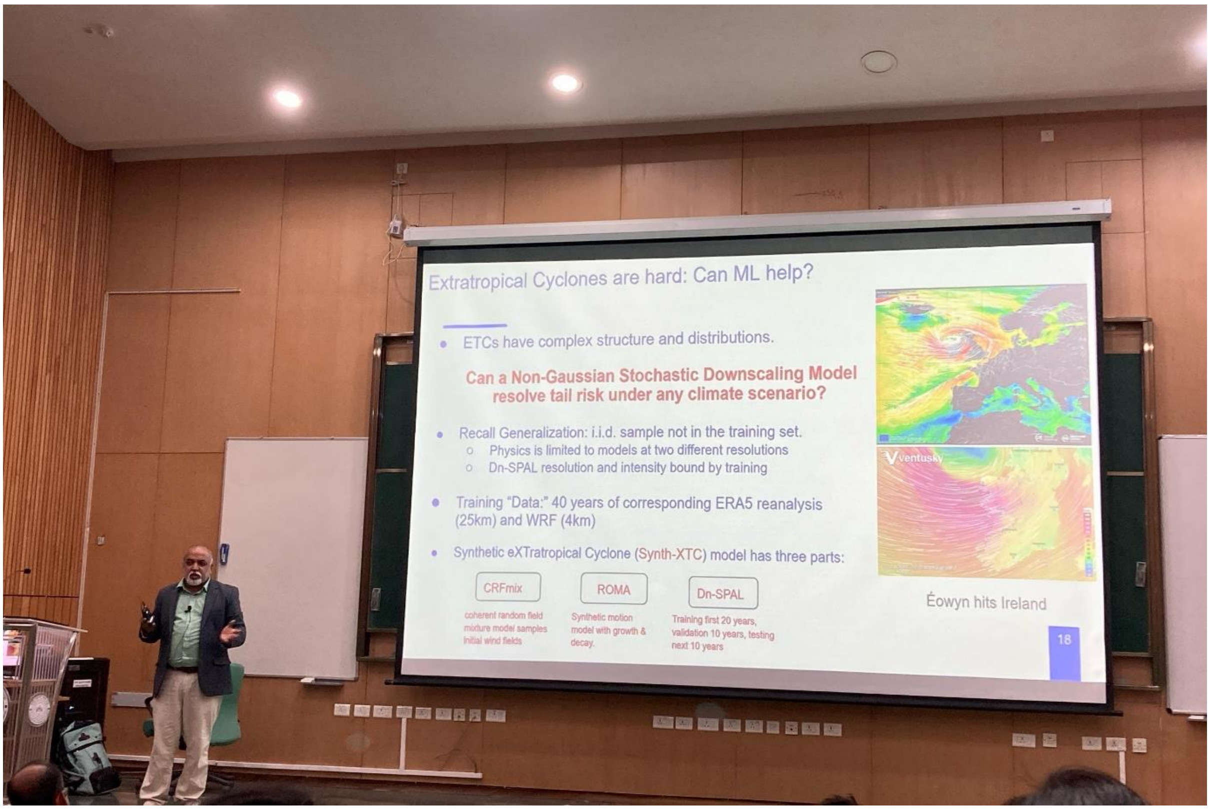
Abstract: Co-optimizing adaptation and mitigation for sustainability is fundamentally a problem of decision-making under uncertainty. Planning for the future requires projecting non-stationary climate risk and using those projections to guide present actions. However, extreme, episodic events—such as cyclones, heatwaves, and floods--or the sudden emergence of tipping points can disrupt carefully prepared strategies that assume a gradually drifting mean climate state. Quantifying the risk of such extremes requires resolving fine-scale dynamics and statistical tails, a challenge for both modeling and observation. Most climate models lack the resolution to capture and adequately sample rare, high-impact events, while observations remain scarce, even for routine environmental variables such as soil salinity. In the first part of this talk, speaker introduced a strategy for generating and resolving extreme events. The approach employs a novel stochastic process for coherent fluids to create large catalogs of synthetic events. It integrates statistics, physics, and foundation models to reconstruct extreme fields at high resolution. This method directly maps coarse climate models to fine-scale observations, ensures physical consistency, overcomes data scarcity at extremes, and is applicable to future climate scenarios. In the second part, the speaker addressed the challenges of model complexity in hybrid AI-physics systems, where over-parameterization limits generalizability and interpretability. Speaker introduced an approach based on stochastic learning dynamics, in which an ensemble approximation to the Fokker-Planck equation tractably enables the co-active optimization of neural structure and function. Finally, the speaker generalized the Co-Active Systems framework, demonstrating how feedback between models, data, theory, and experts enables parsimony for efficient knowledge acquisition and resilient representations. Arguing that parsimony is fundamental to both modeling and observation, speaker discussed emerging opportunities in quantum computation for subset selection problems as a potential future direction.

Bio: Sai Ravela is a Principal Research Scientist in MIT's Earth, Atmospheric, and Planetary Sciences Department and directs the Earth Signals and Systems Group (ESSG). He pioneers a co-active systems theory that exploits feedback between theory, data, models, and experts through uncertainty, information, and parsimony for stochastic, high-dimensional processes in earth, planets, climate, and life. He applies these methods to climate risk and sustainability, co-active observing systems, the physics of learning, statistical inference for coherent signals, fluid imaging, and image recognition for conservation. He received MIT's 2016 Infinite Kilometer Award for pioneering work on statistical approaches to coherent fluids and co-founded Windrisktech LLC, the first company to model cyclone-induced future climate risks. He has advised numerous students, authored many papers, and teaches the popular Dynamics, Optimization, and Learning Systems class. Dr. Ravela holds a PhD in Computer Science (Computer Vision & Robotics) from UMass Amherst (2003) and trained at MIT as a postdoctoral researcher in Stochastic Processes and Geophysical Fluid Dynamics (2004), where he remains.


Extratropical Cyclones are hard: Can ML help?
ETCs have complex structure and distributions.
Can a Non-Gaussian Stochastic Downscaling Model resolve tail risk under any climate scenario?
Recall Generalization: i.i.d. sample not in the training set.
Physics is limited to models at two different resolutions
Dn-SPAL resolution and intensity bound by training
Training "Data:" 40 years of corresponding ERA5 reanalysis (25km) and WRF (4km)
Synthetic eXTratropical Cyclone (Synth-XTC) model has three parts:
CRFmix
coherent random field mixture model samples initial wind fields
ROMA
Synthetic motion model with growth & decay.
Dn-SPAL
Training first 20 years, validation 10 years, testing next 10 years
ventusky
Éowyn hits Ireland
18