Indian Institute of Technology, Kanpur

Proposal for a new course

1. **Course No:** KSS 6XX

2. **Course Title:** Physics-Coupled Artificial Intelligence for Climate and Sustainability: Modeling, Risk, and Resilience

3. **Per Week Lectures:** 3(L), Tutorial: 0 (T), Laboratory: (P), Additional Hours: 0 (A)

4. **Credits** (3*L+0*T+P+A): 9

5. **Duration of Course:** Full Semester

6. **Proposing Department:** Kotak School of Sustainability

   Other departments that may be interested in the proposed course include Civil Engineering, Mechanical Engineering, Electrical Engineering, Computer Science and Engineering, Aerospace Engineering, Industrial and Management Engineering, Design, Earth Sciences, Mathematics and Statistics, Physics, Economic Sciences, and Humanities and Social Sciences.

7. **Proposing Instructor(s):** Prof. Sai Ravela (KSS)

8. **Course Description:** This course develops a complete pipeline from climate science to quantifying risk and decision-making for a warming world, integrating physics (theory), machine learning (AI), and real-world applications. Students learn about the climate system and sustainability framing, then progress through understanding climate modeling and using climate models, including data assimilation and parameterizations using machine learning, designing surrogates and emulators with rigorous uncertainty quantification, downscaling climate extremes that resolve tails for estimating risk, and linking climate scenarios to specific locations. Quantifying risk as the product of hazard, exposure, and vulnerability, they learn to map exposure using computer vision and remote sensing, quantify vulnerability with structured methods and large language model tools, and translate risk metrics into actionable insights using stochastic dynamic programming, reinforcement learning, and serious games. Every topic is anchored in a single case study and specific methods so that the concepts accumulate into an end-to-end workflow. The class is structured to include short preparatory materials, such as tutorials or recorded walkthroughs, made available before class. Guest speakers may be included from time to time to connect students to operating centers and agencies. In addition to regular assignments and exams, the course may comprise a capstone project that presents an integrated, defensible plan for addressing climate risk and resilience, ultimately leading to sustainable outcomes.

9. **Objectives:** On completing this course, students will be able to:

- Understand the foundations of climate and sustainability: explain the climate system, its feedbacks, and its connections to sustainability and resilience.

- Operate and augment climate models by running baseline models, applying data assimilation, and utilizing machine learning for parameterization and calibration.

- Construct AI- and physics-coupled surrogates, quantify uncertainty and extremes, and downscale climate fields to local scales.

- Quantify and communicate climate risk by integrating hazard, exposure, and vulnerability to compute risk portfolios, and clearly communicate uncertainty and trade-offs.

- Design sustainable decisions for resilience using physics and learning: apply optimization, reinforcement learning, and serious games to evaluate adaptation and mitigation strategies in key sectors (FEWS, coastal, and urban systems).

B) Content

1. **Introduction to Climate and Sustainability (2 Lectures):** Overview of Earth's energy and water cycles, circulation, and feedbacks. Introduce climate sensitivity, including radiative forcing and the role of feedbacks in determining Earth's response to greenhouse gases. Links to human systems, SDGs, equity, and institutions. Natural Step, Natural Capital, Precautionary Principles, planetary boundaries, socio-ecological systems, and ecosystem services accounting. Life Cycle Assessment (LCA) fundamentals with limitations and uncertainty.
2. **What is Climate Resilience (2):** Weather vs climate, predictability scales, climate as a distribution; nonstationarity; extremes and risk. IPCC scenarios and CMIP6 models. Adaptation and mitigation portfolios, resilience planning. The integrated cycle of projecting climate forward and backcasting decisions based on time-evolving risk; the key role of AI across the loop.
3. **Informative Data-Driven Mapping and Prediction (3):** Fusion of remote, in situ, and model data with inference and ML. Bias correction in the current climate and future projections using derived latent variable dynamics (e.g., LSTM and neural operators). Informative observatories. Examples with soil, land use, and biodiversity.
4. **A Primer on Climate Models (4):** General circulation models, governing equations, coupled atmosphere–ocean–land, parameterized processes and model parameters, including subgrid processes such as clouds, convection, radiation, and land interactions. Using ML for parameterization. Bias/variance in climate models. Climate Model Selection: Global vs. Regional Climate Modeling for Sustainability. The CMIP6 ensemble, deploying a regional model.
5. **Data Assimilation and Model Calibration (3):** State vs. parameter estimation. Fixed-point vs fixed-interval estimation. Two-point boundary value problems and relationship to ML. Using variational (3DVar/4DVar) and ensemble (EnKF) methods for analysis and reanalysis.

Calibration and overfitting issues. Using ML in DA and calibration with learned components (learned observation operators, amortized inference). Online vs. Offline calibration.

6. **Stochastic Emulators Using Physics and AI (3):** Generating weather sequences and emulating model outputs. Methods such as VAEs, GANs, Diffusion Models, and transport and flow-based models are introduced. Examples of current ML-based models (e.g., Pangu, Aurora, CorrDiff, FourCastNet, GraphCast, Prithvi) are reviewed.
7. **Surrogate Modeling using Physics and AI (4)**: Methods including Gaussian Processes, Embeddings and Manifolds, convolutional architectures, and autoencoder-based surrogates. Physics-informed neural networks, operator learning including Fourier neural operators, and stable hybrid neural-physical operators with structure learning, including equation learning, are introduced.
8. **Sampling Extremes and Uncertainty Quantification using ML (3):** Challenges in UQ—input, parameter, and structural uncertainties. Response Surface Models, GPC, and Limitations. Monte Carlo/posterior sampling and their limitations. ML-based UQ with ensembles, quantile regression, and conformal prediction. Sampling rare events using surrogates and active learning of tails.
9. **Climate Downscaling Using AI and Physics (4):** The rising demand for Kilometer-scale downscaling. Dynamical and Statistical downscaling, bias correction, and spatial disaggregation. Downscaling with ML, including VAEs, GANs, Transformers, Graph Neural Networks, and Diffusion Models. Incorporating physical constraints, downscaling as a two-point boundary value problem, and incorporating historical data in downscaling.
10. **Estimating Climate Risk Using AI (4):** Natural hazards in a changing climate; synthetic event catalogs; modeling frequency and intensity/severity; compounding and cascading hazards; timeline methods. Measures and representations of Risk; extreme value distributions; bias correction and confidence intervals. Exposure mapping using traditional approaches and AI, including automated extraction from imagery (object detection, semantic segmentation, change detection) and night-time activity proxies. Vulnerability mapping using fragility curves, depth–damage functions, and social vulnerability indices, and using large language models (RAG, schema-guided extraction, human-in-the-loop validation) to extract local vulnerability and capacity.
11. **Sustainable Decision Making and Optimization Using AI (4):** Risk neutrality vs risk aversion; handling imprecise probabilities from climate models. Optimization with Stochastic Dynamic Programming, Reinforcement Learning, and Serious Games (with an optional clinic on Mixed-Integer Programming for design formulations). Translating risk, LCA, and natural capital into objectives, constraints, triggers, and policies.
12. **Applications and Engagement (3)**: Food, Energy, and Water Security; Climate Early Warning Systems (CREWS); Coastal Resilience (from agriculture to property); Urban Infrastructure and Networks. AI for Stakeholder Engagement: support communication, consultation, and co-design with AI-based summarization, RAG on policy documents, scenario explainers, and risk graphics; decision theater.

C) **Pre-requisites:** Linear Algebra, Probability and Statistics, Differential Equations, Introductory Machine Learning or Data Science, Introductory Physics, Introductory Climate or Environmental Science, Python Programming.

D) **Short summary for inclusion in the Courses of Study Booklet:** This rigorous course integrates physical climate modeling and modern AI to move from climate science to decisions. Students learn ML-based data assimilation, ML-based parameterizations, neuro-physical surrogates for prediction, uncertainty quantification, and sampling rare events, as well as neuro-physical downscaling of extremes and risk estimation from hazard, exposure, and vulnerability. They map exposure with remote sensing, derive vulnerability with structured and LLM methods, and design actions using SDP, RL, and serious games. The course includes fully provided code and data, as well as a reproducible, stakeholder-ready capstone with a single case study.

E) **Recommended Reading (Core and Supplementary)**

a. Instructor's course notes from MIT class: Sai Ravela, Dynamics, Optimization, Learning and Sustainability, 2023
b. In addition to readings from the following material, additional readings may be assigned
c. Climate Science & Models
    - Vallis, G. K. Atmospheric and Oceanic Fluid Dynamics. 2nd ed., Cambridge University Press, 2017.
    - Trenberth, K. E., et al. Climate System Modeling. Cambridge University Press, 1992, 2010
    - Randall, D. A. An Introduction to Climate Models. Princeton University Press, 2023.
    - Washington, W. M., and Claire L. Parkinson. An Introduction to Three-Dimensional Climate Modeling. 2nd ed., University Science Books, 2005.
d. Estimation, Inversion, Data Assimilation & Uncertainty
    - Kalnay, E. Atmospheric Modeling, Data Assimilation, and Predictability. Cambridge University Press, 2003.
    - Evensen, G. Data Assimilation: The Ensemble Kalman Filter. 2nd ed., Springer, 2009.
    - Tarantola, A. *Inverse Problem Theory and Methods for Model Parameter Estimation*. SIAM, 2005.
    - A. Gelb, Applied Optimal Estimation, MIT Press, 1974
    - A. E. Bryson and Y-C. Ho, Applied Optimal Control, Routledge, 1975
e. Machine Learning for Physics & Climate
    - Goodfellow, I., Bengio, Y., and Courville, A. Deep Learning. MIT Press, 2016.
    - Murphy, K. P. Probabilistic Machine Learning: Advanced Topics. MIT Press, 2023.
    - Karniadakis, George Em, et al. "Physics-informed machine learning." Nature Reviews Physics, vol. 3, no. 6, May. 2021.
f. Surrogates, Emulators, and Generative Models
    - Rasmussen, C. E., and Williams, C. K. I. Gaussian Processes for Machine Learning. MIT Press, 2006.
    - Bond-Taylor, S., et al. Deep Generative Modelling: A Comparative Review of VAEs, GANs, Normalizing Flows, Energy-Based and Autoregressive Models, IEEE Trans PAMI 2021
g. Risk, Sustainability & Decision Science
    - Kunreuther, H., and Michel-Kerjan, E. At War with the Weather: Managing Large-Scale Risks in a New Era of Catastrophes. MIT Press, 2009.

h. Remote Sensing, Exposure & Vulnerability

- Jensen, J. R. Remote Sensing of the Environment: An Earth Resource Perspective. 2nd ed., Pearson, 2007.
- Blaschke, T., et al. Remote Sensing and GIS for Ecologists: Using Open Source Software. Cambridge University Press, 2018.
- Cutter, S. L. Hazards, Vulnerability, and Environmental Justice. Routledge, 2012.

i. Optimization, Reinforcement Learning & Games

- Sutton, R. S., and Barto, A. G. Reinforcement Learning: An Introduction. 2nd ed., MIT Press, 2018.
- Bertsekas, D. P. Dynamic Programming and Optimal Control. Vols. 1 and 2, 4th ed., Athena Scientific, 2017.

10. **Any other remarks:**

a. This course is open to all students in Engineering and the Sciences.

b. Pedagogy: Students will be supplied with a code base and access to datasets used in the course. Short videos, including guided tutorials and recorded walkthroughs, are made available before class. Modeling centers, agencies, and industry professionals also offer occasional guest lectures.

c. Assessments will be based on assignments, exams, a potential capstone project, participation, and other relevant factors.

d. Reproducibility and ethics: Student work will adhere to KSS/IIT GenAI policy, include data licenses/provenance, fair baselines, a rationale for the spatial/temporal split, an environment file and random seed, failure cases and bias notes, and, where applicable, stakeholder-ready risk graphics.

Dated: 29/8/2025 Proposer: Ravela Sai

Prof. Sai Czander Ravela

Dated: 30/8/2025 DUGC/DPGC Convener:

The course is approved / not approved

Chairman, SUGC/SPGC

Dated: ________________________