Climate change stands to have a profound impact on human society, and on political and other conflicts in particular. However, the existing literature on understanding the relation between climate change and societal conflicts has often been criticized for using data that suffer from sampling and other biases, often resulting from being too narrowly focused on a small region of space or a small set of events. These studies have likewise been critiqued for not using suitable statistical tools that address spatio-temporal dependencies, obtain probabilistic uncertainty quantification, and lead to consistent statistical inferences. We first propose a Bayesian framework to address these challenges. Our results exhibit considerably nuanced relationships between temperature deviations and social conflicts that have not been noticed in previous studies. Methodologically, the proposed Bayesian framework can help social scientists explore similar domains involving large-scale spatial and temporal dependencies. Next, we propose a graph neural network-based extension of this Bayesian model. Statistical inference and uncertainty quantification in the graph neural network are discussed.

**Bayesian and Machine Learning Frameworks for Studying Climate Anomalies and Social Conflicts**

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**About the Speaker**

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