ClimateWins: Bias and Ethical Considerations

When using machine learning in the context of climate change, several unique ethical considerations arise, as well as opportunities for bias to creep in. I've observed that human bias can enter climate change modeling at multiple levels from data collection, to feature selection and model building. Ethical concerns become relevant when assessing the fairness and transparency of the machine learning process.

With 18 different locations around Europe serving as the main pipeline for climate data over the last 100+ years, we must consider whether these 18 points are sufficient for completing a picture of the entire continent. For instance, do these data sources coincide with countries or areas that are wealthier and privileged enough to have a data collection facility? Are there any regions of Europe that are not fairly represented, skewing our view of the European climate? If this is the truth, then I believe we'd be doing a disservice to Europe and its inhabitants by not addressing these discrepancies.

I also wonder if the data collection methods have been standardized regarding how and how often the data is being collected. If not, have we improved our ability to detect various weather events, therefore creating a false picture of those events increasing over time, when in reality we simply improved our ability to detect them? I think this can be another area of potential improvement.

If certain regions are overrepresented, and certain weather events are deemed to be falsely increasing, I believe that this can lead to a machine learning process that incorrectly makes decisions about where and what climate changes will occur in the future. This also holds for feature selection- do we bring preconceived notions about which weather features (temperature, wind speed, precipitation, etc.) are the most predictive for future events?

In today's world, we have no excuses not to harness the power of technology to help ameliorate some of these issues: for instance, why not utilize data augmentation, a strategy of creating more training data that can increase the generalizability and diversity of the data we're using? There are other options as well, including tools like AI Fairness 360, Google's Fairness Indicators, and others that serve to uncover inherent bias and improve the equitability and accuracy of these machine learning models.

I think that to defend ourselves against these pitfalls, we must go into the machine learning process with open minds, a healthy dose of skepticism, and a willingness to rethink assumptions and intuitions about what we'll find. If we can successfully navigate these issues, I know we'll produce a model that is more effective and helpful.