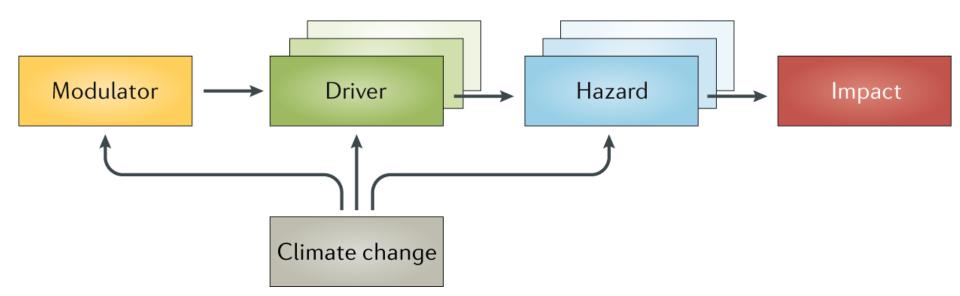
Using interpretable machine learning to identify compound meteorological drivers of crop failure

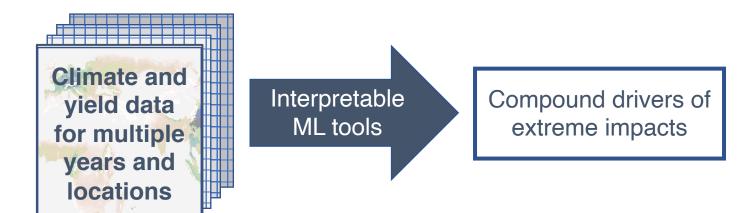
Lily-belle Sweet, Jakob Zscheischler





Motivation

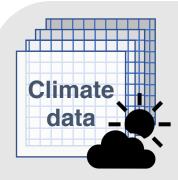
- Crop yield failure can be caused by a combination of non-extreme weather events
- Observed yield datasets are short and not well-distributed globally
- Including data from multiple locations would permit use of more complex models



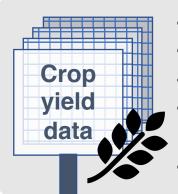
- Good model performance is a prerequisite for useful interpretations
- Aim: Investigate the impact of cross-validation method on model performance metrics and interpretations for spatiotemporal data



Data and model



- Global daily reanalysis data
- Covers 1948-2008
- 0.5 degree resolution
- Variables used: pr, tas, averaged monthly
- Use 3 months before planting date plus the duration of growing season



- Maize yield data from LPJmL
- Covers 1948-2008
- 0.5 degree resolution
- No irrigation, adaptation, fertilization etc considered
- Current cropping areas only



- Maize yield data detrended at each gridpoint
- Lowest 10% of years at each gridpoint are considered to be yield failure years

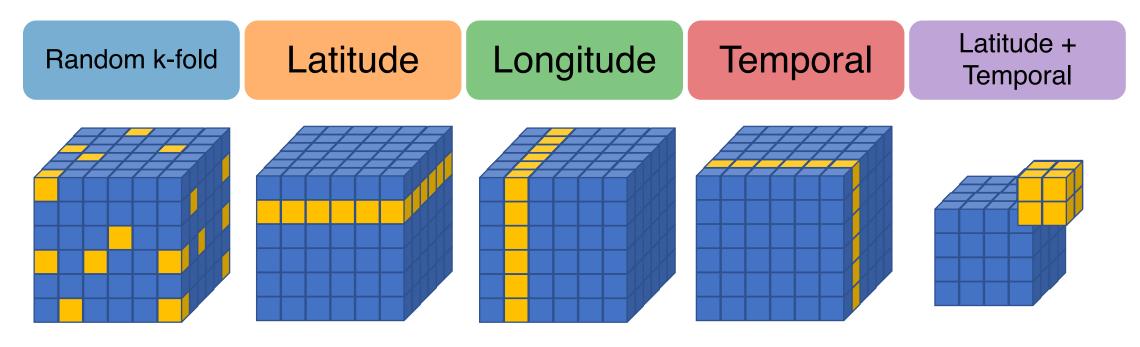


Performance evaluation

Model interpretation

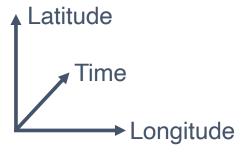


Cross-validation strategies

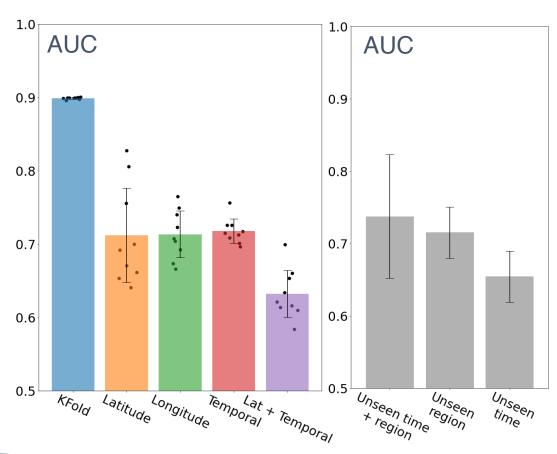


• Germany and Bolivia were kept out of the initial dataset, along with the last 6 years of data, as an additional test set.





Results

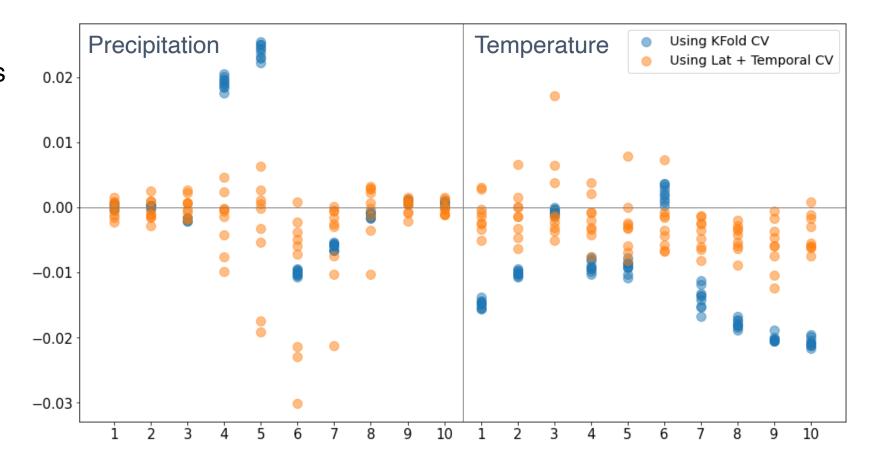


- Performance metrics calculated using random k-fold CV are more optimistic than from spatial or temporal CV
- Spatial and temporal CV better reflects model skill on unseen regions and times



Model interpretation

 Choice of crossvalidation strategy has a large impact on permutation importances





Conclusions

- When using spatiotemporal climate + yield datasets, random k-fold crossvalidation can overestimate model skill.
- Model skill measured using spatial + temporal cross-validation is more representative of performance on new data.
- Choice of cross-validation method should be carefully considered when using interpretable ML methods on spatiotemporal climate data.

References

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- 2. Müller, C. et al. Sci Data (2019)
- 3. Sheffield, J. et al. J. Climate (2006)
- 4. Portmann, F. et al. Global Biogeochemical Cycles (2010)

