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Optimization-based driver detection and prediction of seasonal heat extremes

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As a consequence of limited reliability of dynamical forecast systems, particularly over Europe, efforts in recent years have turned to exploiting the power of Machine Learning methods to extract information on drivers of extreme temperature from observations and reanalysis. Meanwhile, the diverse impacts of extreme heat have driven development of new indicators which take into account nightime temperatures and humidity. In the H2020 CLimate INTelligence (CLINT) project, a feature selection framework is being developed to find the combination of drivers which provides optimal seasonal forecast skill of European summer heatwave indicators. Here, we present the methodology, its application to a range of heatwave indicators and forecast skill compared to existing dynamical systems. First, a range of (reduced-dimensionality) drivers are defined, including k-means clusters of variables known to impact European summer (e.g. precipitation, sea ice content), and more complex indices like the NAO and weather regimes. Then, these drivers are used to train machine learning based prediction models, of varying complexity, to predict seasonal indicators of heatwave occurrence and intensity. A crucial and novel step in our framework is the use of the Coral Reef Optimisation algorithm, used to select the variables and their corresponding lag times and time periods which provide optimal forecast skill. To maximise training data, both ERA5 reanalysis and a 2000-year paleo-simulation are used; the representation of heatwaves and atmospheric conditions are validated with respect to ERA5. We present comparisons of forecast skill to the dynamical Copernicus Climate Change Service seasonal forecasts systems. The differences in timing, predictability and drivers of daytime and nighttime heatwaves across Europe are highlighted. Lastly, we discuss how the framework can easily be adapted to other extremes and timescales.