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Identifying drivers of extreme reductions in carbon uptake of forests with interpretable machine learning

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Forests form one of the major components of the carbon cycle and take up large amounts of carbon dioxide from the atmosphere, thereby slowing down the rate of climate change. Carbon uptake by forests is a highly complex process strongly controlled by meteorological forcing, mainly because of two reasons. First, forests have a large storage capacity acting as a buffer to short-duration changes in meteorological drivers. The response can thus be very complex and extend over a long time. Secondly, the responses are often triggered by combinations of multiple compounding drivers including precipitation, temperature and solar radiation. Effects may compound between variables and across time. Therefore, a large amount of data is required to identify the complex drivers of adverse forest response to climate forcing. Recent advances in machine learning offer a suite of promising tools to analyse large amounts of data and address the challenge of identifying complex drivers of impacts. Here we analyse the potential of machine learning to identify the compounding drivers of reduced carbon uptake/forest mortality. To this end, we generate 200,000 years of gross and net carbon uptake from the physically-based forest model FORMIND simulating a beech forest in Germany. The climate data is generated through a weather generator (AWEGEN-1D) from bias-corrected ERA5 reanalysis data. Classical machine learning models like random forest, support vector machines and deep neural networks are trained to estimate gross primary product. Deep learning models involving convolutional layers are found to perform better than the other classical machine learning models. Initial results show that at least three years of weather data are required to predict annual carbon uptake with high accuracy, highlighting the complex lagged effects that characterize forests. We assess the performance of the different models and discuss their interpretability regarding the identification of impact drivers.