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Gap-filling eddy-covariance data using a complex system of neural networks

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The eddy-covariance technique measures the flux of matter and energy between various ecosystems and the atmosphere. The fluxes characterize an interaction of the ecosystems with their surroundings and provide valuable knowledge to Global Climate Change issues. Among the main assets of the method belongs the possible evaluation of the carbon balance, expressed as the Net Ecosystem carbon Exchange (NEE) parameter.

However, when unfavorable micro-meteorological conditions (e.g., stable stratification and low turbulent mixing) happen, measured fluxes are inaccurate and need to be corrected and/or gap-filled. Thus, there is a long-term challenge for many research teams from the flux community to develop the most accurate gap-filling method – many statistical as well as empirical approaches have been proposed so far (e.g., mean replacement, interpolation, extrapolation, regression analysis, methods based on plant physiology depending on meteorological variables, etc.), each of them having its strengths and weaknesses.

The artificial neural networks (ANNs) – purely empirical non-linear regression models generally able to solve any fitness approximation and pattern recognition problem – were proven as a promising approach and one of the most precise method for gap-filling the eddy-covariance data. However, even though providing encouraging results when considering a prediction error throughout the whole dataset, they considerably fail in fitting inherently present spikes in the NEE values. This drawback results from the nature of ANNs, since their ability to fit spikes is partly in contrast with their ability to reliably approximate previously unseen data – while the spike fitting can be improved by an increasing number of training epochs, this often leads to ANNs over-fitting and thus losing their generalization ability, resulting in higher overall prediction error. Since the proper generalization ability has greater impact on the precision of the results, current applications of ANNs on the gap-filling problem do not take the precise spike estimation into consideration, limiting their ability to get as precise seasonal and annual sums of carbon dioxide flux as possible.

Our research focuses on an application of various types of ANNs to the gap-filling of eddy-covariance data problem, aiming to improve the precision of the ANNs reliability through keeping their generalization ability as well as better fitting the spikes in the NEE dataset. We present an evaluation of several different types of up-to-date ANNs – e.g., multilayer perceptron, wavelet neural networks, focused time-lagged neural networks, etc., – including their variants, as well as the main aim of our research: an elaborated framework, which is able to precisely fit the spikes by building a system of several ANNs of a particular type where each one had been trained for special conditions. To achieve the best precision possible, several types of ANNs simultaneously estimating the particular NEE value are supported – the final value is then chosen according to several statistical properties. The current results show a considerable improvement, resulting in greater than 90 percent correlation between synthetic and real NEE values as well as significantly improving the precision of the spike fitting.