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Integrating data assimilation and a process based model to provide a more complete view of ice-age palaeoclimates

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There are insufficient sites with pollen-based climate reconstructions to produce a continuous data-based map of climate conditions at the Last Glacial Maximum (LGM). Furthermore, modern-analogue climate reconstructions from pollen do not account for the impact of changes in atmospheric CO_2 concentration on water use efficiency, and as a result yield estimates of plant moisture availability (as measured by a moisture index defined as the ratio of mean annual precipitation to mean annual equilibrium evapotranspiration, MI) at the LGM that are lower than indicated by other types of palaeodata. We use a process-based light-use efficiency model of plant productivity (the P model: Wang et al., 2017) to estimate what “apparent” MI (the MI without accounting for the effect of CO_2) would be under LGM conditions, given the palaeoclimate variables of annual precipitation and monthly temperature and relative humidity. We then invert this model by minimising a 3D-variational cost function, using as background the ensemble average and standard deviation of nine LGM climate simulations made by the Palaeoclimate Modelling Intercomparison Project (PMIP3) to create maps of European climate variables from the site-based pollen reconstructions namely apparent MI, mean annual temperature, mean temperature of the coldest month, mean temperature of the warmest month, mean annual precipitation and growing degree days (from the Bartlein et al., 2011 data set). For our inversion we specify a background error correlation matrix which contains a temporal scale determining the strength of correlation between different months and a spatial scale determining the strength of correlation over distance. We examine the condition number (the ratio between the largest and smallest eigenvalues of the Hessian of our cost function), which determines the sensitivity of our solution to perturbations and so determines the computational cost and accuracy of our method. We use a transformation of variables to reduce the bounds on the condition number and show how the condition number changes with different choices of structure for the background error correlation matrix. Finally we consider the changes to the condition number resulting from changes to both the temporal and spatial scales in the background error correlation matrix. A careful analysis of the decisions made in combining data assimilation and model inversion to produce climate reconstructions is required in order to produce robust results.