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Using ensembles to better understand historical climate variability and change

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When creating analyses of past climate, we routinely infer what the temperature anomaly (or other such variable) could have been in areas without measurements. The use of plentiful information from satellites for the last 30 years, in combination with point measurements made in situ, allows us to better reconstruct complete temperature fields for periods in the past when we have relatively few observations, using statistical techniques. Techniques such as Bayesian Principle Component Analysis allow us to produce a set of equally-likely realisations of the reconstructed analysis, which are all consistent with the available measurements, given their uncertainties. Although there was only one true past evolution of the climate, we don't have enough measurements to know perfectly what it was like. In a crossword puzzle, we try to work out words or phrases when we have a series of blank spaces where we should have letters. If we have few letters, the number of possible words or phrases consistent with those spaces is relatively large. The more letters we have, so the number of possibilities reduces. The situation is similar when reconstructing past histories of temperature, or other climate variables: the fewer measurements we have, the more uncertainty in our inferred values. However, as in a crossword puzzle, we also have clues to help us; here we use known statistical relationships between, for example, temperature anomalies in different locations. Bayesian Principle Component Analysis iteratively learns the statistical relationships between the variables and produces reconstructions of every temperature anomaly field since 1850, quickly converging on a stable set of relationships and reconstructed fields. It uses the information about uncertainties in the observations to place appropriate weight on each gridded average; weighting those values with lower uncertainties more highly. It also uses this information, along with knowledge of where observations are not available to assess the uncertainty in the reconstruction. Where few measurements are available and/or the field is naturally variable, the ensemble of equally-likely reconstructions diverges more than where there are many measurements and/or the field is naturally quiescent. Additionally, we use ensembles to explore uncertainties associated with adjustments applied to the measurements to reduce the effects of changing relative biases in time and space. Combining these with ensembles of reconstructions allows the generation of a "super-ensemble" which captures the sampled uncertainties and, importantly, also their covariances. Creating "poor man's" ensembles by blending different data sets also allows us to explore structural uncertainties arising from the choice of analysis technique. This all has benefits to applications of these analyses. For example, a dynamic reanalysis could be run many times (given the resources) to explore the range of uncertainties captured by the ensemble. It could also allow the explicit exploration of the effect of uncertainties on previously controversial differences between uniquely realised analyses, for example in relative trends between the east and west tropical Pacific over the last century. We illustrate these ideas with examples drawn from the development of our new surface temperature data sets and analyses.