Geophysical Research Abstracts, Vol. 9, 08854, 2007
SRef-ID: 1607-7962/gra/EGU2007-A-08854

Empirical satellite rainfall uncertainty modelling using an artificial neural network

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This paper describes a procedure to model the conditional distribution (cdf) of rainfall with respect to pertinent multidimensional satellite input data. The quantification of uncertainty is an essential component of any satellite rainfall retrieval procedure and this is particularly true for very high spatiotemporal resolution products. Previously published work has introduced parametric models for satellite rainfall cdfs, conditioned upon a single scalar rainfall predictor. The predictor may either be a single satellite cloud index or it may be a precipitation estimate derived from a combination of satellite data. In both cases, the cdf is uniquely characterised by the conditional expected rainfall rate. However, it is possible to envisage cases where two separate meteorological conditions, distinguished by different patterns of satellite input data, yield the same expected rainfall rate while being associated with very different distributions of retrieval error. In order to most effectively quantify the retrieval uncertainty in complex satellite precipitation algorithms, it is necessary to model the cdf as a function of multidimensional input data rather than a single scalar predictor variable.

Neural networks provide a flexible tool for non-linear regression and form the basis of a number of multiplatform satellite rainfall algorithms. These techniques may be extended to empirically derive conditional distributions as opposed to simply deriving conditional expected values. The paper will describe the development of such a network architecture, based on a histogram representation of the cdf. The improved representation of retrieval error embodied by this architecture does not only benefit the end user of the precipitation product; it also assists the network training process itself, reducing network complexity, training set size and the overall computational cost of making a precipitation estimate.