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Topographic Kernels for Gaussian Process Regression in Digital Soil Mapping

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Gaussian Processes provide a theoretically well-understood regression framework that is widely used in the context of Digital Soil Mapping. Among the reasons to use Gaussian Process Regression (GPR) are its interpretability, its builtin support for uncertainty quantification, and its ability to handle unevenly spaced and correlated training samples through a user-specified covariance kernel. The base case of GPR is performed with covariance models that are specified functions of Euclidean distance. In order to incorporate information other than the relative positions, regression-kriging extends GPR by an additive regression model of choice, and co-kriging considers a covariance model between covariates and the target variable. In this work, we use the alternative approach of incorporating topographic information directly into the kernel function by use of a non-Euclidean, non-stationary distance function. In particular, we devise kernels based on a path of least effort, where *effort* is locally specified as a function constructed from prior knowledge. It can e.g. be derived from local topographic variables. We demonstrate that our candidate models improve prediction accuracy over the base model. This shows that domain knowledge can be integrated into the model by means of handcrafted kernel functions. The approach is not per se restricted to topographic variables, but could be used for any covariate quantity that is available at output resolution.