The Gaussian geostatistical model has been widely used in Bayesian modeling of spatial data. A core difficulty for this model is at inverting the $n \times n$ covariance matrix, where n is a sample size. This difficulty is involved in almost all statistical inferences of the model, such as Kriging and Bayesian modeling. In Bayesian inference, the inverse of covariance matrix needs to be evaluated at each iteration in posterior simulations. With advanced measurement technology, the sample size n tends to explode nowadays. However, the computational complexity of matrix inversion increases as $O(n^3)$, so Bayesian approach is infeasible for large sample size n due to the current computational power limit.

In this talk, I will propose the auxiliary lattice model (ALM) approach to address this computational issue. The key feature of ALM is to introduce a latent regular lattice which links Gaussian Markov Random Field (GMRF) with Gaussian Field (GF) of the observations. The GMRF on the auxiliary lattice represents an approximation to the Gaussian process. Due to its Markov property, GMRF is more manageable than GF and, with reasonable boundary and neighborhood conditions, GMRF even yields analytical likelihood not involving costly matrix operations. The distinctive feature of ALM from other approximations lies in that ALM avoids completely the problem of the matrix inversion by using analytical likelihood of GMRF. The computational complexity of ALM is rather attractive, which increase linearly with sample size. The practical performance of ALM will be illustrated with simulated data and a real data set of goldmine.