Given that numerous complex networks in real-life are spatially embedded, we ask, can such spatial constraints be exploited (rather than suffered from) to make better inference? Based on the preference of short-range spatial connections, we develop a kernel-based Lasso framework to infer complex spatial networks. We show by numerical experiments that the proposed method improved significantly upon existing network inference techniques. Importantly, such enhancement is achieved even when the exact spatial distribution of the embedded edges is unknown, making the method particularly relevant as a computational tool to efficiently and reliably infer large spatial networks in practice.