

# Short Paper

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## Abstract

This is the abstract.

It consists of two paragraphs.

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## 1. Introduction

### 1.1. Design-Based Philosophy

### 1.2. Model-Based Philosophy

On the other hand, model-based inference imposes additional assumptions on the data with a potential to provide more precise estimates if the additional assumptions hold. Instead of estimating true but unknown parameters, the goal of model-based inference in the spatial context is often *prediction* of an unknown quantity. This is a fundamental philosophical difference between sampling-based and model-based approaches. Instead of *estimating* an fixed unknown mean, we are *predicting* the value of the mean, a random variable. We know that if we sampled all sites, we would have an exact prediction for the mean of our one realized spatial surface, without any uncertainty. But, the true mean of the spatial process that generated our realized data is still not known, and, in the prediction context, we typically do not care much about what value the mean of the underlying process takes.

Figure 1a. Data is fixed. In a finite population example, show a 3d surface that can be generated by anything. If we repeatedly sample the surface, then 95% of all 95% CIs will contain the true mean, which never changes.

Figure 1b. Spatial process is fixed. In a finite population example, show 10 3d surfaces that are generated from some model. If we repeatedly generate the surface and obtain a sample, then 95% of all 95% PIs will contain the realized means. The realized mean changes from surface to surface and it's not necessarily the case that 95% of all 95% PIs will contain the true, underlying mean.

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### 1.3. Comparing Design-Based vs. Model-Based

There have been many comparisons between the two paradigms. . . . .

### 1.4. Spatially Balanced Design and Analysis

#### 1.5. Finite Population Block Kriging

Finite Population Block Kriging (FPBK) is an alternative to sampling-based methods (Ver Hoef, 2008). FPBK expands the geostatistical kriging framework to the finite population setting. Instead of relying on a specific sampling design, we assume the data were produced by a spatial stochastic process with spatial parameters that can be estimated.

Ver Hoef (2008) gives details on the theory of FPBK, but some of the basic principles are summarized below. For a response variable  $\mathbf{z}$  that can be measured on a finite number of  $N$  sites, our goal is to predict some linear function of all of the sample units,  $\tau(\mathbf{z}) = \mathbf{b}'\mathbf{z}$ , where  $\mathbf{b}$  is a vector of weights. One common vector of weights is a vector of 1's to predict the total abundance in the region.

Typically, however, we only have a sample of the  $N$  sites. Denoting quantities that are part of the sampled sites with a subscript  $s$  and quantities that are part of the unsampled sites with a subscript  $u$ ,

$$\begin{pmatrix} \mathbf{z}_s \\ \mathbf{z}_u \end{pmatrix} = \begin{pmatrix} \mathbf{X}_s \\ \mathbf{X}_u \end{pmatrix} \boldsymbol{\beta} + \begin{pmatrix} \boldsymbol{\delta}_s \\ \boldsymbol{\delta}_u \end{pmatrix}, \quad (1)$$

where  $\mathbf{X}_s$  and  $\mathbf{X}_u$  are the design matrices for the sampled and unsampled sites, respectively, and  $\boldsymbol{\delta}_s$  and  $\boldsymbol{\delta}_u$  are zero-mean random errors for the sampled and unsampled sites. Denoting  $\boldsymbol{\delta} \equiv [\boldsymbol{\delta}_s \ \boldsymbol{\delta}_u]'$ , then we assume that  $E(\boldsymbol{\delta}) = \mathbf{0}$ .

We also typically assume that there is spatial correlation in  $\boldsymbol{\delta}$ , which can be modeled using a covariance function. Many common choices for this function assume that spatial covariance decreases with increasing Euclidean distance between sites. The primary function used throughout the simulations and applications of this manuscript is the Exponential covariance function: the  $i, j^{th}$  entry for  $\text{var}(\boldsymbol{\delta})$  is

$$\text{cov}(\delta_i, \delta_j) = \theta_3 + \theta_1 \exp(-h_{i,j}/\theta_2), \quad (2)$$

where  $h_{i,j}$  is the distance between sites  $i$  and  $j$ , and  $\boldsymbol{\theta}$  is a vector of spatial covariance parameters of the partial sill  $\theta_1$ , the range  $\theta_2$ , and the nugget  $\theta_3$ . However, any spatial covariance function could be used in the place of the Exponential, including functions that allow for anisotropy [pg. 80 - 93](Chiles and Delfiner, 1999).

With the above model formulation, the Best Linear Unbiased Predictor (BLUP) for  $\tau(\mathbf{b}'\mathbf{z})$  and its prediction variance can be computed. While details of the derivation are in (Ver Hoef, 2008), we note here that the predictor and its variance are both moment-based. Neither require a particular distribution for  $\mathbf{z}$ .

**Software Implementation:** This probably goes in a different spot (right before simulations?), but putting it here while it's on my mind.

FPBK can be readily performed in R with the `sptotal` package (Matt et al., 2020). We use `sptotal` for both the simulation analysis and the application, estimating parameters with Restricted Maximum Likelihood (REML).

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Here are two sample references: (**Feynman1963118?**; **Dirac1953888?**).

## References

- Chiles, J.-P., Delfiner, P., 1999. Geostatistics: Modeling Spatial Uncertainty. John Wiley & Sons, New York.
- Matt, H., Jay, V.H., Bryce, F., 2020. Sptotal: Predicting totals and weighted sums from spatial data.
- Ver Hoef, J.M., 2008. Spatial methods for plot-based sampling of wildlife populations. *Environmental and Ecological Statistics* 15, 3–13.