predictor of the population total, given the sample size, under the assumption that $Y_1, \ldots, Y_N$ are i.i.d. random variables (cf. Example 3.16). The stratified sampling predictor $\hat{Z} = \sum_{h=1}^{L} N_h \bar{V}_h$ is the best linear predictor of the population total (conditional on the sample) under the assumption that the Y's are independent random variables, with means and variances depending on strata (cf. Example 3.23). With adaptive designs, conditional expectations given the sample s depend on the design, so that in general the same predictors are not unbiased.

3.17 SPATIAL–TEMPORAL EXTENSIONS

In spatial, environmental, and ecological sampling situations the problems go beyond the classical sampling framework in several ways. The variable of interest is defined over a continuous region of space and time rather than a finite set of units. The "units" or sites on which observations are obtained may be points, lines, sets, or filtering operations depending on detectability or weighting functions reflective of the observational method. The natural generalization of classical sampling to the environmental setting has a spatial–temporal pattern or process for the population and a collection of detectability or weighting functions or other "units" from which the sample is selected. A fixed spatial pattern corresponds to the fixed population approach in classical sampling, whereas a spatial stochastic process corresponds to the model-based approach. The index set of the stochastic process corresponds to the population units of finite population sampling. The collection of points, sets, detectability functions, or weighting functions correspond to the sampling units.

With a variable of interest that is continuous in space and time, consider a spatial–temporal stochastic process

$$\{Z(s), s \in \mathcal{S}\}.$$

The index set $\mathcal{S}$ is a region in space and time, an element s is a location or a point in space or space-time, and the random variable $Z(s)$ represents the value of the variable of interest at s. The population total T is the integral of the process over a study region R, namely

$$T = \int_R z(v)\, dv.$$

For a discrete variable, consider a spatial–temporal point process

$$\{N(A), A \in \mathcal{A}\}.$$

The set A is a subset of the (spatial–temporal) study region, the index set $\mathcal{A}$ is a collection of such subsets, and $N(A)$ is the number of the objects of interest in A. A realization of the process gives a spatial pattern $\{z(s), s \in \mathcal{S}\}$ or $\{n(A), A \in \mathcal{A}\}$.

In extending classical sampling theory to accommodate the spatial–temporal setting of ecological resources, the following three connections are made. (1) The unit labels $\{1, 2, \ldots, N\}$ of finite population sampling become the index set $\mathcal{S}$ on which the spatial–temporal stochastic process is defined. (2) The sampling units—which may be complex primary or systematic units—selected in classical sampling are replaced by the set $\mathcal{T}$, which indexes the possible sites, units, detectability functions, or weighting functions used in observing the spatial–temporal pattern or process. For example, in line transect surveys of waterfowl, the set $\mathcal{T}$ is a baseline from which transect locations are selected at random or with probability proportional to transect length. (3) The classical design-based, fixed population approach extends to the fixed spatial pattern $\{z(s), s \in \mathcal{S}\}$ in which no model is involved or in which a design-based analysis proceeds conditional on the specific realization of a model. With these three connections, the population model approach of the finite population sampling literature can be extended to the full spatial–temporal stochastic model $\{Z(s), s \in \mathcal{S}\}$.

3.18 NONSAMPLING ERRORS

Sources of nonsampling errors in surveys include measurement errors, frame errors, nonresponse, and data entry errors (see Biemer et al. [1991], Lessler and Kalsbeek [1992], and Rubin [1987]). Nonsampling errors can introduce biases, which must be adjusted for, and additional variance terms, which must be estimated.

In many surveys the variable of interest y_i for a unit i in the sample is not observed without error. Rather, the observed or measured value is $y_i^{(m)}$, which may differ from y_i due to measurement error or other cause. With measurement error, the data consist of $(s_O, \mathbf{y}_s^{(m)})$. In analyzing surveys with measurement error it is sometimes mathematically useful to consider the hypothetical values $\mathbf{y}_{\bar{s}}^{(m)}$ for units not in the sample. The density of an outcome is

$$\begin{aligned} f(s_O, \mathbf{y}^{(m)}, \mathbf{y}; \boldsymbol{\phi}) &= p(s_O \mid \mathbf{y}^{(m)}, \mathbf{y}; \boldsymbol{\phi}) f(\mathbf{y}^{(m)}, \mathbf{y}; \boldsymbol{\phi}) \\ &= p(s_O \mid \mathbf{y}^{(m)}, \mathbf{y}; \boldsymbol{\phi}) f_m(\mathbf{y}^{(m)} \mid \mathbf{y}; \boldsymbol{\phi}) f(\mathbf{y}; \boldsymbol{\phi}). \end{aligned}$$

For an adaptive design, the selection probability depends only on observed values in the sample, so

$$p(s_O \mid \mathbf{y}^{(m)}, \mathbf{y}; \boldsymbol{\phi}) = p(s_O \mid \mathbf{y}_{\bar{s}}^{(m)}).$$

The conditional density $f_m(\mathbf{y}^{(m)} \mid \mathbf{y}; \boldsymbol{\phi})$ is the measurement error model. An example of a measurement error model is

$$f_m(\mathbf{y}_s^{(m)} \mid \mathbf{y}; \boldsymbol{\phi}) = \prod_{i=1}^{N} f_{mi}(y_i^{(m)} \mid y_i; \boldsymbol{\phi}).$$

With such a model the errors are conditionally independent given the realized true y-values, and the error for unit i depends on y only for that unit. A model commonly assumed has $Y_i^{(m)} = Y_i + \epsilon_i$, where the ϵ_i are independent random variables with