In stochastic simulations of physical systems modeled by partial differential equations, spatially varying uncertain coefficients can present statistically complex sources of variation. When such coefficients are parameterized by hierarchical statistical models, such as Karhunen-Lo\`eve expansions or in a hierarchy of spatial scales, these can be truncated to obtain a simplified, more tractable representation. The resulting lower-dimensional parameter space lends itself well to exploration, partitioning, and the construction of efficient surrogate models, e.g. through interpolation. In applications, this convenience must be weighed against the statistical modeling error resulting from the truncation, which is not always readily observable. In this work, we propose a sequential sampling-based variable selection strategy to build up parameter complexity incrementally. We couple our approach with a data-driven generator that conditionally augments statistical quantities of interest of the model output computed over the lower dimensional parameter space, e.g. simulation samples, statistical moments, and densities, to account for parameter variations at the higher-level hierarchical scales.