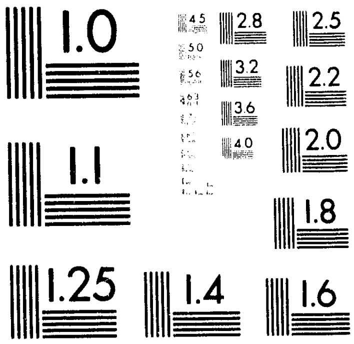
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COMMENTS OF STATISTICAL ISSUE IN NUMERICAL MODELING FOR UNDERGROUND NUCLEAR TEST MONITORING

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Comments on Statistical Issues in Numerical Modeling for Underground Nuclear Test Monitoring

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The Symposium concluded with prepared summaries by four experts in the involved disciplines. These experts made no mention of statistics and/or the statistical content of issues. The first author contributed an extemporaneous statement at the Symposium because there are important issues associated with conducting and evaluating numerical modeling that are familiar to statisticians and often treated successfully by them. This note expands upon these extemporaneous remarks.

Statistical ideas may be helpful in resolving some numerical modeling issues. Specifically, we comment first on the role of statistical design/analysis in the quantification process to answer the question "what do we know about the numerical modeling of underground nuclear tests?" and second on the peculiar nature of uncertainty analysis for situations involving numerical modeling.

The simulations described in the workshop, though associated with topic areas, were basically sets of examples. Each simulation was tuned towards agreeing with either empirical evidence or an expert's opinion of what empirical evidence would be. If agreement was not reached, that is, if the tuning was not successful, a discussion was provided of what was lacking and how the model should be embellished in order to reach agreement. While the discussions were reasonable, whether the embellishments were correct or a forced fitting of reality is unclear and illustrates that "simulation is easy." We also suggest that these examples of simulation are typical and the questions concerning the legitimacy and the role of knowing the reality are fair, in general, with respect to simulation. The answers will help us understand why "prediction is difficult."

Successful prediction demands comprehensive understanding of the relationship between the situation used to develop the model and the situation to be predicted so that in some sense prediction is interpolation (or not-too-gross extrapolation). This brings us now to the first issue with statistical content: with respect to a specific area from numerical modeling, how do we determine what we know? Some sort of a systematical evaluation is in order. Statistical design/analysis offers a tool for such an evaluation. Consider for example a relatively simple and hopefully reasonably well-understood area, that of one-dimensional hydrodynamic modeling, what we must accomplish for simulated yield estimation within a spherical geometry. We think conceptually of the set of simulations that could be done to encompass the reality of 1-D hydrodynamic experimentation. Each point in that space, here called a parameter space, is defined by a set of material properties and modeled using well-established mechanisms. The systematic evaluation begins with a check-off in that parameter space. Where have simulations been done? Where have such simulations been validated by being compared to experimental data? Looking across the simulations that have been done, to what degree is there compatibility? Where in the parameter space are there simulations that in some sense are anomalous and do we have explanations? For example, an interesting and important fact is that in some cases, simulations do not agree with reality, because input parameters, such as material properties, are determined by tests conducted in the laboratory. Glenn [Ref. 1] showed laboratory mechanical behavior that was distinct from the behavior of the same material in a field exercise. Thus in some sense the simulation was placed at the wrong point in the parameter space.

Once this systematic description of what simulations have been done and the level of agreement is established a plan can be formulated for "filling in the holes", that is, for increasing what we know. At that point, because budgets are finite and ever shrinking, we must be economical in our attack in filling in the holes. We need a buy in from the modelers and so that the increased level of knowledge is attained in an efficient, timely, and economical fashion.

A possible interesting application of empirical or statistical modeling here would be to develop a model that would predict the results of a numerical model based on a fit of the numerical model's outputs on the input points in the parameter space [Ref. 2]. Such "modeling the model" approaches have been successful in complex reactor melt down catastrophe situations [Ref. 3] where each simulation of a catastrophe is very computer intensive so that it is really impossible to cover the parameter space in a timely and economical fashion.

The second statistical issue we wish to discuss is uncertainty in the context of numerical modeling. Uncertainties are usually measured by the degree of agreement with an experiment or other description of reality. Uncertainties are either random or systematic. In the context of numerical modeling, random uncertainty, usually thought of as measurement error, is an explanation for why empirical measurements do not exactly agree with a correct model. Random uncertainty is the more familiar, being the one that is usually treated in the statistical literature. Random uncertainty is reduced by doing more of the same. The simplest example is independent repetitions of a simple experiment to estimate a single unknown quantity. That quantity is estimated with the mean over all the repetitions of the experiment. Quadrupling the number of repetitions of the experiment halves the uncertainty as measured by the root mean squared error. In more complicated situations, say where the random uncertainties are correlated from repetition to repetition, the reduction in root mean squared error is not as dramatic. However, in general, with enough repetition, a pre-specified root mean squared error can be attained.

Systematic uncertainty is much more complicated. Here the same error is present in all repetitions, averaging over more does not reduce such error. In the context of numerical modeling, systematic uncertainty as a problem is some fundamental difference between data and model. Systematic uncertainty indicates that deeper thought is necessary, possibly more physics, in order to construct and/or improve the model to include an explanation for the systematic effect. The critical point is that in comparing numerical modeling to reality most of the uncertainties appear to be systematic. The solution is either to improve the models so that the systematic uncertainties are eliminated, or to understand/bound the maximum size of systematic uncertainty and, hence, the maximum disagreement that is possible between model and reality.

Hydrodynamic yield estimation provides an excellent example of the uncertainties that appear to be present in the results of numerical modeling. Figure 1 is such an example of yield estimation as a function of time, determined by yield scaling a hydrodynamic standard to a CORRTEX radius-verses-time curve at each time point. The random uncertainty in the raw CORRTEX crush length data is only several centimeters on a mean squared basis. The several familiar characteristics of the curve are systematics. The short term oscillating pattern is unexplained, but conjectured to be the result of ill-understood dynamics in the cable crushing process. The shape and amplitude of the pattern seems to be dependent on the type of cable. The steep initial rise in yield and low frequency oscillation are systematic discrepancies between reality, the CORRTEX radius-versus-time, and simulation, the hydrodynamic modeled radius-versus-time. Thus, yield appears to be a moving target. The final yield value, usually attained as an average over the analysis window and here illustrated as the horizontal line, clearly depends upon where the window is located.

A critical issue here is, what do we do if we do not know the yield and truly have to depend upon the CORRTEX experiment and the modeling of that experiment with an appropriate hydrodynamic calculation. One might argue that if there is a monotone trend across the time window, then whatever the discrepancy is between experiment and hydrodynamic model, it changes sensibly in the same direction as the shock front moved out to the satellite hole. Hence, the time with the least systematics is the early time. Of course one can argue just as logically for other time windows. The reality is that we do not know which time window gives the best yield estimate. In particular, selection of a time window because the yield-versus-time curve is flat over that window is no more logical than other selections.

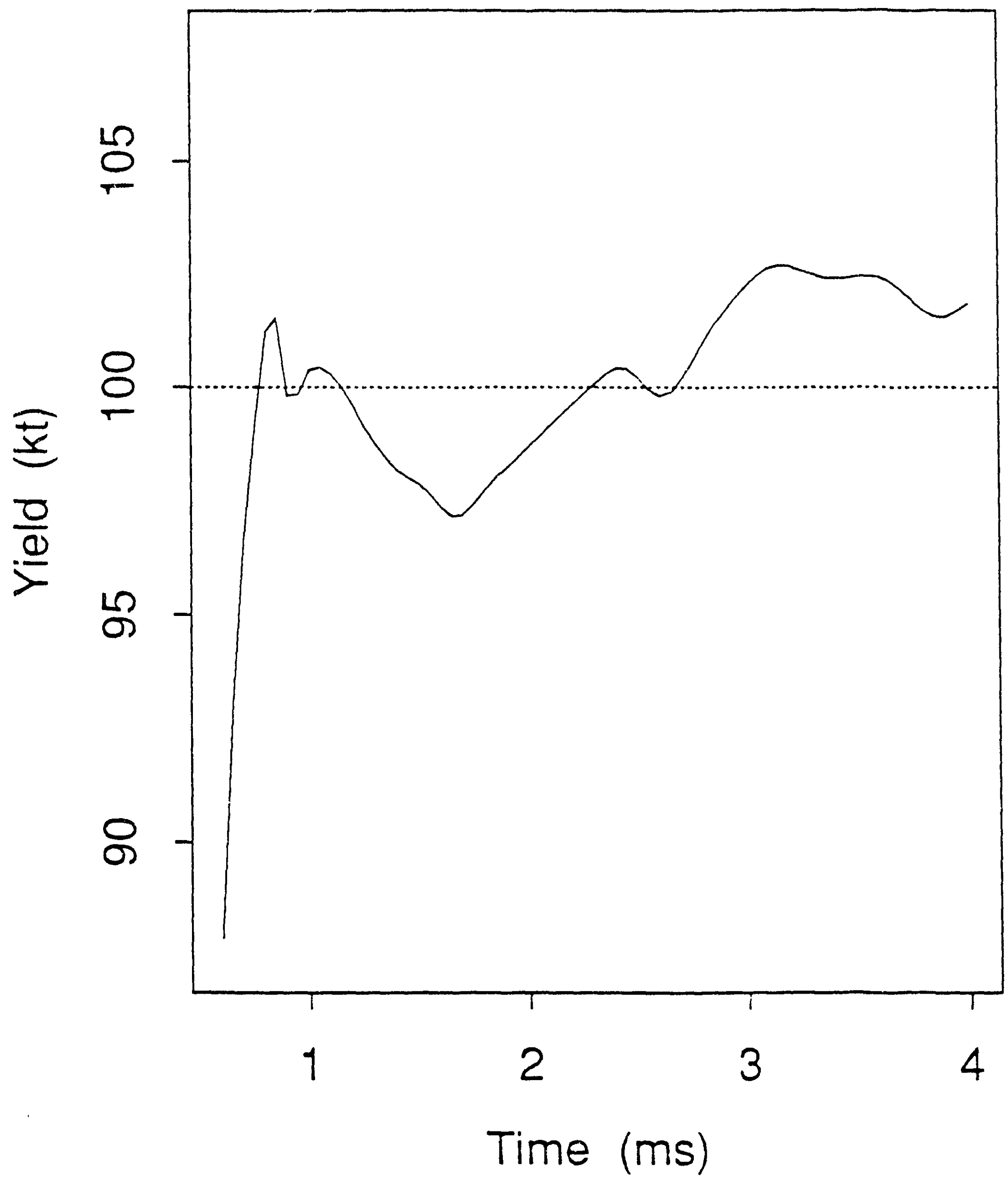

Figure 1. A typical yield-versus-time curve from a single CORRTEX cable. The average yield was set arbitrarily at 100 kt.

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