Performance Based Criteria A Panel Discussion

n July 9, 1991, five panel members representing several sectors of the environmental analysis industry convened in Washington, D.C., at the invitation of The University of Findlay, Wheaton Scientific, I-Chem Research and VWR Scientific. The objectives of the discussion were: 1) to increase awareness of sampling variability in environmental measurements, and 2) to suggest approaches to deal with sampling variability.

The panel was chaired by Michael T. Homsher of the Hazardous Material Management Program at The University of Findlay, Findlay, Ohio. Panel members in alphabetical order included: Dr. Fred Haeberer of the Quality Assurance Management Staff at the U.S. Environmental Protection Agency (EPA), Washington, D.C.; Dr. Paul J. Marsden, senior scientist at Scientific Applications Inc., San Diego, Calif.; Dr. Ronald K. Mitchum, president of Research Triangle Laboratories in Columbus, Ohio; Dr. Dean Neptune, Quality Assurance Management Staff at the U.S. EPA in Washington, D.C.; and Dr. John Warren, Office of Policy Planning for the U.S. EPA in Washington, D.C.

to raise awareness of sampling variability and to
suggest

approaches to

deal with this

problem.

Analytical

experts gather

WHAT ARE PERFORMANCE BASED CRITERIA?

Performance based criteria are quantitative estimates, developed from actual experience in applying experienced sampling and analysis plans, and determined to be appropriate for the intended purpose by the data user and review sources. Frequently, performance based criteria represent initial data quality objectives, qualitative and quantitative statements of data quality needs.

The ability to differentiate and resolve the components of variability in environmental measurement is an important issue. The source of this importance is the regulatory and risk assessment strategies that are increasingly being applied to environmental data for decisionmaking purposes.

Within the past four years, recognition of the components of variability in the environmental measurement process has been discussed at national level quality assurance conferences. It has been estimated that up to 90 percent of all environmental measurement variability can be attributed to the sampling process. Estimates of sampling variability have been determined in the acid rain studies, the Department of Energy Environmental Survey, and Superfund by using sample audit materials and onsite sampling audits. Extensive descriptions of processes to control sampling variability in the environmental measurement process have been prepared by the American Society of Testing and Materials and others. A recent recommendation by the American Chemical Society (ACS) to report data when requested at the Reliable Detection Limit, (the concentration at which a detection decision is extremely likely to be correct), makes discussion of this topic very relevant to any individual making decisions based on sampling and analysis. Figure 1 represents sources of errors in environmental measurements.

Consideration of these components of error in the initial planning for sampling and generation of environmental data is a critical step. The challenge is to ensure that decisionmakers are aware of the components of error and to effectively control these error sources in the form of performance based criteria for sampling. This may be the single most important step in providing data of known and documented quality for environmental decisions.

THE PANEL'S VIEW

Homsher: A quotation that reflects the sampling variability issue is, "It is important to realize that if the error associated with the sample collection or preparation phase is large, then the best our current approach to detection of sampling variability? Marsden: Field dupli-Figure 1 cates would probably be our best effort. It would

be my choice for at least

assessing where we are

on sampling variability. Yet, frequently it is said

that we cannot afford to

take field duplicates and pay for these additional

analyses. It is an after-

burner approach to data

quality. We currently use

post analytical tech-

laboratory quality assurance program is

inadequate." How would you describe

tified and some idea as to the magnitude not in itself sufficient. I think you have to of those can be assessed. look very carefully at the statistical de-**TOTAL ERROR** Sample Sample Laboratory Data Siting Handling Analyses **Analyses**

is to take more samples in the field.

Recognizing that you have a limited bud-

get, simply taking more field samples is

Laboratory Sample Data Handling Collection Handling Cleanup

niques when we should "Harmonization of Federal Agencies' QA Requirements for Environmental Data Operations-An emphasize cost-effective and timely planning, especially experimental design.

Warren: The way to determine sampling variability, from a statistical point of view,

Update," moderator G.L. Johnson, Stanley M. Blacker, Fourth Annual Interagency Meeting on Quality Assurance in Environmental Measurements, Jackson Hole, Wyo., Sept. 24-26, 1990, p. 115. sign of an experiment in order to maximize the amount of information you get from sampling. Research and investigations must be done in making appropriate

Haeberer: I think you have pretty well identified all the categories as far as total error. With environmental methods

frequently we see ana-

lytical variability of ap-

proximately 10 percent.

put out when we come up with figures

of 30 percent differences from the field

Homsher: Do you think

Figure 1 describing total

error accurately illustrates

sampling variability?

trade-offs. From a statistical point of view,

the components of variability that go into

the total error can then be properly iden-

Yet when we take field duplicates from uniform waste streams, the differences we see in the

analyses of these duplicates is technically 30 percent. So we should not be

tion on sampling variability? up with criteria for standard sampling designs so that the sample variability Mitchum: I am not certain that anyone is can be discerned from looking at the collecting information on sampling varianalytical data, given the inputs of the ability. The data may be out there in method variability and operator error. some of the EPA databases that we have, but I am not certain there are Mitchum: Yes, it makes sense in terms catalogs that you could readily access. of the total error being comprised of all That question is one which deals with errors. Typically in laboratory errors it

with analyses. I think we need to come

might range 10 to 15 percent on methods that are measuring very low levels of some analytes. One of the problems I have found in sampling is that in many

cases information we have from the field doesn't get relayed back to the people that are using the data. If you think you have deviations due to sampling error, what do you do? What you

will usually find is that individuals will spend money to go back and run duplicates of the samples in the laboratory. However, the individuals will not go back to the field and collect more samples. The laboratory does not con-

tribute, except for small percentages, to

the error you will find in the data.

to be an integral part of the study. Ideally, what you want is for there to be no variability in sampling. Neptune: I agree that not very much

ance Management Staff (QAMS) has

had the opportunity to facilitate the ap-

Homsher: Who is collecting informa-

sampling design that usually does not,

in many cases, test sampling variability.

Homsher: Would you say this would be

a useful piece of information?

information is available on sampling variability. [The EPA's] Quality Assur-

Mitchum: If I designed the study, sampling variability would certainly have

30 to 10 percent. So when you think about where you might get the best ad-

ses, data handling, data reporting, and data interpretation—makes up that other

plication of the data quality objective

process, an up-front planning tool, with

Superfund sites and have helped them

establish their data performance con-

straints for planning their survey design,

and done some actual field pilots where

We have actually gone to some

several of the regions in Superfund.

other sources in the figure—from sample collection, sample handling, laboratory handling and cleanup, laboratory analy-

real bulk of the error is typically found.

vantage by spending another dollar, in the lab versus spending that same increment of money to get a better handle on that natural population variability, it is obvious that you get a much bigger bang for your buck by determining natural population variability. That is where the

contribution of the variability from the

between 70 to 90 percent. Therefore, the

we have tried to determine what by natural variability of the population, varies

I am not saying that it is always found in the natural population variability and that these other sources are not an important aspect of error. QAMS has been trying to help people understand through a diagram like Figure 1, what the typical major contributors of error are, to get some real world information from actual sites and share that information with people so that they can decide; do I wish to collect this array of quality assessment samples vs. just doing what other people have done in the past? Homsher: What I hear you saying is

that QAMS is working together with individuals to help clarify or draw out the information that will focus on variability. But when this was done in six pilots that you mentioned, you identified the sample population as being the major contributor. Did you use quality assessment samples and processes to make this determination? *Neptune:* Absolutely. One of the key

issues we try to get decisionmakers to

face, who are responsible for survey designs, is to focus on knowing their sampling error vs. measurement error. They should be interested in knowing error levels so that when they complete their sample collection, sample analyses and data interpretation, they can compare their data performance results with their data quality objectives. The reason to bring it down to that ultimate point in the hierarchy of error (simply telling them whether they were successful or failed) is because it does not require a lot of quality assessment samples. This allows them to quickly

come to a conclusion that the data is

good enough for the intended purpose

and therefore, we have been success-

ful. The bad part is that if you tell them

no, they have not been successful, one

of the knee-jerk reactions of most deci-

sionmakers is to turn around and say

"why?" If you have not conducted qual-

ity assessment to delineate the various sources of error, be it in the laboratory or in data handling or in the actual sample collection process, you can't determine where the failure is involved. So we have been trying to help decisionmakers trade off between wanting to know exactly what the diagnostic of as I can identify, much information being collected on sampling variability. That leads us into the question: is there a national mechanism for sharing infor-

Homsher: We really don't have, as far

mation about sampling variability between agencies? I think it would be particularly important in both the short term and long term as we look at the Department of Defense and Department of Energy future involvement in very large multibillion-dollar environmental projects. Identification of those sources of sampling variability will be important.

> point that disturbs statisti-

cians is, what is

the base of

"An important

Topical State of the Section of the

representation?" -Warren

Mitchum: First there are scant mechanisms for any type of information to be shared between government agencies, much less information as detailed as sampling variability. We have a very difficult time sharing information on analytical chemistry and site character-

Homsher: Would this type of national pooling of information be related to the harmonization issue? Haeberer: Exactly. Ken Brown from Environmental Monitoring System

road cars to homogeneous materials. The proceedings of that workshop are currently being prepared. In terms of quality assurance meetings, there have been several. These grew out of meetings between EPA's Superfund and

Laboratory, Las Vegas (EMSL-LV)

held a three-day workshop last Febru-

ary to address how to sample a site

where you have everything from rail-

DOE's staff. The extent to which these agencies get into the statistical design of sampling an environmental site still has to be seen. Currently they have been dealing more on operational levels as opposed to addressing it from the standpoint of meeting data users' needs for

in hasn't yet been made but there is the recognition that this needs to happen. Neptune: This panel might be part of this information sharing, or an initial attempt. QAMS and the Office of Information Resource Management (OIRM)

have begun a collaborative effort to

deal with the important point Ron

Mitchum made when he said, "What

acceptable total error levels. So the tie-

information is really important to collect in order to identify the quality of your data?" What we have begun to do in collaboration with OIRM is to outline an agency approach for database quality identifiers that should be collected and incorporated into that database. We are trying to take a logical approach to identify important data qual-

ture that vital information for interpreting data quality from a future user's point of view. Homsher: So this effort is still in the

ity identifier information so that in the

future, the agency databases can cap-

Mitchum: I think that in many cases we

you should wash it. So, if we scraped the

first six inches off of an acre, piled it all

up and mixed it really well and took

ization. I think right now we don't have confuse sampling error with what I call a very good definition about what might design error and if the end result is not be shared. This topic might be well what you wanted or expected, then you worth bringing up at a QA caucus that is blame the samplers or the sample deheld between the different agencies. sign. We have the same problem in terms of how to design the sampling of the site and the mechanics of taking a sample; how deep you take a sample, what kind of tool you should use, how

informative stages.

have a pretty good composite of what is there. If we took only one sample we probably would not. We need to have generic guidance to describe how you sample various matrices. I think we need to define what we really need and what we are trying to measure in terms of sampling and sampling variability. Warren: From a statistical point of view he concept of com-

three, four or five sample measurements, we would probably

posite sampling is a very important one because it relates to the data quality objectives that Dean Neptune is talking about regarding why are you collecting and what is the decision you are going to make. I am going to go back to your original example of the railroad cars. Are you really going to composite a railroad car? The final decision is to determine whether

composite sampling is appropriate or not. A more important point that disturbs statisticians and is always glossed over is, what is the base of representation?

For example, if we are talking about a hazardous waste site of two acres and we elect to take a single core sample, what area within that site does that core represent? It is of great importance if that single core represents two square meters. However, that is very different than a sample core which represents just that core itself. This must be factored into the actual sample design right from the very beginning. What is the area of support for the sample that is going to be drawn?

then what sampling plan will be used in a composite sense to obtain a sample representative of that area and how does that affect the natural variability, which is what we wish to measure. Evan Englund of EMSL-LV has done some work on this but it still is very much an open question. Marsden: That is certainly true. One thing that has bothered

If the sample must be representative of a certain larger area,

me about environmental sampling and analysis is the amount of disconnects between statistical design, field activities, chemistry and the decision process. Everybody seems to have their own turf. I recently did trawling in the ocean and looked at fish and various other organisms. If you observe the way

biologists sample, there is no conceivable way to imagine that one would hire a sampling contractor to go out and run a trawl, bring the net back and then identify aquatic organisms. Yet, that is the way we do our chemistry measurements. We have a generic map and generate a sampling plan to go out and sample

certain spots...give the map to some group whose specialty is ordering bottles and going out and filling them up. Those bottles are sent to a laboratory which analyzes what is inside of the bottle and they fill out forms and send that information to 15

people who look at those numbers to evaluate and interpret the data.

DRAWING CONCLUSIONS Careful planning, including sampling designs that address the statistical issue of errors in sampling variability in the field, are vital to the overall success of environmental data

generation on which decisions will be based. Part 2 of this article, in the December/January issue of Environmental LAB, will further explore the complexities of sampling variability and discuss the panel's recommendations.

Performance Based Criteria A Panel Discussion: Part II

Analytical
experts gather
to raise
awareness of
sampling variability and to
suggest
approaches to
deal with this

problem.

n July 9, 1991, five panel members representing several sectors of the environmental analysis industry convened in Washington, D.C., at the invitation of The University of Findlay, Wheaton Scientific, I-Chem Research and VWR Scientific. The objectives of the discussion were: l) to increase awareness of sampling variability in environmental measurements, and 2) to suggest approaches to deal with sampling variability.

The panel was chaired by Michael T. Homsher of the Hazardous Material Management Program at The University of Findlay, Findlay, Ohio. Panel members in alphabetical order included: Dr. Fred Haeberer of the Quality Assurance Management Staff at the U.S. Environmental Protection Agency (EPA), Washington, D.C.; Dr. Paul J. Marsden, senior scientist at Scientific Applications Inc., San Diego, Calif.; Dr. Ronald K. Mitchum, president of Triangle Laboratories in Columbus, Ohio; Dr. Dean Neptune, Quality Assurance Management Staff at the U.S. EPA in Washington, D.C.; and Dr. John Warren, Office of Policy Planning for the U.S. EPA in Washington, D.C.

SUMMING UP PART I

From Part I of this article (October/November 1991, Environmental Lab): "Within the past four years, recognition of the components of variability in the environmental measurement process have been discussed at national-level quality assurance conferences. It has been estimated that up to 90

percent of all environmental measurement variability can be attributed to the sampling process."

In Part II, which follows, our panel members continue their discussion of this topic.

Homsher: We are discussing communication issues in terms of disconnects and suggesting an integrated type of approach with oversight, which probably would be QAMS (Quality Assurance Management Staff). Do we have any generic approaches?

Warren: This is a new area, this interaction between engineers taking the samples, the chemists who analyze the samples and the statistician who is doing the planning; we know it as chemometrics or as chemostatistics. I am pleased to say that the American Statistician Association has formed a subset on chemometrics within one of our sections. In addition, there is a new organization within EPA, and also the Center for Vital Statistics. The initial planning attempt is to integrate some of the work being done by DOE and DOD with EPA.

Homsher: It sounds as though an effort is being made to identify important characteristics and prepare a generic plan. A publication from EMSL-Las Vegas entitled "A Rationale for Assessment of Errors in Sampling Soil" discusses important sampling and analysis characteristics. Statistical equations are presented that point out the sources of variability seen in the total error diagram. How is sampling variability, once detected and documented, reduced and actually corrected?

Warren. We are sponsoring research (Office of Policy Training/Evaluation) by Penn State University. We have some of the best sampling statisticians available working on this problem.

How do you use composite sampling when you can only afford a certain number of samples from a site or given matrix? Work is being done on reduction of sampling variability. But don't forget, it has to be in the context of the basic quality objective. It comes back to what do you want. It is not a matter of taking the sample first and then deciding what does the sample tell us; it must be the other way around. Marsden: When you talk about vari-

ability in sampling, we occasionally lose sight of the goal. The goal is to assess the site and clean it up. The erything is a flat plane or homogenous cube, but there are many complications

mathematical model works when ev-

such as soil horizons, clay lenses, etc. It has been my experience that you never see consideration for these factors in the planning or sampling. Warren: In the planning stages of the sampling expedition, the statistician should be told that there are different soil types. This enables the statistician

you are sampling and make it into contiguous units. The precision will be greatly enhanced by the use of this prior information.

to recommend that you stratify the site

Mitchum: I agree. One of the problems is defining what we want to get out of the data when we talk to someone designing the experiment. For example, if gold was being mined and you sampled the first six inches of soil in Nevada, Nevada would be seen as one of the poorest gold producing states in the country. It is known to miners that gold in a particle form lies on the bedrock, not on the strata above it. So you have to dig down to the bedrock to find the gold because that is where it will be. Neptune: This discussion is music to my ears because we have been trying to

the EPA uses to facilitate up-front planning is the data quality objective (DQO) process. Too often, people have a historical recipe they use for collecting field data, bring it in and say, "What does this tell me, or what decisions can I make about this?" Instead, decisionmakers should involve all participants before collection. Mitchum: Let me give an example of just that sort of thing. I did a study for

foster up-front planning. The tool that

dioxins in fish. After I had collected a lot of fish and found very low levels of dioxins, I decided to examine fisheating snakes. I thought I knew that snakes eat fish. I called my local wildlife biologist and asked him to collect 25-30 water moccasins. I chopped, sliced, diced and analyzed the snakes and they had no detectable dioxin in them. In fact, water moccasins don't collect dioxin. My theory was wrong. I needed snakes that bioaccumulate dioxin. I spoke with a herpetologist (an expert on reptiles and amphibians) and learned that water moccasins eat rats, not fish. He recommended a particular species of snake which was then collected and they were very good. They had a bioaccumulation factor for dioxin of about 200.

Haeberer: If I may build upon your

anecdote and our discussion, the herpetologist should have been involved at the planning stage during your DQO process. That is the same thing that Dean and I have been finding. Unless you have the right people involved initially, you have a long up-hill climb. This involvement cuts down repeated sampling, sampling the wrong type of matrix and so on Warren: What Ron's example illustrates is called stratification on the wrong variable. He was absolutely correct in saying that snakes accumulate dioxin, so what he did was essentially stratified. but he stratified on the wrong snake. In statistics we are very sensitive to this. If you have a list of cases and someone just takes one off the shelf and says this is what I want to do, then you run the risk that Ron identified in his example. In fact, it was a right idea, wrong snake. Mitchum: If you had taken enough data you could throw things out that didn't make sense. Warren: Absolutely. As Fred said, there should have been a herpetologist in the made up front.

initial planning stage. Stratification is a very powerful tool. I think the concept of stratification of samples should be Mitchum: Give us a definition of performance based criteria and what you Homsher: Performance based criteria for sampling are quantitative estimates that have been developed by experience in applying sampling and analysis and they are determined to be appropriate for the intended purpose by the data-

really mean by that in this context. user and the review sources. I first became involved with performance based criteria when Fred (Haeberer), Dean (Neptune), myself and others were involved with the Superfund analytical methods for the Contract Laboratory Program. Performance based criteria were one of the things people requested. Now I think we see other areas for variability in the total environmental measurement process. If we look within the sampling area, is it possible that one can find and establish

performance based criteria for sam-

pling?

Warren: I would like to throw the question back to the decisionmaker. If you come to a statistician and say; "I want to know how many samples, I want to know the sampling plan, I want to know the following characteristics," the statistician, given enough information, can work out a plan to do that. The biggest problem for a statistician is to understand the decision you want to make. The decisionmaker should also be able to say what the consequence is of mak-

the consequence if I reached a wrong decision? I think this leads back to data quality objectives. Dean, don't you agree? Neptune: Absolutely! I recognize that managers would like to view data col-

ing the wrong decision. That is where

there is the big disconnect in the agency

process. If it is a health risk, what is the

consequence of not collecting enough

samples to make this decision? What is

decisionmaker has to communicate. during the planning process, what consequences are of great import to him so that they can be accommodated in the development of the data quality objectives. The scientists, engineers and managers need to be specific about their data performance requirements and then involve a statistician to develop a statistically based survey design. Frequently, the statistically based design is not only practical, but also more cost effective than the hodgepodge approach to reducing sampling variability that we have Warren: Unfortunately, there is frequently a failure of decisionmakers to consider what the consequences are in making wrong decisions. If they don't want to make a decision, they don't want to ask questions because they are potentially frightened by the answer. The decisionmaker ducks the issue by throwing it back to the statistician and

lection and data analysis as simply a

technical problem, something that the

scientists and engineers should take care

of. The communication that I have heard

here today needs to be conducted dur-

ing the initial planning, to determine

sions can be many: economic, human

health, environmental and social. The

The consequences of incorrect deci-

what is important.

done in the past.

has done.

is a cultural change and I believe the emphasis in society on quality is helping to bring that cultural change. Homsher: Accountability, responsibility and willingness to face the issues and identification of consequences involved has to come from the decision-

saying; "You tell me how many." The

decisionmaker should make a decision,

not merely endorse what somebody else

Neptune: We have struggled with this

in the Quality Assurance Management

Staff for years and it centers on one

important issue; responsibility and ac-

countability of managers. What we need

maker. Neptune: QAMS is a facilitator to the regional Remedial Project Manager and other decisionmakers. Two prime examples are EPA Regions IV and VII through the data quality objective process, involved all the parties, and management has lived up to their responsibilities to be accountable. It has

where they have successfully gone

taken courage on the part of many of those managers. When we were studying a dioxin site in Region VII, management had to defend it at both the state and headquarter levels. Managers in Regions IV and VII were able to take responsibility for what they were doing, explain it in an understandable way and demonstrate to their colleagues and se-

> done on reduction of sampling variability. But don't forget, it

Work is being

has to be in the context of the basic quality

objective."

cisions; get to the root of the problem

who live in that particular area.

·Warren

nior managers within the agency that this was worthwhile. This approach helped them make more defensible de-

tive, practical manner. This is particularly important in Superfund. The Community Right To Know Program provides funds for communities to hire experts to look over regulators' shoulders. This provides oversight for the agency and contractors. You are going

and remedy it quicker in a cost effecto be held accountable by the citizens

focus on how sampling variability affects our ability to make a decision.

Homsher: Documents on data validation

are almost exclusively analytical. Con-

siderations of the sampling variability are minimal. The topic should be ap-

proached in a focused attempt that in-

volves the data quality objective approach.

Mitchum: The primary objective is to get the data users involved, to define the

Marsden: Is it possible to have perfor-

mance based criteria? I think this is a

tough question. Just as we have method

performance differences matrix to matrix, we are going to have significant

sampling differences matrix to matrix.

This is a critical item in terms of RCRA

permitting; is your waste hazardous or

Homsher: Would you say that there is enough benefit to look into it?

Haeberer: You started out with the state-

ment that about 90 percent error is asso-

ciated with sampling vs. analytical error.

That clearly indicates that effort needs to go into further developing sampling

approaches, sampling schemes, sam-

pling design, whether it is statistical,

whether it is stratified, whether it is

selective. That is where we are finding our error levels. We need to focus a lot

more on sampling than the analytical

Neptune: The first thing we do when we are investigating the Superfund sites is

examine the historical data to determine

if the data will give us a sense of the

variability associated with that population. Frequently, we find that the his-

torical data is lacking and we run a pilot

study to determine the variability for

the population of interest. This allows us to design a survey that is more effi-

cient than if we just tried to take a guess.

Marsden: In terms of doing research to

assess sampling variability, this has to

be an integrated approach. You need to

integrate input from the people who

physically go out and take the samples, the statistical design people, the analyst

and the engineer. The research should

laboratory.

Marsden: I would certainly say so.

decisions and applying this data. With this involvement, sampling can be designed to meet acceptable error levels. Homsher: Can we go around the table

error level they can live with in making

and summarize where we think we are with our discussion? Neptune: First we must engage man-

agement in a proactive way to specify

what is important to them in their decisionmaking process. One of the issues that is very important for managers to resolve is to determine what is on the critical path for decisions. By giving that focus up-front, the efficiencies in our overall environmental data collection activities can be tremendous. The ability to speak with greater confidence and specificity about a given question and the data that we are now collecting

to support answering that question, gives us the chance to engage our statistical colleagues up-front in the planning. Now we can give the specificity to the statisticians to allow them to help us develop a probability-based survey design. Mitchum: I think where we are headed is, yes, we can put a number on the

variability in the laboratory. Now, can we put a similar error bar on something that happened in the field?

I think the most important thing is

representativeness and what was the sample just taken and what did it really represent. There are a lot of errors in sampling design, where we take the samples and representativeness. A sampler can make very few errors in the field if you tell him how to sample, you

watch him, and you have a procedure. When he gets back to the laboratory, we start getting into representativeness of the sampling in terms of the composite the laboratory is going to take and the distribution of these analytes in the site you are looking at. We need to define what will minimize sampling error, but I think the rest

that we get the answer and the kind of quality we desire. Unfortunately, I think what is happening is that people don't like the numbers. The conclusion is there must have been sampling error since that is an item we don't know much about.

of it simply is how to design the study so

ability of making an incorrect decision, not just in the performance and error bars around a given number one might generate. Just generating information on how good a measurement is falls short of where we really need to be. We need to understand what the impact of that error

Neptune: We are interested in the prob-

tion being sampled: those are all components of that error in the decision. Mitchum: Exactly right. At the limit you are trying to regulate, or at a risk

in the decision is, not the error in the

measurement, not the error in the popula-

and willingness to face the issues

"Accountability

of consequences

and identification

come from the

involved has to

decisionmaker."

Homsher

level, the probability for making a mistake is very high. That is the problem in making the measurements and the criteria we use in the laboratory. These are the best criteria we have, but especially near the detection limit, we neglect what sort of errors are associated with those measurements. In some cases measurements may have error as high as 30 to 40 percent, not even counting sampling

Haeherer: Let me try to give a little more of a philosophical view. We in QAMS have been busy for the past few years attempting to institutionalize the

error, but we are making decisions.

the education of the data user. Hopefully we can come to a point where we can design a sampling and analysis operation to adequately and consistently meet the needs of the data user.

DQO process. What is really needed is

Warren: I am going to address the question of the importance of sampling variability in environmental measurements. First, the fact that the decisionmaker and the error rates must be specified and

discussed at the early planning stage. Second, determination of the area of support; what does this sample really tell me about where it came from? Third, the importance of stratification of the areas of interest so that the planner can

get the biggest bang for the buck. And

lastly, the importance of including a statistician in the planning stages so that

there can be some form of integration

Marsden: I believe we should develop

some systematic information about how

across the entire process.

much variability we really are talking about. If the numbers are bad, we can't make a decision. I think that the multidisciplinary approach to planning would result in an initial buy-in from everyone involved. I think we need to break down

communication barriers between plan-

ners, samplers, analysts, validators and

IN CONCLUSION...

Efforts should continue and increase

to define the criteria needed for accurate

decisionmaking to occur for all environ-

decisionmakers.

mental sampling projects. This can best

be achieved through the cooperative efforts of decisionmakers, planners, statis-

ticians, chemists and engineers from the initial stages and throughout all phases of

member's comments was inadvertently omitted from Part I of this article (Environ-MENTAL LAB, October/November, page 14). It

should have read:

Neptune: So we have been trying to help decisionmakers trade off between

wanting to know exactly what the diagnos-

environmental projects.

tic causes of failure might be versus just

knowing whether the data collected is adequate or not. It is a balancing act and it is not an easy job.

CLARIFICATION: A portion of one panel