**WHAT INFLUENCES THE SUCCESS**

**OF AQUACULTURAL RESEARCH PROJECTS?**

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Paper delivered at the

*9th Asian Fisheries & Aquaculture Forum*

and

*9th International Symposium of Tilapia Aquaculture*

Shanghai Ocean University, Shanghai, China, April 21 – 25, 2011

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This study is supported by the USDAID-sponsored AquaFish Collaborative Research Support Program (AquaFish CRSP), <http://www.aquafishcrsp.oregonstate.edu>. We thank the AquaFish CRSP staff at Oregon State University for their strong administrative support.

**What Influences the Success of Aquacultural Research Projects?**

**Introduction**

No research program can enjoy long-run success without a periodic assessment of how it is performing and what factors influence success and failure. While most such assessments are informal and specific to a particular study, formal evaluations eventually become important at the program level. A formal analysis the same as an informal one in the sense of comparing research outputs with the inputs or efforts expended to achieve them (a “knowledge production function”). Approaches to research assessment thus differ only in how such outputs and inputs are to be understood, measured, and compared.

Assessment methods can be either quantitative – typically statistical – or the kinds of institutional evaluation one sees in a case study. In biological disciplines, at least, most statistical analyses of the factors affecting research success employ the scientists’ publication counts, citations, or intellectual property as measures of research output. Methods are parametric or non-parametric, dynamic or static. In the parametric approach, the bibliographic output measures are regressed against current and lagged research expenditures, against other inputs or conditions poorly represented by expenditures, and sometimes against a time trend.

Adams and Griliches (1996), for example, examine U.S. university research performance in eight scientific fields during the 1980s. They find at the level of a particular university or field that diminishing returns to scale prevail in academic research. That is, increases in study size bring less-than-proportionate increases in the study’s publication output. At the aggregate level, however, there appears to be approximate equality between research expenditure and publication (or citation) performance, possibly because aggregate data incorporate cross-study knowledge spillovers that are not captured in more disaggregated data. These methods have more recently been applied to life-science research by Smith (1998), Xia and Buccola (2005), Groot and Garcia-Valderrama (2006), Buccola, Ervin, and Yang (2009).

The bibliometric approach is, despite its widespread use, inadequate in a number of respects. The first and probably most important difficulty is that publication, patent, and journal citation rates mask much of the detail of a study’s findings and thus only grossly reflect the findings’ nature, magnitude, and importance. Much published output also becomes available only years after the study has been completed. Finally, the bibliometric approach is poorly suited to an exact matching of a study’s outputs and inputs.

To help solve these difficulties, we examine here a new approach to research assessment. The new method focuses directly on the information a research study has generated, enabling a more exact and more contemporaneous matching of that information to the skills, expenditures, and capital devoted to the study. We apply the approach to the 55 past and on-going aquacultural research investigations which AquaFish CRSP is pursuing in eleven countries.

**Conceptual Framework**

To place this approach in its broadest context, let *K* represent the knowledge an aquacultural study has generated; *E* the study’s expenditures; *M* the research management policies, such as choice between control and survey methods; *C* the human capital devoted to the study (and which can be only imperfectly captured in expenditures); *I* the institutional, cultural, and environmental conditions under which the study is pursued; and  the unexplained variation. We then can relate the magnitude *K* of the study outcome to the inputs affecting that magnitude:

1. 

and in this way individually examine the impacts of factors *E*, *M*, *C*, and *I* on knowledge output *K*. For example, we can estimate the effectiveness of research management policies while holding expenditure, such human-capital dimensions as researcher education and experience, and environmental conditions statistically constant.

*Difficulties in Measuring Research Output*

Relationship (1) is best characterized with disaggregated data, that is with observations on many individual studies. With disaggregate data, information about research expenditures, the composition of the research team, research management practices, and the institutional environment will be available if enough effort is made to collect it. The more difficult task, even in disaggregate settings, is to characterize and measure research output magnitude *K*. Output measurement difficulties arise from several sources.

First, an aquacultural research study typically focuses not only on a variety of research treatments but on a variety of outcomes per treatment. An examination of alternative fish feed rations, for instance, typically is interested in the survival rate, feed conversion, final body weight, and flesh quality associated with each ration. The reason is that all such outcomes affect profitability in a separate way. Yet these outcomes are incommensurable with one another unless expressed in terms of their impact on profit, an impact that varies with market conditions and hence is unknown to the investigator at the time the project is initiated. Even greater outcome incommensurability is encountered from one study to another. For example, one study in our AquaFish dataset may be seeking to boost tilapia exports, while another seeks to improve pond water quality.

Second, an aquacultural research study's contribution is information rather than something tangible like per-hectare fish yield or pond oxygen content. Because information is intangible, we cannot measure its magnitude by counting tons or hectares.

Third, research studies in our dataset frequently will be found to have started on different dates and to have progressed at different rates. Our assessment procedures must therefore account for differences in the stages at which a given study will be encountered. That is possible only if our assessment method is updatable, permitting us to evaluate progress as a study proceeds as well as when it is completed.

Fourth, some research projects fail in the sense that the hypothesized improvement – enhanced oyster management practices, say – does not materialize. Such failures do not necessarily imply that the study expenditures have been wasted, since the experimental disappointment can be valuable in pointing to more fruitful directions in subsequent research (CGIAR Science Council 2009).

The first or incommensurability problem can be solved by expressing study output units in terms of percentage changes, relative either to the originally anticipated improvement, the improvement the study manages to obtain, or the outcome levels already achieved before the study was inaugurated. Percentage changes in, say, one study's per-hectare yields are directly comparable to percentage changes in another study's water quality index. However, such proportional measurement makes no progress in solving the remaining three measurement difficulties.

*Bayesian Approach to Research Output Measurement*

An approach that does solve the second through fourth problem is to take advantage of Bayesian statistics, which are complementary to the classical statistics employed in most aquacultural research (Robert 2001; Schimmelpfennig and Norton 2003; Carlin and Louis 1996; Press 1989; Winkler 1972). In contrast to classical statistics' focus on estimating a population parameter like a water-quality improvement rate, Bayesian statistics concentrates on the *new* information the water-quality study provides. The old information can be either the results from earlier experiments or surveys or the aquaculturalist's subjective, pre-experiment hunches about how the experiment will turn out.

More particularly, the Bayesian method regards any new information as the difference between the study outcome probabilities (e.g. fish mortality rate or feed/gain ratio) that the researcher had surmised before the study began and the probabilities she encountered during or as a result of the study. Provided those outcomes are expressible in frequency terms, they can never generate less information than what the researcher originally had possessed, since the least the new outcomes can do is to exactly confirm the researcher’s prior expectations. For example, early success of a proposed new Tilapia seed production method may boost the pond yield rates relative to those farmers presently achieve or to those the investigators had anticipated. If, on the other hand, the study fails to boost yields, its success is reflected instead in the experimental lesson learned, which in turn is expressed as the narrowing of the probability distribution of possible yield outcomes.

To summarize the Bayesian approach, let *Y* be the percentage improvement in a particular study outcome such as pond water quality. Let *Z* be the performance of the new technology the researchers are examining and which is intended to improve pond water quality. The probability the investigator initially assigns to a particular level of water-quality improvement is, in light of the study’s current progress, updated as

(2) 

where ** is the probability of the first term in each parenthesis, and  indicates that the following term is held constant. That is, after the researchers have observed performance *Z* of the new technology, the probability of a particular pond improvement level equals the probability that experimental outcome *Z* will occur given that the new technology improves pond quality by a stated amount, times the prior probability of pond improvement and divided by the prior probability of experimental outcome *Z*.

The likelihood that experimental outcome *Z* will occur depends in turn on study expenditures and other inputs **X** such as the investigators’ human capital. We may represent this dependence as , where are unanticipated research findings. Furthermore, once the experiment is complete,  is a known constant. Combining these two considerations gives, at the end of the experiment,

(3) 

in which ∝ signifies “is proportionate to.” That is, the probability of the given pond improvement once experimental results have been obtained is proportionate to the probability that experimental outcome Z (a function of research inputs **X)** will be obtained assuming the new technology will be pond-enhancing at a stated level, times the pond enhancement originally expected. Expression  in equation (2) is the investigator’s prior (baseline) pond quality probability. In contrast,  is the posterior improvement expectation elicited at a midpoint – then at the termination – of the research process, reflecting the intervening experimental or other study results. Well-developed methods are available for eliciting the prior probabilities (Stael von Holstein 1970). They involve casting the probability questions in the context of the study’s institutional and technical environment and employ the researcher's judgment about the situation at hand, a judgment that will partly be based on the previous literature.

The value to a decision maker of basing her decisions on the prior probability distribution rather than on posterior distribution , that is the value the aquacultural study has provided her, is reflected in the “loss” difference

(4) 

where  is the prior information available to the decision maker. This loss is the difference between the utility of acting in the absence of the study results and the (higher) utility of acting after knowing those results. Thus also, it is the disutility a fish farmer, buyer, supplier, or other interested party suffers if deprived of the research study. Function (4) can be specified in a variety of functional forms (Robert 2001).

For example suppose an oyster producer’s decision *d* is that he promises, on the basis of his present management practices **X**, to deliver oysters at a particular quality grade A. If he delivers the oysters at lower than the promised grade, his quality reputation suffers; if at a higher grade, he sells at a price lower than he could have achieved had he predicted the quality more accurately. His profit, that is, rises with his accuracy in predicting quality grade. By improving our understanding of the true quality probabilities related to a particular management practice, oyster management research is precisely what improves such prediction accuracy. The negative of Loss (4) thus reflects the value of the oyster study's contribution to the improvement in prediction accuracy. A measure of the study's knowledge output *K* that solves all four of the research-output measurement difficulties listed above is therefore

(5) 

the negative of the Bayesian Loss value (4). If we consider decision *d* to be a function of sample information Z itself, and prior information  to be unobserved error , we get

(6)  ****

namely, knowledge production function (1).

**Characterizing the Knowledge Production Relationship**

In order to characterize how the magnitude of such new research knowledge responds to the type and quantity of research inputs, namely in order to depict relationship , we treat each AquaFish research study as a production unit employing research inputs -- such as money and personnel – to produce knowledge outputs. Most AquaFish studies are designed to examine a variety of experimental or survey dimensions, and they involve a variety of alternative treatments for a given dimension. For example, a controlled-experiment investigation focusing on feed rations can examine both the weight-gain and fish mortality effects of a given ration. A variety of rations are examined in each study – each constituting a separate research treatment – for their weight-gain and mortality effects. Considering instead a non-controlled-experiment situation, a survey investigation focusing on fish export opportunities can examine a marketing program’s implications for both fresh and dried fish.

If the investigator employs *m* alternative feed-ration or marketing-program treatments, and examines the implications of each of them for such *n* outcome dimensions as mortality, weight gain, or dried exports, she will generate *mn* utilities (3), that is *mn* items of utility-enhancing new knowledge. Because *p* AquaFish investigations have been pursued over *t* years, we thus have *N* = *mnpt* observations for estimating equation (1). The result is to reveal, for each of a group of investigations, how much research output *K* has been achieved for each given set of research inputs and each scenario of institutional, management, and environmental conditions. Importantly, our method can be used to examine research performance not only at its conclusion, but at earlier project stages; that is relative not only to other studies but to its own earlier efforts.

**Research Inputs We Are Examining**

We examine in knowledge production function (1) the research impacts of the following study inputs and conditions:

*Expenditures (E)*

At U.S. Project University

In Host Country

*Research Management (M)*

Controlled Experiment *versus* Statistical Survey

Sample Size

*Investigator and Collaborator FTE and Human Capital (C)*

Scientist and Collaborator Age Distributions

Distributions of Highest Degrees

Position Rank Distributions

*Institutional and Environmental Conditions (I)*

On-Station *versus* Off-Station research

Transportation Modes

Road Conditions and Distances

Climate and other Environmental Conditions

Knowledge production function (1) or, equivalently, (6) can be estimated with distance-function methods (Fare and Primont 1995). Attention to unexplained variation  in equation (1) is useful. If we consider  to be the sum two independent random variables, , the latter may be used to represent frontier or best-research-practice performance, and the former to represent negative deviations from that frontier. Error thus provides the basis for conducting cross-study comparisons of the efficiency with which research resources are used to achieve knowledge.

**Utility Computation Example**

An example from Investigation 07MNE04UM, a University of Michigan AquaFish study conducted in China, will illustrate the method we are using to compute an AquaFish study’s knowledge contribution. The purpose of 07MNE04UM is to examine ways of reducing effluent and settling-pond pollution from Chinese shrimp production. Fish yield is compared in that study with water quality as measured by settling-pond chemical content. Statistical-survey rather than experimental-control methods are used. Relevant data in one of its treatments are:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Outcome | Level | Prior probability | Posterior mean | Posterior standard deviation |
| Fish yield (kg/ha) | Low 7000 | 0.10 | 8255.06 | 1438.05 |
| Medium 8000 | 0.60 |
| High 9000 | 0.30 |
| Dissolved oxygen (mg/L) | Low 6 | 0.20 | 6.74 | 1.05 |
| Medium 7 | 0.70 |
| High 8 | 0.10 |
| Total suspended solids (mg/L) | Low 20 | 0.10 | 47.12 | 12.33 |
| Medium 30 | 0.70 |
| High 40 | 0.20 |

One thing that is clear from this table is that an econometric model in which several dimensions of outcome – such as fish yield, dissolved oxygen, and suspended solids – are pooled, we first must normalize the outputs in a way permitting comparisons among them. Kilograms per hectare and micrograms per liter are not directly comparable. A natural way to do so is to divide each outcome level by the sum of its Low, Medium, and High levels, so that outcome levels are expressed essentially as percentage differences from their mean. Thus, for example, we can restate the three alternative fish yield levels as 7/24, 8/24, and 9/24, where 24 = 7+8+9. Loss function values are invariant to this normalization.

The prior probabilities in the table are elicited from the scientists on the basis of their best understanding, prior to conducting the research, of what the yield and chemical readings would be in response to the particular treatment or set of management practices. The posterior mean and standard deviation are, in contrast, taken from the statistical survey’s ANOVA results. To demonstrate the value of this research, we compare the advantage of using these posterior rather than prior distributions of when making shrimp production management decisions.

The mean of the shrimp producer’s prior distribution is

(7) 

where *L*, *M*, and *H* are the low, medium, and high levels shown in the table, and the *P*’s are the associated prior probabilities. This is what, prior to the research study, the producer expects his yields or dissolved oxygen levels to be. To derive the mean of the posterior distribution – namely what the producer expects, by virtue of the new study, the yields or dissolved oxygen to be, we first generate the normal density function corresponding to the posterior mean and posterior standard deviation shown. We then compute from that density function the low, medium, and high outcomes (, , ) whose cumulative probabilities would – to keep our results comparable to the prior distribution – equal to those in the prior. The result is the mean outcome as corrected by the research results, namely by the information in the posterior distribution:

(8) 

We next use these two respective means in (7) and (8) to compute two important measures of random variation in the producer’s shrimp yield or pond dissolved-oxygen content. The first is the variation the producer anticipates around his naïve (pre-research) outcome expectation , but evaluated in terms of the outcome probabilities *estimated from the new research*. This models the risk which the new study shows the producer actually was facing when she used the pre-research outcome expectation. It is the post-study view of the producer’s pre-study thinking. The relevant measure of this variation is the outcome variance expressed in terms of the outcome deviations from the pre-study mean but in which the outcome levels (, , ) are those the study indicates are associated with the given probability levels – that is, essentially in terms of the *posterior* probability distribution:

(9) 

The appropriate variance of the posterior distribution is based on the respective distances between the posterior mean and the same three outcomes predicted. This of course is the posterior variance itself:

(10) 

The knowledge or utility gained from the research is the difference between this prior and posterior variance:

(11) 

It is easy to show that this difference is non-negative, so that the knowledge gained from properly conducted research can never be negative.

Data on AquaFish research treatments, probabilities, and inputs were provided by the host-country AquaFish investigators. Coordinators were (by US university base of respective project): Steven Amisah (Purdue U), Gertrude Atukunda (Auburn U), Remedios Bolivar (North Carolina Stat U), Wilfrido Contreras (U Arizona), Eladio Gaxiola (U of Hawaii), So Nam (U of Connecticut), and Gao Zexia (U of Michigan). Our study covers 55 aquacultural research studies conducted during AquaFish’s 2007 – 2009 and 2009 – 2011 phases. Twenty-seven of these were conducted during the 2007 – 2009 phase and 28 in the 2009 – 2011 phase.

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