

APPLICATION OF A DYNAMIC STOCHASTIC ADAPTIVE BIOECONOMIC MODEL TO EVALUATE THE ECONOMICS OF OFFSHORE BLUEFIN TUNA AQUACULTURE

Gina Louise Shamshak, University of Rhode Island, shamshak@uri.edu
James L. Anderson, University of Rhode Island, jla@uri.edu

ABSTRACT

Over the past fifteen years, the market for bluefin tuna has evolved in an attempt to further enhance the economic value of bluefin tuna landings. Historically, the US East Coast has been a major supplier of high quality bluefin tuna to Japan, the primary market for sashimi grade tuna. To date, many questions regarding the economic feasibility of offshore aquaculture, and in particular offshore bluefin tuna farming in the United States, remain unanswered. This research assesses the economic feasibility of an offshore bluefin tuna aquaculture industry located on the East Coast of the US by developing a dynamic stochastic adaptive bioeconomic model of such an offshore enterprise. The bioeconomic model incorporates the biological constraints of the species, the interaction of relevant economic parameters and constraints, and stochastic sources of risk, to solve for the profit maximizing behavior of a farmed bluefin tuna producer. This research identifies the optimal harvest schedule for an offshore bluefin tuna farming facility that maximizes the net present value of the operation under a variety of economic, biological and regulatory conditions. Economic feasibility is analyzed using profitability indicators including net present value (NPV) and internal rate of return (IRR). This research is relevant given the continued expansion of bluefin tuna aquaculture globally, the increasing demand for high-quality bluefin tuna, and the uncertainty regarding the economic feasibility of an offshore bluefin tuna aquaculture industry in the United States.

Keywords: aquaculture, bioeconomics, bluefin tuna, stochasticity, dynamic models

INTRODUCTION

Capture based bluefin tuna aquaculture has transformed the bluefin tuna industry over the past 15 years, altering how bluefin tuna is supplied to the market. As it is currently practiced, this form of production involves the capture, penning, and fattening of wild caught bluefin tuna for a period of time to increase their weight and fat content before slaughter. While researchers in Japan have closed the life cycle for Pacific bluefin tuna, this form of production has not yet been implemented on a commercial scale to date [1]. Recently Australian and European researchers successfully created artificial breeding regimes for Southern bluefin tuna and Atlantic bluefin tuna, respectively [2, 3]. This is a major step towards the closed-cycle breeding of bluefin tunas for farming purposes; however, until the closed cycle breeding of bluefin tuna is commercially implemented, the industry will remain reliant upon wild bluefin tuna populations for sourcing bluefin tuna for their farming operations.

Bluefin tuna farming is an interesting and complex form of production; however, to date there are very few published studies that address this form of production. This research is a first step in filling this gap in the literature by empirically modeling the economics of farmed bluefin tuna production. This research also contributes to the more general fields of offshore aquaculture economics and aquaculture economics.

Specifically, this research identifies the optimal harvest schedule for an offshore bluefin tuna farming facility that maximizes the net present value of the operation under a variety of economic, biological and regulatory conditions. Further, this research explicitly incorporates stochasticity into the model in order to analyze how the presence of risk alters the optimal harvest schedule for a producer. Very few studies have incorporated risk into the economic analysis of offshore aquaculture [4-7] and none have incorporated the role of risk in the analysis of the economics of farmed bluefin tuna production.

BRIEF BACKGROUND ON BLUEFIN TUNA FARMING

Bluefin tuna is a highly migratory species that inhabits a variety of oceans throughout the world. There are three species of bluefin tuna, Atlantic bluefin tuna (*Thunnus thynnus*), Pacific bluefin tuna (*Thunnus orientalis*), and Southern bluefin tuna (*Thunnus maccoyii*), all three of which are farmed at present. Many countries are involved in this practice including: Australia, Japan, Mexico and Mediterranean countries including, but not limited to, Croatia, Spain, Malta, and Turkey. Due to its high quality flesh and fat content, bluefin tuna is a prized commodity in

Japan's Tsukiji market, the primary market for sashimi grade tunas. In Japan, bluefin tuna is typically consumed raw as *sashimi* or with rice as *sushi*. On a per pound basis, bluefin tuna is one of the most valuable species in the world [8]. In 2001, one bluefin tuna sold at the Tsukiji market set a record price per kilogram for the 202 kilogram fish that still stands today (100,000 JPY/kg / 832 USD/kg) (OPRT, 2008). One important characteristic of bluefin tuna is how it is priced in the market. In contrast to most seafood species, the price of a bluefin tuna is determined on an individual basis, where each fish is graded on various characteristics including freshness, fat content, color and shape [9]. Quality is of utmost importance with regard to the Japanese market, and as such, quality is a very important distinguishing factor in determining the price of a bluefin tuna. A key quality characteristic influencing the price of an individual bluefin tuna is the fat content of the fish. All things being equal, a fish with a higher fat content will receive a higher price in the market [9]. Thus, the incentives to farm bluefin tuna relate back to the manner in which bluefin tuna is priced in the market. The market rewards those who employ methods of production that either maintain or enhance a fish's underlying quality characteristics. The farming of bluefin tuna is one method by which the quality and fat content of the fish can be enhanced over a period of time. This form of production can transform leaner fish that, when initially caught, are not as desirable or valuable in the market, into fatter fish that can command higher prices. One major economic question stemming from this form of production is: how long should a producer retain and feed a given quantity of wild caught bluefin tuna before harvesting and selling those fish? That is to say, what is the optimal harvest schedule for a producer looking to maximize profits over a farming season?

APPLICATION OF THIS RESEARCH TO THE UNITES STATES

The US, and in particular the US East Coast, has been a major supplier of high quality bluefin tuna to Japan. Potentially, the establishment of bluefin tuna farming in the US could increase the value of the US Atlantic bluefin tuna fishery. There has been an interest in bluefin tuna aquaculture on the US East Coast among industry participants; however, no bluefin tuna farms presently exist. Currently, the only farmed bluefin tuna operations in North America are in Mexican waters just south of the US border near Baja California, Mexico. Assessing the economics of this form of production, in particular production on the US East Coast is useful given the continued expansion of bluefin tuna farming globally, the increasing demand for high-quality bluefin tuna, and the uncertainty regarding the economic feasibility of an offshore bluefin tuna aquaculture industry in the United States.

To accomplish this goal, a bioeconomic model of an offshore bluefin tuna farming facility operating on the US East Coast is developed based on the predominant methods of bluefin tuna farming as practiced around the world. The model will be formulated and parameterized with data acquired from an actual site visit to a farming facility in Cartagena, Spain, data obtained from consultation with experts in the field, and from available peer-reviewed and gray literature.

The model has been developed and coded to be highly adaptable. All key parameters and equations in the model can be customized by the user to reflect different locations, scenarios, and starting values. This makes the model capable of analyzing offshore bluefin tuna farming not only on the US East Coast, but anywhere in the world.

THEORETICAL FOUNDATION OF THE MODEL

The theoretical underpinnings of this model are closely tied to the forestry economics literature which seeks to identify the optimal harvest cycle which maximizes the net present value of a stand of trees over time. The modeling framework involves the specification and optimization of a bioeconomic model of the resource in question, whether the resource is a stand of trees or a species of fish. The biological component of the model describes the growth of the resource over time while the economic model incorporates the prices and costs associated with production and harvesting of the resource. Combining both the relevant biological and economic components allows for the identification of the optimal harvest schedule that maximizes the net present value of the resource over a given period of time. In the case of a single cycle of production, the model seeks to solve for the optimal cycle length (t^*) that maximizes the objective function.

$$\Pi(t^*) = V(t^*)e^{-rt} \tag{Eq. 1}$$

Where

$V(t) = P(t)*B(t)$, Value at time t .

$P(t)$ = Price at time t .

$B(t) = Re^{-Mt} W(t)$, Biomass at time t .

R = Number of fish (recruits) stocked at $t(0)$.

$W(t)$ = Weight function, which can be specified as a function of time, $\{w=f(t)\}$ or a combination of variables, such as a function of time, feeding, water temperature $\{w=f(t, \text{Feed}, \text{WT})\}$.

M = Mortality rate, which can be specified as either a function of time $(M(t))$ or a constant, M .

The optimal harvest time (t^*) that maximizes the net present value is solved by taking the first derivative of Equation 1 with respect to time.

$$\frac{V'(t^*)}{V(t^*)} = r \quad (\text{Eq. 2})$$

Equation 2 is commonly referred to as the Fisher Rule, which states that at the optimal harvest time (t^*) the return one would receive from harvesting the resource and depositing the money in a bank account ($rV(t^*)$) is equal to the return one would receive from forgoing harvest and allowing the resource's value to increase over the period ($V'(t^*)$). Thus, there is a tradeoff between the return that can be gained "in a brick and mortar bank" versus the return that can be gained "in nature's bank".

The specification of a bioeconomic model for an offshore bluefin tuna farming operation will be very similar to the specification of a bioeconomic model in the forestry literature. Growth functions describing the biology of bluefin tuna and relevant economic parameters will be specified. Further, stochasticity can be incorporated to add additional complexity and realism to the model.

INCORPORATING STOCHASTICITY INTO THE BIOECONOMIC FRAMEWORK

In explicitly modeling the stochastic nature of production, this model incorporates the risks associated with the offshore production of bluefin tuna, including biological, technical, economic, and regulatory sources of risk. This modeling approach is especially useful given the uncertainty surrounding the values and behavior of certain parameters associated with bluefin tuna farming. In many cases, specific knowledge of growth rates, mortality rates, input costs and output price are unknown. However, such parameters can be specified as stochastic within the model in order to capture the potential effect of these stochastic variables on the optimal harvest schedule and overall economic performance of the operation. The use of a dynamic stochastic adaptive bioeconomic model to optimize the production of farmed bluefin tuna will be a novel application of a sequentially adaptive model of a bluefin tuna farming enterprise operating in a stochastic environment. The model is a useful tool for those in the farming industry as well as investors and regulatory agencies. The model can be used to quantify the economic benefits and tradeoffs associated with the farming of bluefin tuna, in particular in situations where key variables are uncertain or are known to be stochastic. Furthermore, the model can be useful in analyzing how various rules and regulations would affect optimal production decisions and the economic performance of an operation or the industry as a whole.

FORMAL DEVELOPMENT OF THE BIOECONOMIC MODEL

The objective function for a profit maximizing offshore bluefin tuna aquaculture producer is defined as follows:

$$\text{Max } \prod = \left\{ (P_t(W_t, H_t)W_t H_t - C_{HC} H_t - C_{VC_t} N_t) * \frac{1}{(1+r)^t} \right\} - A \quad (\text{Eq. 3})$$

Subject to:

$$\begin{aligned} W_t &= f(FCR_b, FR_t(WT_t)) \\ N_t &= N_{t-1}(1-M_{t-1}) - H_{t-1} \\ N_t, H_t &\geq 0 \\ N(0) &= N_0 \end{aligned}$$

Where:

P_t = Price of an individual bluefin tuna, as a function of the weight and harvest quantity of fish at time t .

W_t = Weight of a individual bluefin tuna at time t , as a function of the feed conversion ratio and the daily feeding rate, which itself is a function of water temperature.

H_t = Harvest quantity of bluefin tuna at time t . This is the control variable of the farmer.

C_{HC} = Harvesting costs.

C_{VC_t} = Aggregation of variable costs at time t .

A = Acquisition Costs associated with acquiring bluefin tuna for farming.

M_t = Mortality rate at time t , which can be time invariant or a function of time.
 FCR_t = Feed Conversion Ratio at time t , which can be time invariant or a function of time.
 FR_t = Feeding Rate at time t , which is also a function of the Water Temperature (WT) at time t .
 r = Discount rate (weekly).

The optimal harvest schedule is solved for by maximizing the above objective function numerically through the use of a non-linear constrained optimization algorithm found within Matlab’s Optimization toolbox.

DISCUSSION OF SUB-MODEL COMPONENTS

A bioeconomic model generally consists of biological sub-model which describes the production system and an economic sub-model which relates the production system to market prices and resource constraints [10]. The following sections explain each component of the bioeconomic model for an offshore bluefin tuna farming operation in greater detail. Figure I below is a schematic of the essential features of the bioeconomic model. The top box (shaded red) depicts the biological sub-model, where growth, mortality, water temperatures and feeding rate influences the changes in the biomass of bluefin tuna each period. The model starts with an initial number of fish at $t(0)$, which undergo growth and mortality over the period until $t(1)$. At $t(1)$, the farmer has a decision to make: continue feeding and allow the fish to undergo an additional period of growth and mortality or harvest all or some of the fish at $t(1)$ with the remaining fish undergoing an additional period of growth and mortality until $t(2)$. The bottom box (shaded blue) depicts the economic sub-model, where feed costs and other relevant costs as well as revenues are accounted for in each period they are incurred or earned.

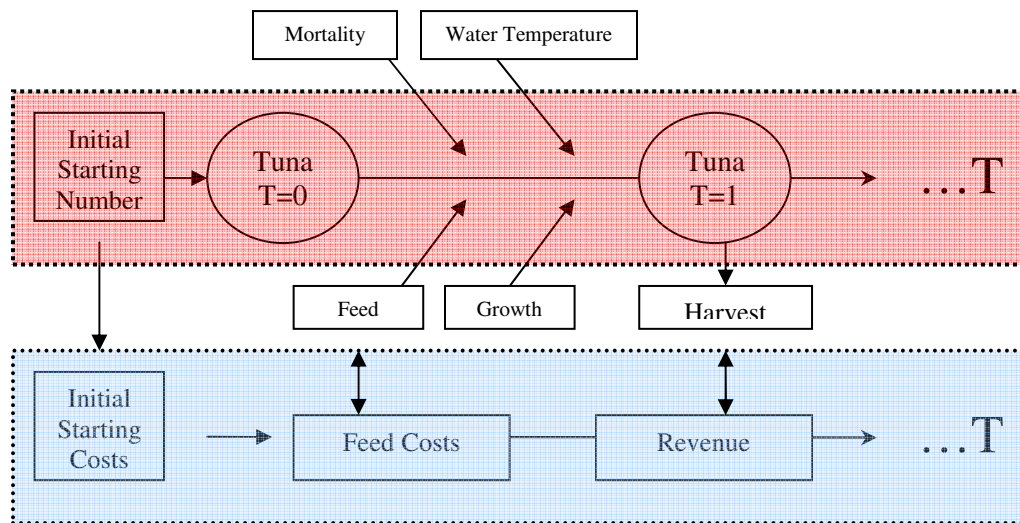


Figure 1. Basic schematic of the bluefin tuna farming bioeconomic model

BIOLOGICAL SUB-MODEL

Growth and Weight Function Component

Increases in the weight of a bluefin tuna over time will be modeled as follows. Based on the research of Katavic et al. (2003) a relationship between water temperature and daily feeding rate was estimated for farmed Atlantic bluefin tuna in Croatia through the use of linear regression techniques. The following is the estimated equation relating the daily feeding rate (FR) of a bluefin tuna to the daily water temperature (WT).

$$FR_t = 1.29 WT_t - 20.29 \tag{Eq. 4}$$

(12.73) (-9.99) $R^2=0.97$
 $0.1\% \leq FR_t \leq 11\%$

Where

FR_t = Daily Feeding Rate.

WT_t = Water Temperature.

Currently the industry relies on the feeding of whole fish (fresh or previously frozen) to fatten the tuna over time. Types of small pelagic fish include, but are not limited to, mackerel, herring, sardines, and sprats. Daily feeding rates (FR_t) are constrained to be less than or equal to 11%, and greater than or equal to 0.1%. This prevents the model from feeding fish in excess of their observed biological ability and also prevents negative feeding and negative growth of the fish if FR_t is allowed to be less than zero [11]. More sophisticated functional forms could be estimated from the data from [10], however for now the modeling approach is to use a linear approximation of the true relationship.

Using Equation 4, one can incorporate the influence of water temperature on the daily feeding rate in order to estimate growth over a farming season. Growth in this model is assumed to be density independent. Applying a vector of water temperatures to Eq. 4 yields an estimate of the daily feeding rate. Given a specification of the initial starting weight, one can multiply the daily feeding rate at time t by the weight of the fish at time t to solve for the quantity of feed fed daily.

$$QFD_t = FR_t * W_t \quad (\text{Eq. 5})$$

Where

$QFD_t =$ Quantity of feed fed to an individual fish per day.

Multiplying QFD_t by 6 provides an estimate of the quantity of fish fed for an entire week to an individual fish. Farmed bluefin tuna are typically fed until satiation once or twice daily, 6 days a week. The fish are given a day off to minimize potential damage to their livers due to overfeeding [12]. Rewriting Eq. 5 therefore results in

$$QFW_t = (FR_t * W_t) * 6 \quad (\text{Eq. 6})$$

Where

$QFW_t =$ Quantity of feed fed to an individual fish per week.

Once the quantity of feed fed per week, which is a function of the water temperature and weight of the fish at time t , is known, then the feed conversion ratio (FCR) can be incorporated into the model to determine the increase in biomass each period given the quantity of feed consumed per week. FCR is defined to be

$$FCR_t = \frac{B_t}{QFW_t} \quad (\text{Eq. 7})$$

Where

$FCR =$ Feed conversion ratio (wet weight)

$B_t =$ Quantity of Increase in Biomass at time t .

Manipulating Eq. 7 one can solve for the quantity of increase in biomass each week:

$$B_t = \frac{QFW_t}{FCR_t} \quad (\text{Eq. 8})$$

FCR can be specified as either a function of time or time invariant. In the basic formulation of the model, FCR will be a constant parameter over the course of the farming season. This assumption can be relaxed in future extensions of the model.

Thus, growth over a week of feeding is modeled as follows:

$$W_{t+1} = W_t + B_t \quad (\text{Eq. 9})$$

This allows the model to capture the influences of water temperature, feeding rate and FCR on the increase in weight of a fish each period.

Water Temperature

As mentioned earlier, this bioeconomic model will be applied to analyzing the economics of farmed bluefin tuna production on the US East Coast. Three sites along the Eastern Seaboard have been identified as potential locations for bluefin tuna farming: Nantucket, MA; Virginia Beach, VA; and Gray's Reef, GA. These sites were chosen to capture a range of potential production environments along the US East Coast. Estimates of the average weekly water temperatures for all three sites were taken from the NOAA National Data Buoy Center database.

Mortality

Mortality can enter the model as a constant, a random function of time, or a function of time and other relevant model parameters, such as weight, number, or water temperature. In future extensions, the model can be modified to accommodate more a more sophisticated specification of mortality.

ECONOMIC SUB-MODEL

Price Component

The price function is taken from [9] who estimated a hedonic price function for Atlantic bluefin tuna. A modified version of the price function is used in this model and takes the form:

$$\ln P_t = \alpha + \beta_1 \ln W_t + \beta_2 W_t + \beta_3 \ln H_t \tag{Eq. 10}$$

where

$$\alpha = .58, \beta_1 = 0.5901, \beta_2 = -0.0021 \text{ and } \beta_3 = -0.0518$$

$P(t)$ = Price per kilogram (dressed weight) of an individual fish

$W(t)$ = Weight (kg) of an individual fish at time t .

$H(t)$ = Harvest (number) of US Bluefin tuna at time t .

Price is a function of weight at time t and harvest quantity of fish at time t from the US on the Tsukiji market. It is implicitly assumed that a farmer on the US East Coast controls all of the fish being sent to the Tsukiji market from the United States. All variables of the hedonic price function are set at their mean values, except for the variables Dressed Weight and US Harvest Quantity, which take on their endogenous values as determined by the model. Appendix 3 provides a list of the variables in the hedonic price function and their respective means.

Variable Cost Components

Using the estimates of weekly average quantity of feed consumed per fish, one can solve for the average weekly feed costs per fish.

$$WFC_t = QFW_t * FC \tag{Eq. 11}$$

Where

WFC_t = Weekly average feed costs per individual fish

FC = Feed costs (US\$ per pound)

Vessel Costs

Another relevant variable cost for the offshore operation is weekly vessel transportation costs associated with feeding the fish daily and/or harvesting the fish. The model calculates the estimated number of daily trips needed for either harvesting or feeding and chooses the greater of the two to form an estimation of the number of vessel trips required per week.

$$WT_t = \max\left(\frac{QFW_t}{\text{Payload}}, \frac{H_t}{\text{Payload}}\right) \tag{Eq. 12}$$

Where

WT_t = Number of weekly vessel trips

QFW_t = Quantity of feed fed to an individual fish per week.

H_t = Quantity of fish harvested per week

Payload = Payload of Vessel (measured in kilograms)

Once the number of weekly trips is known, this value is multiplied by the cost of a vessel trip, in order to determine the total weekly vessel trip costs. Vessel trip costs are defined by the following.

$$VC = \left(\frac{2 * \text{Dist.}}{VGH}\right) * \text{FuelCosts} \tag{Eq. 13}$$

Where

VC = Weekly vessel trip costs

Dist = Nautical miles from shore

Fuel Costs = US \$/gallon

VGH = Vessel Gallons per hour

Harvesting Costs

Harvest costs are specified to be a per unit cost of harvesting a fish.

Acquisition Costs

The acquisition of wild caught bluefin tuna is an important stage of production and source of costs for an operator. The acquisition of bluefin tuna can be modeled in a variety of ways to capture the complexity of the process. In its most basic form, the acquisition could be specified as deterministic process. Alternatively, the acquisition could occur through a stochastic process. For example, the starting weight of the bluefin tuna could vary according to a specified distribution and/or the starting number of fish could vary according to a specified distribution. In the basic formulation of the model, acquisition costs will be modeled as a deterministic process, where the starting number and weights of the fish are known with certainty *ex ante*; however, this assumption can be relaxed in future extensions of the model.

DISTINCTION FROM PREVIOUS RESEARCH

This research differs from previous studies in the field of aquaculture research with regard to the treatment of stochasticity within the model. In general, many economic optimization models solve the entire production or planning horizon at once. That is to say, the optimal harvest solution is solved for all periods given the assumptions and parameters that are specified *ex ante*. This modeling framework implicitly assumes that these parameters will not deviate from their *ex ante* values over the course of the production horizon, which may or may not be true. Employing Monte Carlo analysis is an improvement over models which are based on deterministic, fixed-point estimates of key parameters because they allow for the calculation of multiple fixed-point estimates which are chosen to hold over a production horizon.

Previous researchers have incorporated risk into the bioeconomic modeling framework via the Monte Carlo method to simulate possible ranges of outcomes, typically the net present value (NPV) stemming from the presence of stochasticity in underlying parameters within the model. Zucker and Anderson [13] developed a dynamic stochastic model of a land-based summer flounder aquaculture firm which incorporated both production and marketing risk into the bioeconomic modeling framework. Their model examined the economic feasibility of a hypothetical land-based aquaculture firm by specifying distributions for stochastic parameters and then conducting a Monte Carlo analysis to estimate the mean and expected distribution of the NPV of the operation. Jin et al. (2005) presented a similar treatment of risk in their bioeconomic model of offshore salmon and cod production by similarly specifying distributions for stochastic parameters and simulating the NPV of the operations using Monte Carlo simulation.

In a Monte Carlo analysis framework, a model is set to run a given number of iterations, and for each iteration, new values for key stochastic parameters are chosen to hold over the entire production or planning horizon. The solution for the entire operating horizon is then solved and saved, and then the model again draws from the distribution of stochastic parameters and recalculates the model to identify the optimal harvest schedule for that iteration. The result of this process is a collection of (NPVs) from each iteration which form a distribution of NPVs representing expected NPV for the process under consideration given variation in the stochastic parameters specified within the model.

The use of Monte Carlo analysis is useful to demonstrate the ranges of possible or expected outcomes given the presence of stochastic parameters within the model. What these models do not always do, however, is allow for firms to change or alter their behavior during the operating horizon in response to the presence of stochasticity. Instead, these models often assume that an optimal solution is solved for, and adhered to, for the duration of the operating horizon. This implicitly assumes that operators would not change their optimal harvest strategies in the middle of the operating horizon. If all parameters were known with certainty *ex ante* for the duration of the planning horizon, then the problem would reduce to the classical maximization problem; however, in many cases the model's key parameters will deviate from their *ex ante* values over the course of the production horizon. Using the best available information, the farmer will develop a set of expectations regarding the value of those stochastic parameters *ex ante*, and he or she will use those values to solve for the optimal harvest strategy. However, once production begins, natural and economic conditions can change and previously optimal decisions based on old information will be suboptimal in light of this new information [14]. Therefore, the optimal harvest schedule based on parameters that were specified *ex ante* can prove to be inferior because they fail to account for changing natural and economic conditions.

The dynamic stochastic adaptive bioeconomic model explicitly incorporates the adaptive behavior of the firm over the course of the operating horizon. In each period, the entire operating horizon is resolved iteratively from $t=t_n$ to $t=T$. Thus, rather than calculating and relying on one fixed optimal schedule for the entire operating horizon, the model recalculates a new optimal schedule each period as new information regarding the behavior of stochastically specified parameters changes over time. Thus, in the first period, an expectation of stochastic parameter values is formed and is used to solve the initial optimal schedule, and the first optimal solution is executed. However, at the end of the first period, the operator observes the actual values of the stochastic parameters, which are drawn from a distribution with a defined mean and standard deviation. Using this new information, the operator updates his or her expectation of next period's stochastic parameters and recalculates a new optimal schedule for the remainder of the operating horizon, given that a decision has already been made for the first period. The operator then uses this information to dictate his or her actions for the second period. Even though the optimal solution is solved for across the entire operating horizon for each iteration, the decision maker only makes a decision period by period as new information is observed. In this way, the operator is not constrained to stick to an optimal harvest schedule for the duration of the operating horizon. Rather, the operator is able to re-solve the optimal harvest schedule each period, in an adaptive manner. Hence, this model is dynamic, in that it solves for the optimal harvest schedule over time, it is stochastic since it allows for the specification of stochastic parameters, and it is adaptive in that it allows a farmer to adapt to changing parameters in-season.

Such a model allows for a more realistic representation of risk and a firm's response to risk over time. Compared to a non-adaptive model that solves the optimal harvest schedule for the entire operating horizon once, the adaptive model's performance is typically higher (the NPV of the adaptive model equals or exceeds the NPV for a non-adaptive model) when operating under stochastic situations where parameters change each period. The adaptive model performs better since it can alter the optimal schedule, unlike the non-adaptive model, which is limited to a single optimal harvest schedule based on *ex ante* estimates despite the fact that the value of those parameters change in-season due to the stochastic nature of the operating environment.

ECONOMIC FEASIBILITY ANALYSIS

The outputs from the bioeconomic model (revenues and variable costs) are integrated into an enterprise budget framework to assess the overall economic feasibility of the offshore bluefin tuna aquaculture operation under a variety of scenarios. A production system, project or policy is typically considered economically feasible if the sum of the discounted net present value of its profit stream is greater than or equal to zero over the relevant operating horizon [15].

SPECIFICATION OF THE BASIC MODEL

The rest of the paper will present and discuss results based on a basic formulation of the bioeconomic model. The basic model will be used to demonstrate the essential features and performance of the dynamic stochastic adaptive model relative to the performance of a non-adaptive model. The values of key model starting parameters are specified in Appendix 2.

Acquisition of Bluefin Tuna

The producer is assumed to acquire all bluefin tuna deterministically. The starting number and starting weight of bluefin tuna are known with certainty and are taken as given by the operator. Acquisition costs are known with certainty at the beginning of the farming season and are set as a fixed cost per day in the Basic Model.

Water Temperature

The Basic Model operates under a "Virginia Beach, VA" temperature regime, where relevant weekly average water temperatures correspond to the data in Appendix 1. Increases in weight proceed according to Equations 4-9. The change in weight for a 100 pound bluefin tuna in a "Virginia Beach, VA" temperature regime is depicted in Figure 2.

Prices

Prices are determined according to the hedonic price function estimated by [9]. All variables of the hedonic price function are set at their mean values, except for the variables Dressed Weight and US Harvest Quantity, which take on their endogenous values as determined by the model. Appendix 3 provides a list of the variables in the hedonic price function and their associated means.

Costs

The variable costs associated with feeding and vessel costs are defined by equations 11-13.

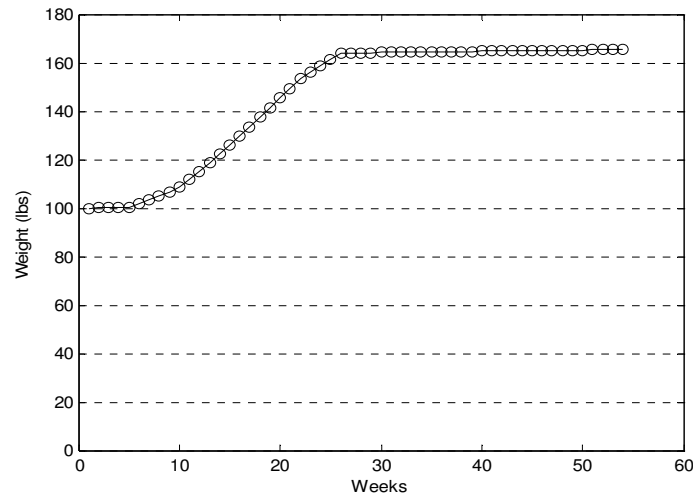


Figure 2. Increase in weight for a 100 lb bluefin tuna over a 52 week period (Temp=VA)

Mortality

In the Basic Model, there are two specifications of mortality: one deterministic and one stochastic. In the first specification, mortality is assumed to be deterministic, where the farmer faces a constant mortality rate, which he or she knows with certainty ahead of time. Under the second specification, the farmer does not know the mortality rate with certainty. When the farmer doesn't know the mortality rate with certainty, he or she forms an expectation of next periods' mortality rate to formulate and solve the optimal harvest schedule for the remaining periods. This expectation can be as simple as using last period's mortality rate as a forecast of the next periods' mortality rate, or it could be a more complicated weighting of past periods' mortality rates. For the purposes of the base model, it will be assumed that the farmer forms an expectation of the next period's mortality rate based on the average of observed mortality rates. In future extensions, the model can be modified to accommodate a more sophisticated specification of the mortality rate as well as a more sophisticated formulation of expectations.

Other Assumptions

All net profits are before taxes. Labor costs are assumed to be fixed costs.

PRELIMINARY RESULTS FROM THE BASIC MODEL

This basic specification model is used to solve for the profit maximizing harvest schedule so that the essential drivers of farmed bluefin tuna production can be examined and analyzed. For now, the only stochastic variable under consideration is the mortality rate. In future extensions of the model, many parameters can be specified as stochastic in the model, including biological, economic, technological and regulatory sources of risk.

To illustrate the behavior and advantages of a dynamic stochastic adaptive model over a non-adaptive model, the following stylized example is presented and discussed. In a non-adaptive modeling framework, the farmer would formulate an expectation of the mortality rate, which is used to solve for the optimal harvest schedule. Assuming the farmer knew the mortality rate with certainty, the following optimal harvest schedules would emerge. In Figure 3-a, the model is solved assuming two weekly average mortality rates (0.2% and 1.0%), which the farmer knows with certainty. In this figure, one can see that when the mortality rate is 1.0%, the optimal harvest schedule (C-1.0) is shifted closer to the present relative to the optimal harvest schedule (C-0.2) when the mortality rate is 0.2%. This result makes intuitive sense and conforms to the theoretical model, which suggests that as the mortality rate increases, the optimal harvest schedule moves closer to the present. Now, in reality, it is unlikely that the farmer will know the mortality rate with certainty *ex ante*. Therefore, his or her expectation of the mortality rate may deviate from the actual (observed) mortality rate. If this is the case, and the farmer cannot adapt to this new information and change the optimal harvest schedule solved using the expected (and incorrect) mortality rate, then adherence to that harvest schedule is suboptimal. Figure 3-b depicts the harvest schedule, labeled NA for Non-Adaptive, for a farmer who assumed that the mortality rate was 0.2% but in fact the farmer faced a mortality rate of 1.0%. As can be seen from Figure 3-b, the farmer proceeds to harvest following the harvest schedule dictated as if the mortality rate was 0.2%; however since it is actually 1.0%, the farmer is sub-optimally delaying harvest and the fish are dying faster than anticipated, and by week 41, the farmer has run out of fish to harvest. This is why line NA

ends at week 41 and does not continue tracking line C-0.2. If the farmer had known the actual mortality rate was 1.0%, then he or she would have shifted harvests closer to the present.

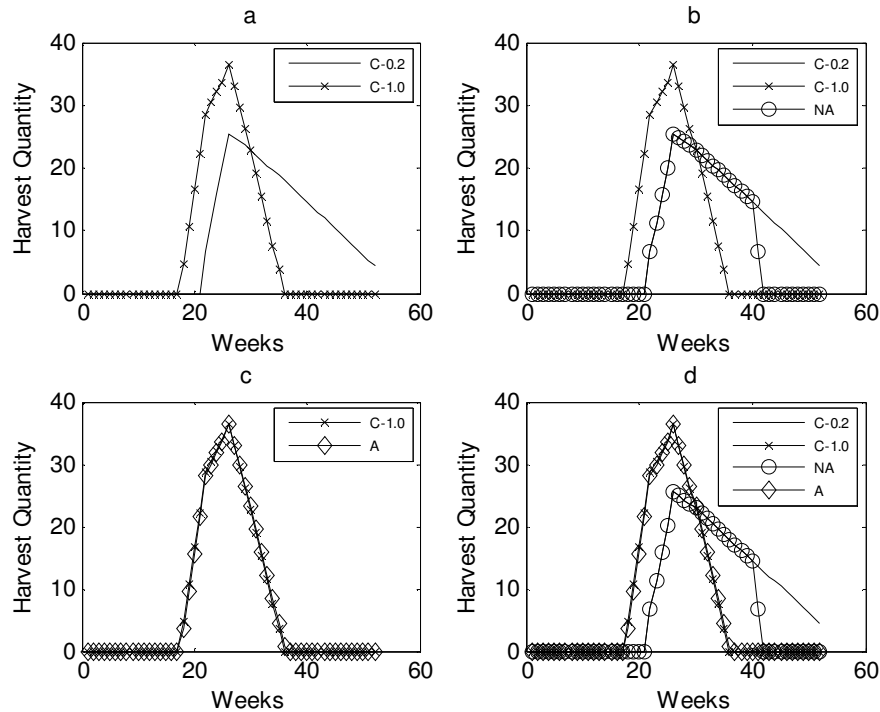


Figure 3. Optimal harvest schedules under a variety of scenarios

Now, let's compare this outcome to a situation where the farmer can alter the optimal harvest strategy in-season through the use of an adaptive model. The optimal harvest schedule resulting from allowing the farmer to adapt in-season is depicted by line A in Figure 3-c. Here the farmer forms an expectation for the mortality rate by assuming that for the first period, the mortality rate will be 0.2%; however, at the end of period 1, the farmer notices that the mortality rate for that period was in fact 1.0%. Now the farmer adjusts his or her expectation of tomorrow's mortality rate based on this observed value. In this basic formulation of the model, the farmer incorporates this new information and forms an expectation regarding tomorrow's mortality rate through a simple averaging of observed mortality rates. Since the true underlying mortality rate is a constant in this stylized example, the simple average quickly converges to the true mortality rate. As a result, the farmer now uses an expected mortality rate that is very close to the actual mortality rate, and as a result, the optimal harvest schedule formed under the adaptive bioeconomic framework is nearly identical to the optimal harvest schedule that would exist if the farmer knew the mortality rate was 1.0% with certainty. This result is depicted in Figure 3-c. Figure 3-d is the combination of figures 3-b and 3-c.

Thus, the power of the dynamic stochastic adaptive bioeconomic model is that under situations where stochastic parameters are not known with certainty, the adaptive nature of the model allows the farmer to adjust to such deviations from the *ex ante* estimates in-season. This allows the farmer to identify a harvest schedule that is either equal to or superior to an optimal harvest schedule identified through a non-adaptive model. Further, it is more realistic to model the behavior of a farmer in this manner because farmers are constantly observing and adjusting production decisions in response to changes in key parameters.

FUTURE EXTENSIONS OF THE MODEL

In future extensions of the model, additional parameters can be specified as stochastic in the bioeconomic model and the farmer can form expectations of those variables each period and adapt to those changing variables each period as new information becomes available. Possible stochastic variables include mortality rate, growth parameters, including FCR, as well as economic variables such as feed costs and prices. The results of this bioeconomic model will be used in a larger assessment of the economic feasibility of offshore bluefin tuna farming by integrating these

results into an enterprise budget framework. The NPV and IRR of various scenarios can be compared against one another and against other alternative investment opportunities to assess the overall attractiveness and viability of this form of production on the US East Coast.

CONCLUSIONS

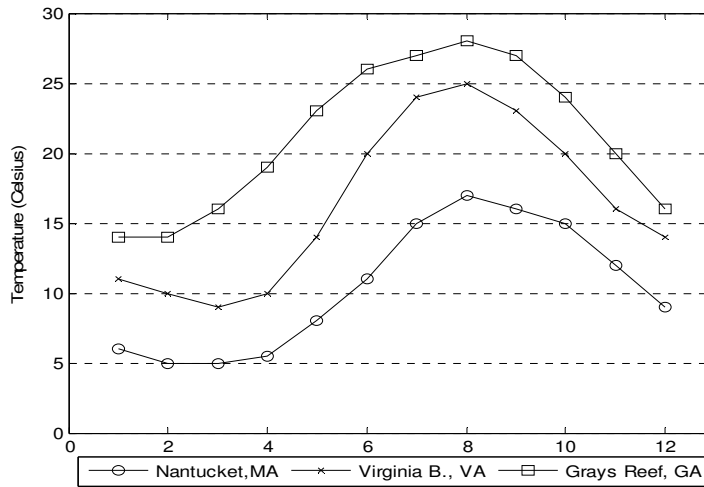
This research empirically models the economics of farmed bluefin tuna production through the use of a dynamic stochastic adaptive bioeconomic model. Under stochastic conditions, the adaptive model is able to provide results are superior to models that cannot adapt in-season. The application of this bioeconomic model to offshore bluefin tuna farming allows for the quantification the economic benefits and tradeoffs associated with the farming of bluefin tuna, in particular the impact on the optimal harvest decision in situations where key variables are uncertain or are known to be stochastic.

REFERENCES

1. Sawada, Y., et al., *Completion of the Pacific bluefin tuna *Thunnus orientalis* (Temminck et Schlegel) life cycle*. Aquaculture Research, 2005. **36**(5): p. 413-421.
2. Clean Seas Tuna Limited. *European Breakthrough on Bluefin Tuna Boosts Clean Seas' Artificial Breeding Regime*. <http://www.cleaneasttuna.com.au/documents/nr-Europeanresearchsuccess.pdf> 2008 [cited].
3. Clean Seas Tuna Limited. *Southern Bluefin Tuna Larvae Born in World-First Artificial Breeding Regime*. <http://www.cleaneasttuna.com.au/documents/nr-SBTlarvae5308.pdf> 2008 [cited].
4. Posadas, B.C. and C.J. Bridger, *Economic Feasibility of Offshore Aquaculture in the Gulf of Mexico*. Open Ocean Aquaculture: From Research to Commercial Reality, ed. C.J. Bridger and B.A. Costa-Pierce. 2003, Baton Rouge, Louisiana: The World Aquaculture Society. 307-317.
5. Jin, D., H. Kite-Powell, and P. Hoagland, *Risk assessment in open-ocean aquaculture: A firm-level investment- production model*. Aquaculture Economics & Management, 2005. **9**(3): p. 369-387.
6. Kam, L.E., P. Leung, and A.C. Ostrowski, *Economics of offshore aquaculture of Pacific threadfin (*Polydactylus sexfilis*) in Hawaii*. Aquaculture, 2003. **223**(1-4): p. 63-87.
7. Brown, J.G., et al., *Economics of cage culture in Puerto Rico*. Aquaculture Economics & Management, 2002. **6**(5-6): p. 363-372.
8. Deere, C., *Net Gains: Linking fisheries management, international trade, and sustainable development*. 2000, Washington, DC: Union for Conservation of Nature and Natural Resources.
9. Carroll, M.T., J.L. Anderson, and J. Martinez-Garmendia, *Pricing U.S. North Atlantic Bluefin Tuna and Implications for Management*. Agribusiness, 2001. **17**(2): p. 243-54.
10. Cacho, O.J., *Systems modelling and bioeconomic modelling in aquaculture*. Aquaculture Economics & Management, 1997. **1**(1): p. 45-64.
11. Katavic, I., V. Ticina, and V. Franicevic, *Bluefin Tuna (*Thunnus thynnus* L.) farming on the Croatian Coast of the Adriatic Sea-Present Stage and Future Plans*. Cahiers Options Mediterraneennes, 2003. **60**: p. 101-106.
12. Zertuche-Gonzalez, J., et al., *Marine Science Assessment of Capture-Based Tuna (*Thunnus orientalis*) Aquaculture in the Ensenada Region of Northern Baja California Mexico: Final Report of the Binational Scientific Team to the Packard Foundation*. 2008. p. 94.
13. Zucker, D.A. and J.L. Anderson, *A Dynamic, Stochastic Model of a Land-based Summer Flounder Aquaculture Firm*. Journal of the World Aquaculture Society, 1999. **30**(2): p. 219-235.
14. Antle, J.M., *Incorporating Risk in Production Analysis*. American Journal of Agricultural Economics, 1983. **65**(5): p. 1099-1106.
15. Jolly, C.M. and H.A. Clonts, *Economics of Aquaculture*. 1993, Binghamton, New York: Food Products Press. 319.

APPENDICIES

Appendix 1: Ten Year Average Water Temperature by Area



Appendix 2: Key Parameters for Basic Model

| Parameter | Value | Units | Description |
|-----------|-------|------------|---|
| N_0 | 500 | Number | Starting number of wild bluefin tuna at t_0 |
| W_0 | 100 | Pounds | Starting weight of wild bluefin tuna at t_0 |
| T | 52 | Weeks | Duration of Farming Season |
| FC | 0.11 | US\$/pound | Feed Costs |
| FCR | 20 | Number | Feed Conversion Ratio |
| r | 5% | Percent | Discount Rate |

Appendix 3: Continuous Hedonic Price Function from Carroll et al. 2001

$$\ln P = a + \delta_1 \text{Fresh} + \delta_2 \text{Fat} + \delta_3 \text{Color} + \delta_4 \text{Shape} + \beta_1 \ln \text{DRW} + \beta_2 \text{DRW} + \beta_3 \text{CONS} + \beta_4 \text{XPORT} + \beta_5 \ln \text{XRATE} + \beta_6 \ln \text{US} + \beta_7 \ln \text{JAP}$$

| Parameter Name | Mean Value | Coefficient Value |
|----------------|------------|-------------------|
| a | | 0.366 |
| Fresh | 5 | 0.0409 |
| Fat | 5 | 0.3326 |
| Color | 5 | 0.2486 |
| Shape | 5 | 0.1927 |
| CONS | 1 | 0.0588 |
| XPORT | 1 | 0.5176 |
| ln_XRATE | 106.16 | -0.905 |
| ln_JAP | 59.57 | -0.0516 |
| ln_US | Active | -0.0518 |
| ln_DRW | Active | 0.5901 |
| DRW | Active | -0.0021 |