A Risk Programming Model for Shrimp Farming in Honduras

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Abstract. A linear programming (LP) profit-maximization model and a Target MOTAD risk programming model were developed to identify optimal management strategies and associated risk levels for the aquaculture of penaeid shrimp in Honduras. Data for this study were provided by three cooperating shrimp farms and included complete production records of 1,004 ponds during the period 1997-99. Production records were analyzed to characterize pond productivity on a month-to-month basis. Subsequently, an LP model was developed which was used to formulate a profit-maximizing annual plan of activities. For each month of the year, the model assumed that the farm manager had the option of selecting among 18 production activities characterized by varying stocking densities, lengths of grow-out periods, and water exchange regimes. The basic model was adapted to three different farm-size scenarios. Results of the LP model indicated that farm income is maximized by selecting intermediate densities, long grow-out cycles, and low water-exchange rates. Additionally, ponds should only be stocked in specific months of the year. Next, Target MOTAD matrices were developed for each farm-size scenario to quantify the levels of risk associated with the profit-maximizing solutions and identify alternative production plans. However, resolution of the Target MOTAD models indicated low risk levels associated with the LP solutions and an unnecessary reduction of profit if risk levels were to be further depressed. It then appears that the management strategies selected by the LP models enable farm managers to achieve the two-fold objective of maximization of farm profit coupled with low risk levels.

Keywords: economic optimization, risk, Target MOTAD, shrimp farming.

1. INTRODUCTION

Honduras is the major producer of farm-raised shrimp in the Central American region with 12,000 metric tons (live weight) produced on 14,000 ha of shrimp farms during 1998 (Rosenberry 1998). However, shrimp production in this country has been characterized by fluctuating annual pond yields and total production levels for the last ten years. A reported deficit of wild post-larvae (PL) in 1989 and the introduction of viral diseases in 1994 (Taura Syndrome Virus – TSV) and 1999 (White Spot Syndrome Virus – WSSV) brought about significant reductions in pond yields and negatively affected the finances of shrimp farms. In the wake of adversity, Honduran farmers have responded with a variety of management strategies intended to maintain profitability of operations under conditions of risk and uncertainty.

Shrimp farming is a relatively new industry that has grown at an accelerated pace worldwide. However, this rapid growth has been accompanied by fluctuating prices and quantities supplied that have contributed to an unstable market. The collapse of the shrimp farming industries in China, the Philippines, and Taiwan primarily caused by unplanned intensification of culture strategies further contributed to the instability of the shrimp market. Therefore, there is currently a recognized need for tools that quantify the uncertainties and risks associated with shrimp production as well as for methods that help identify those management strategies conducive to maximization of farm income.

Economic optimization models seeking the efficient allocation of limited resources have been formulated for the shrimp farming industries of several Latin American countries. The primary objective of these models is to identify the most adequate scheduling of harvesting and stocking dates based on seasonal variations of production parameters such as survival and growth rates. Pérez (1986) demonstrated the use of linear programming (LP) for the optimization of management strategies in Panama. Dunning (1989) developed an additional LP model to conduct the economic optimization of shrimp farming in Ecuador. Stanley (1993) adapted this model to describe optimal management strategies for a typical shrimp farm in Honduras. However, none of these studies addressed the risk issue associated with the optimal production plans. Hatch et al. (1987) demonstrated the usefulness of explicitly considering risk in the formulation of optimal plans for shrimp aquaculture in Latin America. According to these authors, although profit-maximizing models indicate that farmers should pursue the most intensive farm plan within their farming capabilities, less experienced or less financially secure farmers may select farm plans that are more conservative than those chosen by more experienced or more financially secure farmers if consideration is given to potential losses associated with more intensive strategies. Hatch et al. (1987) recommended the utilization of risk programming techniques such as Target MOTAD (Minimization of Total Absolute Deviations) which enable the development of LP models with risk addressed parametrically.

The objective of this study was to conduct an updated economic optimization study of shrimp farming in Honduras and characterize the risk levels inherent to the profit-maximizing solution and alternative farm plans. The Stanley model (1993) was developed before the onslaught of TSV and WSSV and assumed high survival rates characteristic of the pre-Taura years (around 70%). Other assumptions of the Stanley model do not correspond to the current reality of shrimp farming in Honduras. The present study introduces a risk programming Target MOTAD model based on a extensive collection of data covering the last three years of production (1997-99). This risk programming model was geared to identify different sets of optimal management strategies associated with varying risk levels which were modeled to reflect the current conditions surrounding shrimp farming in Honduras.

A brief discussion of the LP problem and the Target MOTAD methodology follows below.

1.1 Linear Programming (LP)

Linear programming refers to the computational procedure used in the allocation of limited resources to maximize profit or minimize costs of producing a specific commodity (Shang 1990). It is a technique widely used in agricultural economics as a tool for solving the resource allocation problem. Essentially, an LP problem consists of three elements:

1) Decision variables (x_j, where j = 1, 2, …, n) that represent the levels of the activities undertaken;
2) The linear objective function (Z) which equals $c_1x_1 + c_2x_2 + \dots + c_nx_n$. Here, c_j is the contribution (or objective function coefficient) of each unit of x_j to the objective function; and
3) Constraint functions. The i^{th} linear constraint can be expressed as $a_{i1}x_1 + a_{i2}x_2 + \dots + a_{in}x_n \le b_i$ (i = 1, 2, …, m), where b_i denotes the upper limit imposed by the constraint and a_{ij} denotes the usage of the items in the i^{th} constraint by one unit of x_j.

Given these definitions, the objective of an LP problem is to select $x_1, x_2, \dots, x_n$ such as

$$\textit{Maximize} \quad Z = c_1x_1 + c_2x_2 + \dots + c_nx_n \qquad (1)$$

$$\textit{subject to} \quad a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n \le b_1 \qquad (2)$$

$$\vdots$$

$$a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n \le bm \qquad (3)$$

$$x_1 \ge 0,\ x_2 \ge 0,\ \dots,\ x_n \ge 0 \qquad (4)$$

1.2 Target MOTAD

Frequently, objective function coefficients are not known with certainty, but have an associated probability distribution. In such a situation, dependence of linear programming on parameter means is particularly inappropriate. In an aquaculture context, mean net return is clearly an important criterion by which producers select among alternative activities; however, producers may also have interest on the worst outcome associated with a decision. Risk programming techniques have been developed to address this concern and incorporate risk in farm management decision. Markowitz (1959) developed quadratic programming (QP) methods to address the risk issue but these techniques proved to be computationally difficult and require certain assumptions on part of the decision maker. Hazell (1971) proposed an alternative method, MOTAD (Minimization of Total Absolute Deviations), in which mean absolute deviations are used as the risk measure. MOTAD allows the development of an LP model with a parametric approach to risk. Additionally, no particular assumptions about the behavior of the decision maker are needed. Tauer (1983) developed a further extension, Target MOTAD, in which a safety level of income (T) is incorporated but a second risk parameter (λ) allows negative deviations from that safety level. Given a target level T, the formulation is

$$\textit{Maximize} \quad \sum_{j=1}^{n} \bar{c}_j x_j \qquad (5)$$

$$\textit{subject to} \quad \sum_{j=1}^{n} a_{ij} x_j \le b_i \text{ for all } i \qquad (6)$$

$$\sum_{j=1}^{n} c_{kj} x_j + Dev_k \ge T \text{ for all k} \qquad (7)$$

$$\sum_{k} p_k Dev_k \le \lambda \qquad (8)$$

$$x_j,\quad Dev_k \ge 0 \text{ for all j, k} \qquad (9)$$

where:
- c_{kj} = objective function coefficient to x_j under the k[th] state of nature.
- $\bar{c}_j$ = mean objective function coefficient.
- p_k = probability of the k[th] state of nature.
- Dev_k = negative deviation from income.
- T = target income level.
- λ = maximum average income shortfall permitted.

McCamley and Kliebenstein (1987) outlined a procedure to define the range of relevant T values for any given Target MOTAD model. In this procedure, the expected income maximizing plan X^* is first identified, which is equivalent to the LP solution that would have resulted if no risk constraint existed in the model. Next, the vector W^* is calculated using the equation

$$W_k^* = \sum_{j=1}^{n} c_{kj} X_j^* \qquad (10)$$

The relevant T values are then those between the smallest and largest values in W^*. McCamley and Kliebenstein (1987) developed an additional equation that establishes an upper bound for λ, i.e., it identifies the minimum value of λ that yields the profit maximizing LP solution. This upper bound can be calculated for any given level of *T* and it is defined as

$$M(T) = \sum_{k} p_k \max(0, T - W_k^*) \qquad (11)$$

2. MATERIALS AND METHODS

2.1 Net Return Coefficients

Personal interviews were conducted with several Honduran farm managers during 1999 in order to secure the data base needed for this study. Ultimately, complete production records were provided by three cooperating shrimp farms. These three groups of data were pooled together to form an aggregated collection of data. One shrimp farm provided records covering the last three years of production (1997-1999) whereas records from the other two farms corresponded exclusively to the year 1999. The majority of data referred to the farming of white shrimp *Litopenaeus vannamei* while only scattered records were observed for the blue shrimp *L. stylirostris*. To facilitate calculation of the net return (objective function) coefficients of the LP model, production data for *L. stylirostris* were disregarded. In total, production records were collected from 1,004 individual ponds. These records provided information on the technical aspects of shrimp culture, i.e., stocking and harvesting dates, survival rates, growth rates, feed conversion ratios (FCR's), etc.

Since the collection of pond records comprised information from three years of production, records were reorganized according to stocking month and data for each stocking month were pooled together. Thus, the resulting data base integrated information from the period 1997-99 itemized on a monthly basis. Within each stocking month, correlation analyses were conducted in order to detect possible effects of stocking densities on survival rates, growth rates, and/or FCR's. In general, no clear correlation was observed between stocking densities and survival rates or FCR's, but there was a strong indication of the influence of stocking densities on growth rates (density-dependent growth). Although no clear correlation was observed between the entire range of stocking densities and survival rates, examination of the pond records suggested that the occurrence of high mortality rates (>90%) was more common in ponds stocked at elevated stocking densities (>20 PL/m^2). Results of a binomial comparative trial indicated that the occurrence of aggravated mortality rates was in reality significantly higher at stocking densities of more than 20 PL/m^2 (α=0.05).

The objective of the LP model was to elaborate an annual plan of activities conducive to maximization of farm income. To this end, it was assumed that for each month of the year, the farm manager had the option of selecting among 18 production activities, which referred to different combinations of three stocking densities, two lengths of grow-out cycles, and two regimes of water exchange. Productivity of farm-raised shrimp is lower during the dry season, which runs from October through March, as compared to the wet season, which goes from April through September (Teichert-Coddington et al. 1994). As a consequence, farm managers tend to lower stocking densities and shorten grow-out cycles during the dry season. Hence, options regarding stocking rates and duration of grow-out cycles were varied from one season to the other. It was assumed that stocking of shrimp during the dry season may occur at 5, 12, or 20 PL/m^2 while stocking densities during the wet season were 5, 15, and 25 PL/m^2. Likewise, grow-out cycles during the dry season could be extended for 11, 15, or 19 weeks, while the corresponding cycle lengths during the wet season were 13, 17, and 21 weeks. The model also considered two different water exchange regimes which remained unaltered during both climatic seasons. The first regime corresponded to the typical pattern of water exchange practiced in Honduras: exchanges are initiated after the third week of the grow-out cycle at a daily rate of 10%. In the second regime, water exchange is only initiated after week ten of the rearing cycle at a lower daily rate of 2%. Supplemental aeration is provided to the ponds to maintain dawn concentrations of dissolved oxygen above 3 mg/L. Green et al. (1999) demonstrated that such a conservative regime of water exchange rates does not significantly affect pond yields or growth rates of shrimp.

A total of 216 production activities (18 per month) were defined in the LP model. The next step was to calculate net return coefficients for each production activity. These coefficients indicate the net income (US $) generated by the realization of one hectare (ha) of the respective production activity. The calculation of these coefficients required the determination of parameters such as survival rates, FCR's, and growth rates. The integrated collection of pond records was used to determine average monthly values for each one of these parameters. As suggested by the correlation analyses, survival rates and FCR's were assumed not to be affected by varying stocking densities; thus survival rates and FCR's remained constant across the range of stocking densities considered for each month. In contrast, higher growth rates were assumed for those activities with lower stocking densities, and these values were selected in concordance with the information contained in the pond production records.

International price indexes were consulted to determine shrimp prices prevailing at the US market for each tail count. These international indexes also allowed the incorporation of seasonal variations in shrimp prices. Production costs associated with each production activity were obtained from Valderrama (2000).

The development of the Target MOTAD risk programming model required the definition of states of nature for each net return coefficient. States of nature refer to different net return outcomes for the same production activity, which may be related to different levels of management success. This model assumes five states of nature for each production activity which range from the "worst" to the "best" management scenario. An associated probability distribution was defined according to the subjective probabilities of management success developed by Hatch et al. (1987) and presented in Table 1.

Table 1: Probability levels defined for five levels of management success for the risk programming model of shrimp farming in Honduras.

State of nature	Probability of outcome
Best	0.05
Above average	0.20
Average	0.50
Below average	0.20
Worst	0.05

For each production activity, the "best" level of management success assumed high survival rates, low FCR's, and slightly retarded growth rates (because of overcrowding caused by the high survival rates), with respect to the "average" state of nature. In contrast, the "worst" level of management success assumed low survival rates and high FCR's which was partially compensated by slightly superior growth rates. Probability distributions were thus defined for survival rates, growth rates, and FCR's according to the variability of these parameters evinced in the pond production records. Within each stocking month, wider probability distributions for survival rates were defined for those production activities with the highest stocking densities (20 and 25 PL/m^2 during the dry and wet season, respectively) in order to connect these densities with the occurrence of high mortality rates, as demonstrated by the binomial comparative trial.

Table 2 presents the different states of nature assumed for survival rates, growth rates, and FCR's of an October production activity. Variation of these parameters determined different yield, tail count, and net return outcomes for the same production activity. Gross receipts and costs of production associated with this activity are presented in Table 3. An expected net return value was calculated as the weighted average of the five net return outcomes and corresponds to the net return coefficient used as an objective function coefficient in the LP model. It must be indicated that, for reasons of simplification, these coefficients only represent net returns over selected variable costs (seed, feed, fuel, and aeration).

Modifications to the basic procedure used to calculate the net return coefficients were introduced to adapt the LP and risk programming models to three different farm size scenarios: small (<150 ha), medium (150-400 ha), and large farms (>400 ha). Economies of scale with respect to feed input were commented by Valderrama (2000). A different set of net return coefficients and associated states of nature was prepared for each farm-size scenario which differ only in the assumed unit price of shrimp feed.

2.2 The LP Matrices

Resolution of the LP and Target MOTAD risk programming models required the development of an LP matrix for each farm-size scenario. Each matrix related the production activities to the objective and constraint functions defined for the LP model. In total, each matrix consisted of 36 stocking activities, 216 production activities, 41 saving, borrowing, and repayment activities, and 98 row constraints (110 in the case of small farms). In addition to the production activities, objective function coefficients were also assigned to the saving and borrowing activities. A description of the row constraints follows below.

2.2.1 Physical Constraints

Each LP matrix contained 36 transfer row constraints, 10 land constraints, and 24 harvest constraints. Additionally, 12 monthly PL constraints were defined for the small farm scenario, limiting the available supply of PL each month to 5 million. Interviews with farmers revealed that small farms frequently lacked sufficient infrastructure to handle a higher number of PL. The function of the transfer row constraints was to relate each stocking activity with six production activities. This would ensure that all stocked hectares were harvested at the end of the production cycle. Land constraints ensured that total pond area put into production at any given moment did

Table 2: States of nature and associated probability levels assumed for survival rates, growth rates, and FCR's of an October production activity.

Activity	Probability	Survival rates (%)	Growth rates (g/week)	FCR	Yield	Count size (no./lb)
11-week production	0.05	45	0.70	1.3	113	91-110
cycle stocked in	0.2	32	0.74	1.9	85	71-90
October at 5 PL/m^2.	0.5	18	0.78	2.5	50	71-90
High water exchange	0.2	15	0.82	2.9	44	71-90
rates.	0.05	10	0.86	3.5	31	71-90

not exceed farm size. Finally, harvest constraints limited the number of hectares to be harvested any given month to 70% of the farm area in order not to exceed the stated labor and machinery capabilities of the farm. Upper limits imposed to the land and harvest constraints varied among farm-size scenarios.

2.2.2 Financial Constraints

These constraints were incorporated to assure the fulfillment of periodic cash flow needs. Financial row constraints included 14 cash flow minimum requirements, 13 debt balancing rows, and one annual borrowing limit. The cash flow minimum requirements conformed an annual cash flow schedule that ensured that sufficient funds would be generated every month either by harvesting of ponds or the availability of saved or borrowed funds. Saved funds were generated when there was a surplus of farm income from preceding cash flow periods. Saved funds earned an annual interest of 21% while borrowed quantities were charged 39% annual interest. Both earned and charged interests were effectively added to the objective function by the inclusion of the appropriate coefficients. Monthly cash flow requirements varied with farm size and were estimated based on the amount of farm income needed to cover fixed costs and those variable costs not already accounted for during the calculation of net return coefficients. The debt balancing rows enforced the payment of any borrowed funds in the next cash flow period. The annual borrowing limit imposed a restriction on the amount of debt outstanding after the last production activity was completed.

2.3 Resolution of LP Matrices and Target MOTAD Formulations

The LP matrices developed in this study were solved with the computer program GAMS Version 2.50 (GAMS Development Corporation). Formulations used in the resolution of the LP and Target MOTAD models were adapted from McCarl and Spreen (1994). All simulations were run with the default solver (BDMLP) invoked by GAMS for the resolution of LP problems. The maximum number of iterations and maximum amount of CPU time (in seconds) allowed for each simulation were set to 1,000.

3. RESULTS AND DISCUSSION

3.1 LP Models

Table 4 presents the profit-maximizing combination of production activities selected in the resolution of the LP matrices. The majority of these activities involved intermediate stocking densities (12 and 15 PL/m^2 for the dry and wet season, respectively) and long production cycles (19 and 21 weeks). In addition, low-water-exchange activities were always selected as they were associated with a reduction in fuel costs with no adverse effects on pond yields. The density-dependent-growth assumption used in the calculation of net return coefficients resulted in a higher potential for profit for those activities with intermediate densities. Stocking of shrimp at high stocking rates resulted in the production of small tail counts that fetched an inferior price with respect to the larger tail counts produced at lower densities. The largest tail counts (size 26-30 during the wet season) were obtained at the lowest stocking densities, but total pond yields were not sufficient to generate the highest net return coefficients. Only occasionally did high stocking densities result in superior net return coefficients, such as in March (the stunting effect caused by overstocking was not very pronounced during this month).

Identical optimal plans were selected for the medium and large farms, differing only in the number of hectares assigned to each production activity. These are very simple plans that involve stocking of ponds only at selected months of the year: October, November, March, May, and June. The distribution of pond area among the different production activities was primarily determined by the harvest constraints. In the case of medium farms, up to a maximum of 200 ha could be harvested any single month. This restriction determined that a total of 200 hectares were stocked in October, March, and June.

Table 3: Calculation of expected net returns and associated states of nature for an October production activity.

Yield (kg/ha)	Gross receipts ($/ha)	Seed cost ($/ha)	Feed cost ($/ha)	Fuel cost ($/ha)	Aeration cost ($/ha)	Net return ($/ha)	Probability of outcome	Expected net return ($/ha)
11-week production cycle stocked in October at 5 PL/m^2. High water exchange rates.								
113	702	250	76	33	-	343	0.05	
85	619	250	83	33	-	252	0.2	
50	367	250	65	33	-	19	0.5	66
44	321	250	66	33	-	-28	0.2	
31	225	250	56	33	-	-114	0.05	

Table 4: Summary of production activities selected in the resolution of the LP models as outlined by the GAMS output. Annual farm yields and objective function values are indicated for three different farm-size scenarios.

	Farm-size scenario		
	<150 ha (73 ha)	150-400 ha (293 ha)	>400 ha (966 ha)
Annual farm yield (kg/ha)	1,256	1,384	1,401
Objective function value (Dollars)	790,878	3,439,390	12,057,904
Production activities (ha)			
10 05 11 LW[(1)]	8		
10 12 19 LW	25	200	700
11 12 19 LW	40	93	266
01 12 19 LW	8		
03 20 11 LW	25	200	700
04 15 21 LW	6		
05 15 21 LW	33	93	266
06 15 21 LW	33	200	700

(1) Activity codes: Stocking month (10=October); stocking density (5 PL/m^2); length of grow-out cycle (11 weeks); water exchange regime (LW = low water exchange rates).

Supplemental stocking (93 ha) occurred in November and May. Throughout the year, there was an evident transfer of land resources among activities: ponds stocked in October were harvested in February and stocked again for a short period of time (11 weeks) in March. Harvesting of these ponds occurred in May and they were re-stocked in June to initiate the last production cycle of the year. A more diversified optimal farm plan was outlined for the small farm scenario because of the additional restriction imposed by the seed constraint, which determined that a maximum of 40 ha and 33 ha were available for stocking during any month of the dry and wet season, respectively. As a result, new production activities were introduced in October (a short production cycle), January, and April. Table 4 also indicates the objective function values (total annual net returns over selected variable costs) and the annual farm yields associated with the profit-maximizing solution for each farm size scenario. The calculated annual pond yields (between 1,200 and 1,400 kg/ha) are superior to the common annual yields of Honduran shrimp farms. ANDAH (1997) and Rosenberry (1998) reported farm yields of 850 kg/ha/year during the post-Taura years (1997-98); however pond productivity declined in 1999 to 640 kg/ha/year as a consequence of the onset of WSSV (A. Zelaya, personal communication). Results of the LP models indicate that Honduran shrimp farms possess the potential to increase current annual pond yields (and total annual net income) in spite of the reduced survival rates caused by disease outbreaks. To achieve this objective, shrimp farmers should target the production of large tail counts (51-60 and 31-40 during the dry and wet season, respectively) which can be obtained through intermediate stocking densities and long production cycles. Stanley (1993) had demonstrated that linear growth of shrimp can be safely assumed during the first 21 weeks of culture. However, it is not uncommon to observe grow-out cycles shorter than 21 weeks in Honduras. In personal interviews conducted by the authors, farm managers have stated that the bulk of production in Honduras come out in the sizes 61-70 and 41-50 (dry and wet season, respectively) which may be a result of overcrowded conditions, short grow-out cycles, or a combination of factors therein.

The highest net return coefficients were calculated for the May and June production activities because of the superior survival rates (around 40%) and growth rates (over 1 g/week if stocked at 15 PL/m^2) observed for these months. Despite conditions of high productivity, pond yields achieved during the subsequent months of the wet season (July through September) do not sustain the production levels observed in May and June. As a result, the model determined that stocking of ponds during the wet season should be undertaken only in May and June to take full advantage of the superior conditions of productivity characteristic of these months. Examination of the pond production records indicated that shrimp farmers in Honduras have implemented a pattern of continuous stocking and harvesting of ponds. Thus, land resources that could be concentrated in May and June are being allocated to months like August and September, which have a lower potential for profit. It then appears that this practice of continuous stocking and harvesting is preventing shrimp farms from reaching higher profit margins.

Contrary to what was expected, the inclusion of financial constraints did not prompt the realization of production activities in order to satisfy periodic cash flow needs. In every instance, the model enforced borrowing activities so as to avoid alterations in the optimal plans of activities that would have also resulted if cash flow requirements were ignored altogether. The selected plan of activities had such a potential for profit that borrowing interests represented a minor financial charge.

3.2 Target MOTAD Risk Programming Models

The development of Target MOTAD models require the definition of two risk parameters: the target income level (*T*) and λ, or the maximum amount of deviation allowed. In turn, λ can be parameterized to yield different solutions reflecting varying degrees of risk aversion. Low λ values indicate little tolerance for risk-bearing combinations of production activities. As λ is allowed to increase, the risk constraint is relaxed and new mixes of production activities associated with larger deviations from *T* but with a higher potential for profit are selected.

For each farm-size scenario, a target income level was selected equivalent to the annual income needed to cover fixed costs and those variable costs not already accounted for in the calculation of net return coefficients. These quantities corresponded to the summation of monthly cash flow requirements. Table 5 presents the selection of target income levels for each farm-size scenario. Associated with each *T* value, an upper bound for λ was calculated according to the procedure outlined by McCamley and Kliebenstein (1987). These upper bounds are also presented in Table 5.

Results of the risk programming model for the small and medium farm scenarios are presented in Tables 6 and 7. In each table, λ was parameterized from zero to the upper bound λ_{up}. For brevity reasons, results obtained for the large farm scenario were not detailed in a separate table. However, variations in the optimal mixes of activities followed an identical pattern to that observed for medium farms.

Modifications to the optimal array of activities for the small farm scenario caused by the parameterization of λ can be summarized as follows (Table 6): a January activity (H011219LW) was selected when λ was set equal to zero, but thereafter it was replaced by a short production cycle in March (H032011LW). In addition, this March activity gradually substituted another March production activity characterized by lower stocking densities (H031211LW). A new June activity (H061521LW) was introduced when the deviation limit exceeded the value 3,846. This activity gradually replaced another pre-selected June activity (H060521LW) characterized by lower stocking densities. Additional modifications were introduced at $\lambda =$ 8,700 that approached the final mix of activities to the profit-maximizing mix defined by the LP model (the upper bound of λ is 8,783).

Relatively few modifications were introduced to the optimal combinations of activities for the medium farm scenario (Table 7). The selected mixes only differed in the levels of the two June activities, with the 15-PL/m^2 activity (H061521LW) gradually replacing the 15-PL/m^2 activity as the deviation limit was allowed to increase.

Total annual net returns generated by the optimal mixes of activities are also presented in Tables 6 and 7. Obviously, higher net returns were observed as λ_{up} was approached. The degree of risk associated with each solution can be expressed as the ratio between the respective λ value and total annual net returns. Similarly, risk levels associated with the LP solutions correspond to the ratio between λ_{up} and the respective objective function value. Table 8 summarizes risk percentages calculated for the profit-maximizing (LP) solutions for each farm-size scenario. This Table also indicates the reduction in total annual net returns that could be expected if the 0%-risk optimal mix of activities provided by Target MOTAD were implemented. Very low risk levels were associated with the LP solutions for each farm-size scenario (1% or less), which suggests that Honduran shrimp farms have a large potential to generate income over the selected target level. Modifications introduced by Target MOTAD to the optimal mixes contributed to further reduce initial risk levels; however, this was accompanied by significant reductions in total

Table 5: Target income levels (T) selected for three farm-size scenarios of the Target MOTAD risk programming model of shrimp farming in Honduras. An upper bound for the parameter λ is indicated for each target level T. Units for T and λ are US Dollars.

<150 ha		150-400 ha		>400 ha	
T	λ_{up}	T	λ_{up}	T	λ_{up}
195,466	8,783	592,739	28,835	926,543	36,939

Table 6: Results of the Target MOTAD risk programming model for production of penaeid shrimp in Honduras, small farm scenario (<150 ha), T = $195,466.

	Deviation limit (Dollars)				
Production activities	0	1,538	3,846	5,385	8,700
10 05 11 LW					2
10 12 19 LW	42	39	31	31	30
11 12 19 LW	23	34	42	42	42
01 12 19 LW	8				2
03 12 11 LW	42	35	16	16	12
03 20 11 LW		4	16	16	18
04 15 21 LW	1	2	2	2	2
05 15 21 LW	22	32	39	39	39
06 05 21 LW	50	39	24	15	
06 15 21 LW			7	17	31
Total annual net returns ($)	717,096	739,943	757,279	768,831	790,391

annual net returns (almost 10% for the small farms) which appears to be unnecessary given the low risk values of the LP solutions.

Stanley (1993) concluded that maximization of farm income (under pre-Taura conditions) could be achieved by intensification of stocking densities. Her study did not point out the intrinsic risk associated with this recommendation. The profit-maximizing farm management plans presented in this paper were characterized by high profit margins coupled with low risk levels, which was primarily determined by the selection of intermediate stocking densities in lieu of the highest stocking rates considered in the model. In addition to their reduced potential for profit, a greater chance for financial crashes was associated with the high-stocking activities due to the model assumption that assigned wider distributions of survival rates to these activities. In contrast, the narrowest distributions of net returns were defined for the 5-PL/m^2 production activities, which resulted in a very low potential for financial losses.

The optimal farm management plans outlined by the LP models selected the use of high stocking densities only in March. This activity was associated with a wide distribution of net returns that included the occurrence of financial losses. In the small farm scenario, this activity was excluded from the optimal plan at $\lambda = 0$ but it was called into solution at increasing levels as larger amounts of deviation were allowed. In the medium farm scenario, the model determined that there was no need to exclude this activity because risk levels could be effectively reduced by lowering stocking densities in June.

4. CONCLUSIONS

Resolution of the LP models for each farm-size scenario outlined optimal farm management plans with a considerable potential for profit over the most important variable costs (seed, feed, and fuel). Results indicated that, regardless of farm size, Honduran shrimp farms possess the ability to generate total annual net returns/ha of more than $10,000/ha. However, the achievement of these profit levels implies annual farm yields between 1,200 and 1,400 kg/ha and the production of large tail counts (predominately sizes 31-35 and 51-60 during the

Table 7: Results of the Target MOTAD risk programming model for production of penaeid shrimp in Honduras, medium farm scenario (150-400 ha), T = \$592,739.

	Deviation limit (Dollars)				
Production activities	0	5,769	11,538	17,308	28,000
10 12 19 LW	200	200	200	200	200
11 12 19 LW	93	93	93	93	93
03 20 11 LW	200	200	200	200	200
05 15 21 LW	93	93	93	93	93
06 05 21 LW	161	125	88	52	3
06 15 21 LW	51	87	112	148	197
Total annual net returns (\$)	3,209,527	3,255,519	3,301,511	3,347,503	3,432,741

Table 8: Total annual net returns corresponding to the optimal farm management plans outlined by the resolution of the LP and Target MOTAD risk programming models. A risk percentage is calculated for each plan of activities. Results are presented for three farm-size scenarios.

Target income level (Dollars)	Total annual net returns (Dollars)	Deviation limit (Dollars)	Risk (%)	Change in income
		Small farm scenario (73 ha)		
195,466	790,878	8,783	1.1	
	717,096	0	0	-73,782 (-9.33%)
		Medium farm scenario (293 ha)		
592,739	3,439,390	28,835	0.84	
	3,209,527	0	0	-229,863 (-6.68%)
		Large farm scenario (966 ha)		
926,543	12,057,904	36,939	0.31	
	11,745,985	0	0	-311,919 (-2.59%)

wet and dry seasons, respectively). Actual annual pond yields in Honduras fluctuate between 600 and 800 kg/ha and the predominant tail counts range from 41-50 to 61-70. The optimal farm management plans involve the use of intermediate stocking densities (12 and 15 PL/m^2 during the dry and wet season), long production cycles (19 and 21 weeks), and low water-exchange rates. Occasionally, high stocking densities and short production cycles fit into these plans of activities. The optimal management plans recommend a pattern of continuous production throughout the year with stocking of ponds conducted only in specific months. This results in the attainment of more than two crops per year. Growth and survival rates of shrimp are clearly superior in the stocking months of May and June, thus the model recommended the stocking of all available pond area during these months. Currently, a scheme of monthly stocking and harvesting of ponds is being practiced in Honduras that may be preventing shrimp farmers from taking full advantage of the superior conditions of productivity characteristic of the first months of the wet season. The profit-maximizing model is also emphatic as to the convenience of extending grow-out periods to at least 19 weeks to ensure the production of larger tail counts.

The considerable potential for profit and the selection of intermediate over high stocking densities resulted in relatively low risk levels associated with the LP solution. Resolution of the Target MOTAD risk programming models provided alternative production plans which contributed to further reduce risk levels. However, these alternative solutions were accompanied by reductions in total annual net returns. Given the low risk initial values, it appears that the optimal plans of activities outlined by the LP models provide the best management guidelines for shrimp farmers in Honduras.

In conclusion, results of this study indicated that, in spite of recent problems with disease outbreaks and natural calamities, Honduran shrimp farms have the potential to increase current pond yields and profit margins without resorting to further intensification of activities. In fact, selected management strategies involve intermediate stocking densities and regimes of low water exchange rates. The formulated farm management plans are consistent with the production strategies commonly recommended to reduce the impact of WSSV in shrimp ponds. They also address current concerns on the quality of estuarine waters. Finally, the importance of top-level farm management can never be over-emphasized. The implementation of the optimal culture strategies contained in this paper assumes excellent farm management skills, which are essential if efficiency and profit margins in shrimp aquaculture are to be improved.

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