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Stock model and multivariate analysis for prediction of semi-intensive production of shrimp *Litopenaeus vannamei* as a function of water quality and management variables: A stochastic approach

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ABSTRACT

We use a stock model, multivariate analysis, and a stochastic approach to predict shrimp production under commercial semi-intensive conditions as a function of water quality and alternative management schemes. Larger final weight of shrimp was obtained when temperature and duration of cultivation increased. Increases in the mortality of shrimp were associated with lower dissolved oxygen levels, shorter durations of cultivation, and higher stocking densities. There was a direct relationship between temperature and stoking density, while dissolved oxygen was inversely related with stocking density and duration of cultivation. Stocking density was inversely correlated with pond size and directly correlated with duration of cultivation. The lowest yields were predicted, using the lowest stocking densities and shortest duration of cultivation; the highest yields were predicted using the highest stocking densities and longest duration of cultivation. Yields increased from 938 to 2326 kg ha^{-1} (spring production cycle), and from 982 to 1907 kg ha^{-1} (summer production cycle). Improved management resulted in increased shrimp production and diminished variability. Sensitivity analysis indicates that final weight of shrimp and stocking density were the major factors affecting variability of shrimp yields. We conclude that stock models, multivariate analysis, and a stochastic approach constitute an effective method for studying the relationships between production parameters, water quality, and management variables, and, for analyzing variability of semi-intensive shrimp production.

1. Introduction

Cultivation of shrimp is one of the main aquacultural activities in Mexico. During 2008, shrimp production reached 130,000 t, 66% of aquaculture production (CONAPESCA, 2010). More than 90% of shrimp production comes from the States of Sonora, Sinaloa, and Nayarit in northwestern Mexico, where semi-intensive cultivation systems are the most common.

Shrimp *Litopenaeus vannamei* is the main species used in shrimp cultivation in Mexico and worldwide (FAO, 2010). The role that water quality and management variables have on growth and survival parameters of *L. vannnamei*, when cultivated under semi-intensive conditions has been analyzed using experimental data (Griffin et al., 1981; Pardy et al., 1983). There are no antecedents of investigations studying the role that such variables have on growth and survival parameters of *L. vannamei* using stock models and multivariate analysis; nor are there antecedents of studies specifically dealing with the stochastic variability of shrimp yields in semi-intensive commercial farms.

In this study, we follow the methodological approach presented by Ruiz-Velazco et al. (2010a,b) who established relationships between the parameters of a stock model and water quality and management variables for predicting shrimp production under intensive cultivation. We used the stock model of Ruiz-Velazco et al. (2010a) and a multivariate analysis to predict shrimp production under semi-intensive conditions as a function of water quality and alternative management schemes. We also studied the stochastic variability of shrimp yields under alternative management schemes. In this case, we determined the management

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scheme that maximized production and minimized variability. The model was calibrated with a database from semi-intensive commercial farms in the State of Nayarit.

2. Materials and methods

2.1. Data survey

A database of operations in 2009 and 2010 were used, where the operation units were 31 ponds selected after confirming that biometric data, water quality, and management variables were adequately monitored, and that there was no evidence that the shrimp were affected by disease. For each pond, the following variables were analyzed: mean individual body weight of shrimp (g), number of survivors, biomass yield (kg ha^{-1}), dissolved oxygen (mg L^{-1}), water temperature (°C), salinity (ppt), initial stocking density of postlarvae (PL m^{-2}), pond size (ha), and duration of cultivation (weeks).

Farmers conducted estimates of shrimp growth using 0.01 and 0.1 precision balances (Ohaus, Pine Brook, NJ). Dissolved oxygen and pond water temperature were monitored daily at 0600 h and 1800 h, using an oxymeter (Model 55, YSI, Yellow Springs, OH), salinity were measured weekly with a refractometer (Aquafauna Bio-marine, Hawthorne, CA).

2.2. Stock model

The stock model presented by Ruiz-Velazco et al. (2010a) was used. The model predicts shrimp biomass as a function of time as the product of individual mean weight of shrimp and surviving shrimp population. Individual mean weight of shrimp was calculated, using:

$$w_n = w_i + (w_f - w_i)\left[\frac{(1-k^n)}{(1-k^h)}\right]^3 \quad (1)$$

where w_n is the shrimp weight (g) after n time events have passed, w_i is the initial weight (g), w_f is the final weight (g), k is a growth coefficient (dimensionless), and h is the number of time events that have passed until harvesting time. The equation applies when the time intervals are equally spaced and the initial time is zero, that is, when the number of time events analyzed is numerically equivalent to elapsed time. For estimating the parameters, there must be a single estimate of mean weight for each time. Since the model is nonlinear in its parameters, residual sum of squares was used for fitting (Ratkowsky, 1990; Quinn and Keough, 2002). Growth parameters were estimated using nonlinear regression procedures available in Statistica 6.0 (StatSoft, Tulsa, OK).

The exponential equation used to calculate the surviving shrimp population:

$$n_t = n_0 e^{zt} \quad (2)$$

where n_0 is the initial population and z is the instantaneous mortality rate (weeks^{-1}), which was estimated from Eq. (2) as:

$$z = \frac{\ln(n_t/n_0)}{t} \quad (3)$$

where n_t is the surviving population at harvest.

2.3. Multivariate analysis

Relationships between parameters of the stock model and water quality and management variables were analyzed using multiple linear equations in the form:

$$Q = a_0 + a_1 T + a_2 DO + a_3 SD + a_4 PS + a_5 DC + \varepsilon \quad (4)$$

Table 1
Range and mean values of water quality and management variables used for multivariate analysis.

Variable	Production cycle					
	Spring			Summer		
	Min	Max	Mean	Min	Max	Mean
Temperature (°C)	30.0	32.2	31.3	30.5	32.6	31.1
Dissolved oxygen (mg L^{-1})	3.6	6.5	4.5	3.8	4.8	4.3
Stocking density (PL m^{-2})	13.0	37.0	19.6	14.0	25.0	20.1
Pond size (ha)	1.0	2.5	1.7	1.1	7.0	2.5
Duration of cultivation (weeks)	9.5	13.0	11.0	9.0	14.0	12.8

where Q represents any of the stock model parameters: w_f, k, or z, depending on pond water temperature (T), dissolved oxygen (DO), initial stocking density (SD), pond size (PS), duration of cultivation (DC), $a_0 - a_5$ are regression coefficients, and ε is the statistical error. Salinity was not considered for analysis after ANOVA showed that it did not vary significantly among ponds ($P > 0.05$).

To predict stochastic values of the stock model parameters, ε values in Eq. (4) were predicted, using normal distributions fitted to residual values resulting from regression analyses. When no significant regressions were established, normal distributions were directly fitted to values of the stock model parameters. The Shapiro–Wilk test was used to test for normality of the residual values (Zar, 2010).

The relationship of temperature and dissolved oxygen with management variables were in turn determined using:

$$W = a_0 + a_1 SD + a_2 PS + a_3 DC + \varepsilon \quad (5)$$

where W is either temperature or dissolved oxygen. Stochastic elements in these relationships were incorporated by predicting ε values following the same method used to predict stochastic values of the stock model parameters, as explained above.

Eq. (4) was fitted as follows: (1) parameters of Eq (1) were estimated separately for every case (pond); (2) datasets consisting of parameters estimated in step (1) and the corresponding water quality and management variables were integrated for each case; (3) the 31 datasets integrated in the previous step were used together to conduct multiple regression analysis. The mean values of water quality variables during the cultivation period were used for analysis. The range of these mean values, together with the range of management variables is presented in Table 1. Additionally, correlation analyses between water quality and management variables were conducted. Eq. (5) was fitted similarly to Eq. (4), excepting that the dependent variables were not the parameters of Eq. (1), but the water quality variables.

2.4. Parsimony and predictive capability of the models

Parsimony and predictive capability of the models were evaluated in two steps. Step 1 uses a stepwise procedure for selecting predictor variables in the multivariate analysis. The backward stepwise regression procedure in Stata 10 (StataCorp, College Station, TX) was used with $P < 0.05$ to accept or reject predictors. This regression procedure deals automatically with collinearity, according to the methods described in Rencher (2002).

Following Poole (1974), Step 2 tests whether the proposed multiple linear regression models were adequate and whether most of the significant factors affecting the parameters of the stock model were included. For Step 2, the coefficients estimated from multiple regression analyses were used to calculate the expected biomass at harvest for each pond; this was compared with the corresponding observed yield in the database. Following this, a simple linear regression analysis between observed and expected shrimp biomass was performed, setting the intercept to zero. After determining that the regression slope did not differ significantly from 1 (t-test), an equivalence test (Chow and Liu, 2004) was used to protect against falsely not rejecting the corresponding null hypothesis (Type-II statistical error; Zar, 2010; Hauck and Anderson, 1986). The residuals resulting from this simple linear regression were tested for normality, using the Shapiro–Wilk test. Equivalence was tested with a tolerance error of 5% (Garret, 1997).

2.5. Management schemes

Shrimp production was calculated corresponding to alternative management schemes, using the stock model, the multiple regression equations, and the corresponding stochastic elements. Alternative management schemes were defined by determining, in a first step, the values of the management variables that minimized (the worst scheme) and maximized (the best scheme) mean production and, in a second step, using intermediate values of the management variables that produced intermediate levels of production.

Monte Carlo simulation (10,000 iterations) was used to predict stochastic variability of shrimp production corresponding to the alternative management schemes. Variability in production was measured using the coefficient of variation (CV; Mun, 2006):

$$CV = \frac{\text{standard deviation}}{\text{mean}} \quad (6)$$

Variability in production was standardized to kg ha^{-1}.

2.6. Sensitivity analysis

Sensitivity of shrimp production to stochastic variability of zootechnical parameters and water quality variables was determined with multivariate stepwise regression, where the values of the regression coefficients indicate the sensitivity of production to inputs. Sensitivity analysis was also used to determine the contribution that management variables have on the variability of shrimp production. For this, the minimum and maximum values of the management variables in the database were used in the calculations (Table 1).

2.7. Software

Normality tests and regression and correlation analyses were conducted, using Statistica 6.0 and Stata 10.0, setting significance at $P < 0.05$. The stock model was programmed in worksheets of Excel 2007 and the stochastic elements were programmed using @Risk 5.5. The genetic algorithm available in @Risk Optimizer 5.5 was used to determine the worst and best management schemes. For this, the minimum and maximum values of the decision variables (stocking density and duration of cultivation) were used as restrictions, and the objective function was to maximize and minimize mean production for the worst and best schemes, respectively. Procedures available in @Risk 5.5 were used for simulation and sensitivity analysis.

3. Results

From regression ANOVA, there were significant results when fitting parameters of the growth model (Eq. (1)). The model adequately fitted the different types of growth curves (Fig. 1) described in the 31 cases contained in the database.

Multivariate analysis indicated that larger final weight of shrimp (w_f) was obtained when temperature and duration of cultivation increased (Table 2). Increases in the instantaneous mortality rate (z) were associated with lower dissolved oxygen, higher stocking densities, and shorter durations of cultivation (Table 2). The growth coefficient (k) was not significantly associated with any water quality and management variables ($P > 0.05$).

Multivariate analysis also indicated that there was a direct relationship between temperature and stocking density, while dissolved oxygen was inversely related to stocking density and duration of cultivation (Table 3). Correlation analysis confirmed these findings (Table 4). Additionally, stocking density was inversely correlated with pond size, and directly correlated with duration of cultivation (Table 4).

There was a significant linear relationship between production of shrimp biomass in the database and production calculated by the stock model, using the equations listed in Tables 2 and 3 (Fig. 2). The coefficient from the linear regression did not differ significantly from 1 and equivalence between the coefficient and 1 was determined, meaning that there were not statistical differences between observed and predicted shrimp biomass. Residual analysis did not indicate directional deviations from the fitted straight line and no

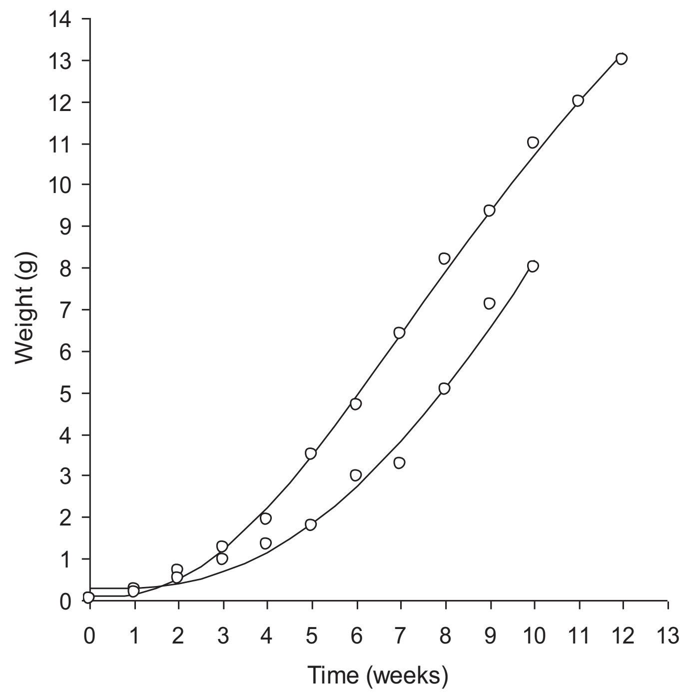

Fig. 1. Sample-fitted growth curves using Eq. (1). The two typical types of growth curves observed in the database are presented, regardless of the cultivation cycle.

Table 2
Multiple regression models relating final weight of shrimp and instantaneous mortality rate to temperature, duration of cultivation, dissolved oxygen, and stocking density.

Model	P
$w_f = -25.2436 + 0.9678T + 0.5329DC$	0.0032
$z = 0.0916 - 0.0081DO + 0.0010SD - 0.0034DC$	0.0030

w_f, final weight (g); z, instantaneous mortality rate (weeks^{-1}); T, temperature (°C); DC, duration of cultivation (weeks); DO, dissolved oxygen (mg L^{-1}); SD, stocking density (PL m^{-2}).

Table 3
Multiple regression models relating pond water temperature and dissolved oxygen to stocking density and duration of cultivation.

Model	P
$T = 30.36 + 0.049SD$	0.011
$DO = 6.51 - 0.036SD - 0.1175DC$	0.017

T, temperature (°C); SD, stocking density (PL m^{-2}); DO, dissolved oxygen (mg L^{-1}); DC, duration of cultivation (weeks).

Table 4
Values of the significant coefficients of correlation between water quality and management variables.

	T	*DO*	*SD*	*PS*	*DC*
T			0.447		
DO			−0.437		−0.406
SD	0.447	−0.437		−0.488	0.427
PS			−0.488		
DC		−0.406	0.427		

T, temperature (°C); *DO*, dissolved oxygen (mg L^{-1}); *SD*, stocking density (PL m^{-2}); *PS*, pond size (ha); *DC*, duration of cultivation (weeks).

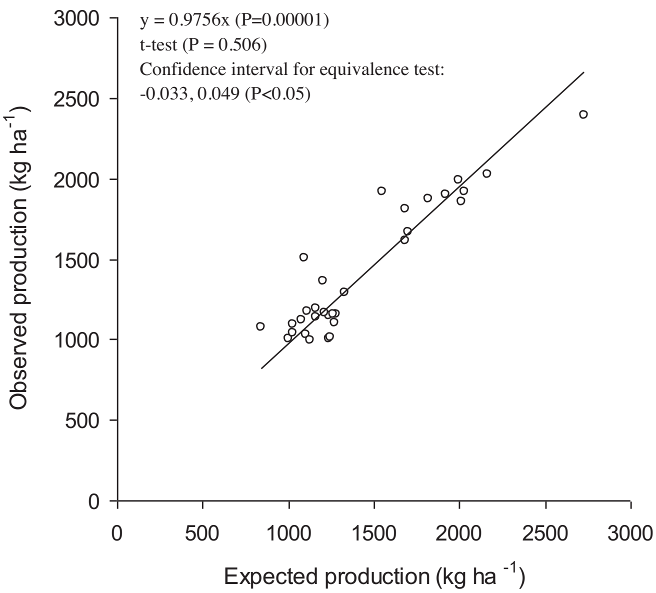

Fig. 2. Relationship between observed and predicted production, using the stock model and the multiple regression models.

evidence was found that the residual values were not normally distributed. We concluded that: (1) The functional relationships used were correct; (2) Most of the significant factors affecting biomass yields were included; and (3) There was no need for predictors other than those considered in the multivariate analysis (Eqs. (4) and (5)).

Using the stock and regression models resulted in the lowest predicted production when stocking densities was low and the duration of cultivation was short; highest production was predicted when stocking densities were high and the duration of cultivation was long (Fig. 3). Yields increased from 938 to 2326 kg ha^{-1} (spring production cycle; Fig. 3a), and from 982 to 1907 kg ha^{-1} (summer production cycle; Fig. 3b). The management schemes resulting in the lowest and highest production, together with the schemes for intermediate production are predicted (Table 5).

Table 5
Values of the management variables used to define the alternative management schemes.

Management strategy	Production cycle			
	Spring		Summer	
	DC	*SD*	*DC*	*SD*
1 (worst)	9.5	13	9	14
2	10.37	19	10.25	16.75
3	11.25	25	11.5	19.5
4	12.12	31	12.75	22.25
5 (best)	13	37	14	25

DC, duration of cultivation (weeks); *SD*, stocking density (PL m^{-2}).

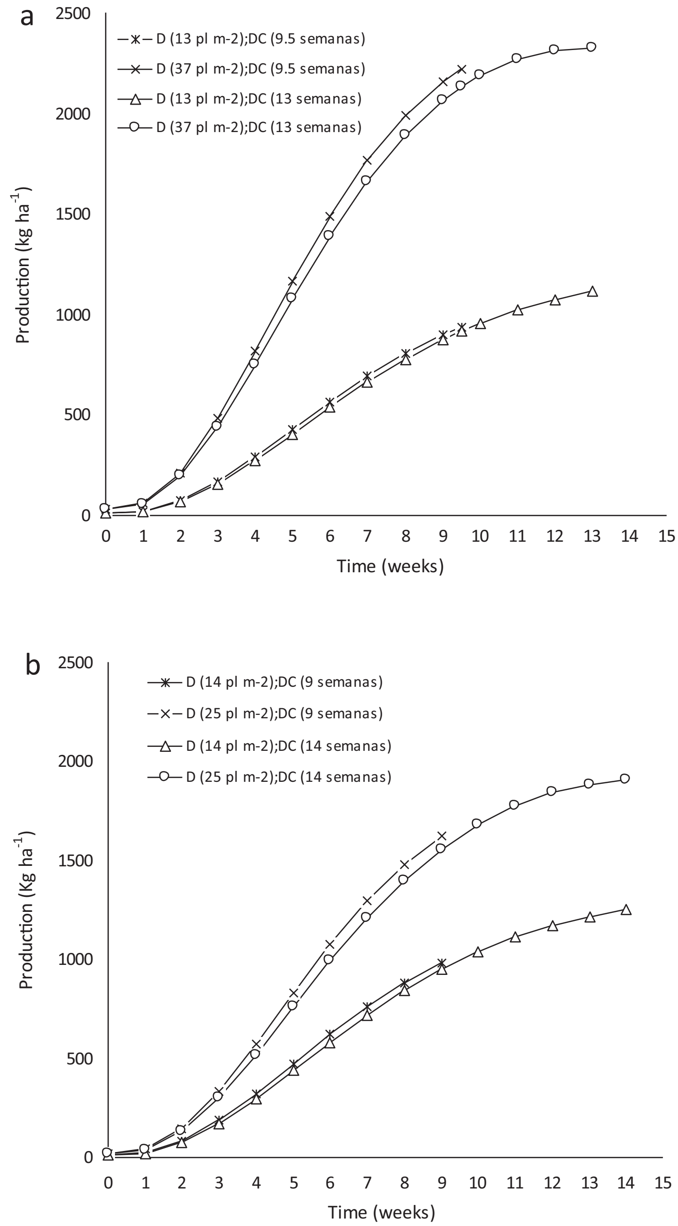

Fig. 3. Predicted shrimp production for alternative management schemes of stocking density (*D*) and duration of cultivation (*DC*). (a) Spring cycle and (b) summer cycle.

The mean values and standard deviation of the normal distribution obtained after fitting the error distribution (ε) in Eqs. (4) and (5) are presented in Table 6. No significant relationship was found between the growth coefficient (k) and water quality and

Table 6
Values of mean and standard deviation of the normal distribution obtained when fitting the distribution to residual values (ε) in Eqs. (4) and (5). The distribution was directly fitted to k values contained in the database, after no significant regression was obtained.

	Q			W	
	w_f	z	k	*T*	*DO*
Mean	0	0	0.8296	0	0
SD	1.389	0.0001	0.03534	0.61	0.6

Q, stock model parameters; *W*, water quality variables, w_f, final weight (g); z, instantaneous mortality rate ($week^{-1}$); k, growth coefficient (dimensionless); *T*, temperature (°C); *DO*, dissolved oxygen (mg L^{-1}).

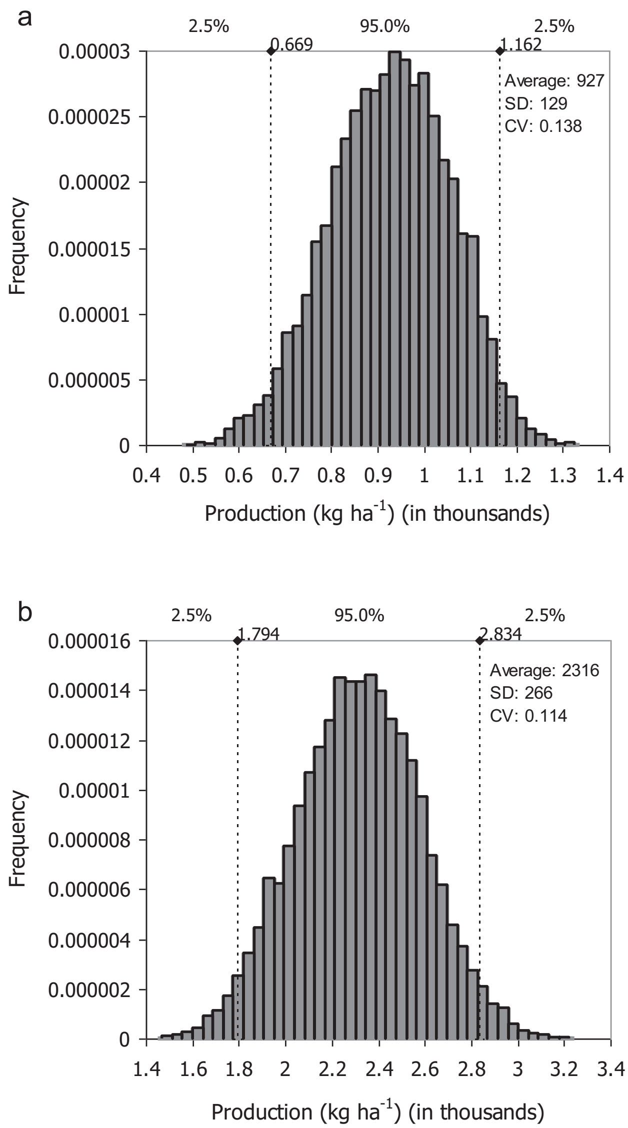

Fig. 4. Output probability distributions of shrimp production for the spring cycle. (a) Management strategy 1 (worst) and (b) management strategy 5 (best). See Table 5. SD is standard deviation; CV is the coefficient of variation.

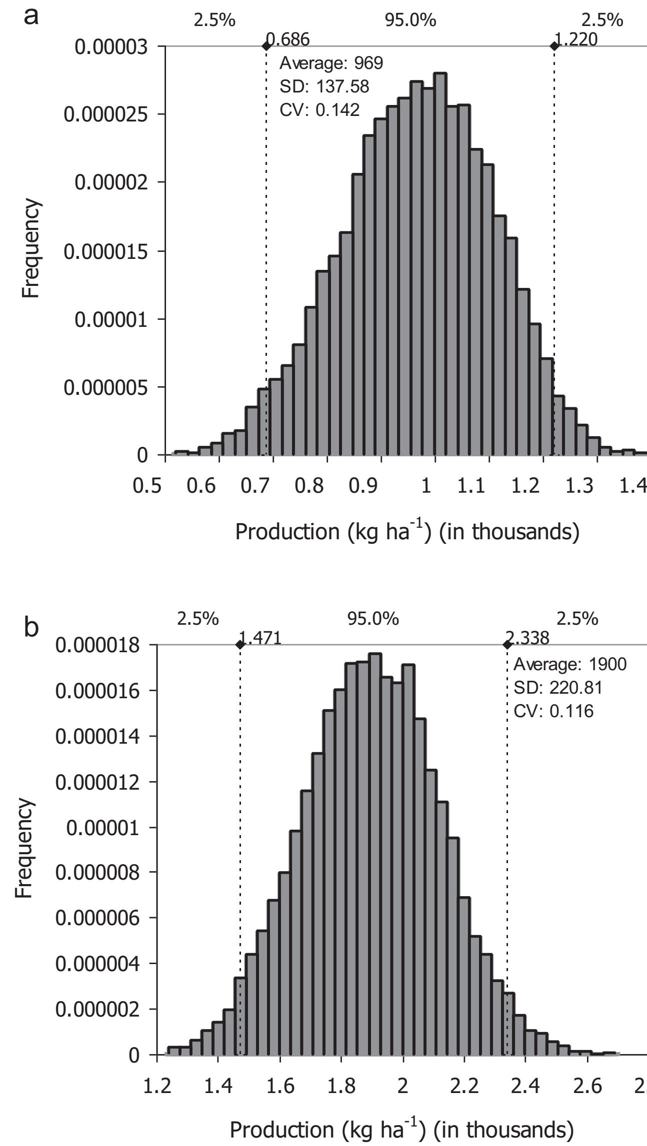

Fig. 5. Output probability distributions of shrimp production for the summer cycle. (a) Management strategy 1 (worst) and (b) management strategy 5 (best). See Table 5. SD is the standard deviation; CV is the coefficient of variation.

management variables; the normal distribution was directly fitted to k values. Using these values of mean and standard deviation resulted in output probability distributions of shrimp production for spring (Fig. 4) and summer (Fig. 5) production cycles under the worst and best management schemes presented in Table 5. Mean production increased and the coefficient of variation diminished, as a consequence of improving management in both production cycles. The stochastic variability of shrimp production predicted for the alternative management schemes are presented in Fig. 6. Mean production increased and the coefficient of variation diminished, as management progressively improved.

Sensitivity analysis indicated that final weight of shrimp (w_f) and stocking density (*SD*) were the most sensitive zootechnical parameter and management variable influencing the variability in shrimp production (Table 7 and Fig. 7).

4. Discussion

The modeling approach allowed us to analyze and satisfactorily predict the semi-intensive production of *L. vannamei*, as evidenced from alternative management schemes and seeding schedules.

Table 7
Sensitivity analysis of shrimp production to stochastic variation of parameters of the stock model and water quality variables. Higher absolute values of regression coefficient (RC) indicates higher sensitivity.

Production cycle			
Spring		Summer	
Parameter or variable	RC	Parameter or variable	RC
Worst strategy			
w_f	0.878	w_f	0.879
T	0.383	*T*	0.384
DO	0.287	*DO*	0.265
K	0.000	*k*	0.000
Z	0.000	*z*	0.000
Best strategy			
w_f	0.807	w_f	0.803
DO	0.474	*DO*	0.506
T	0.352	*T*	0.350
K	0.000	*k*	0.000
Z	0.000	*z*	0.000

w_f, final weight (g); *DO*, dissolved oxygen (mg L^{-1}); *T*, temperature (°C); *k*, growth coefficient (dimensionless), *z*, instantaneous mortality rate (week^{-1}).

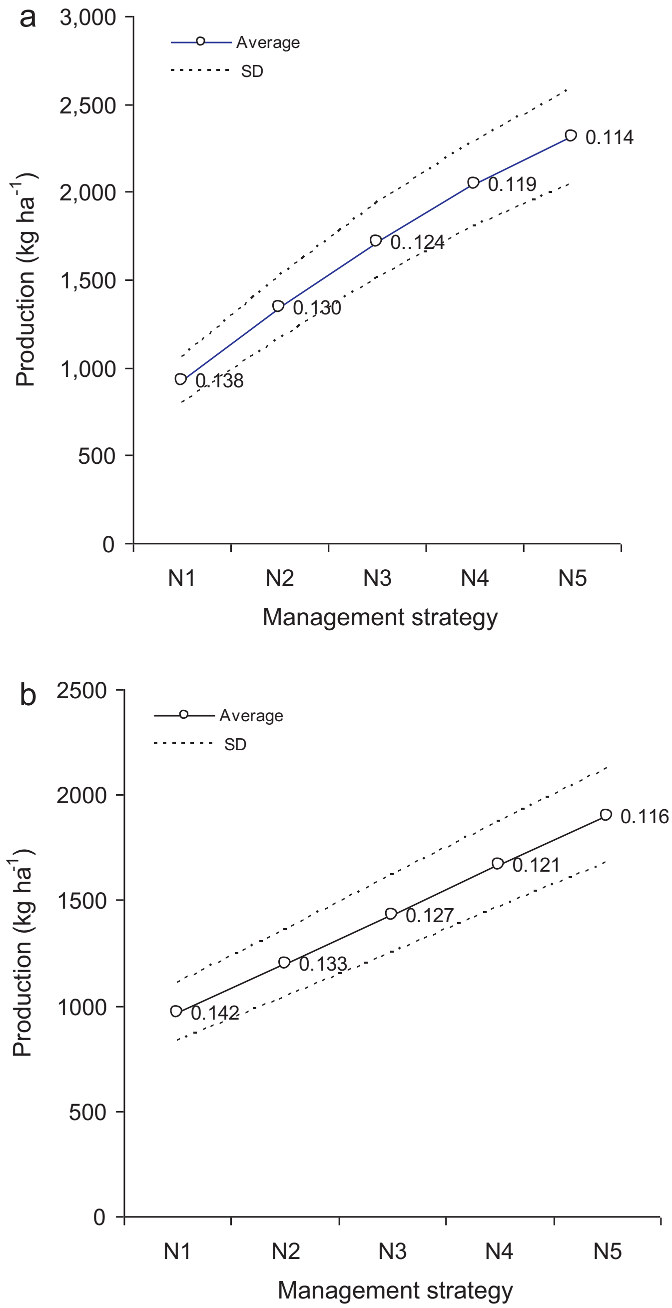

Fig. 6. Shrimp production as a function of management strategies, as defined in Table 5. Dashed lines indicate ±SD and the plotted values correspond to the coefficient of variation.

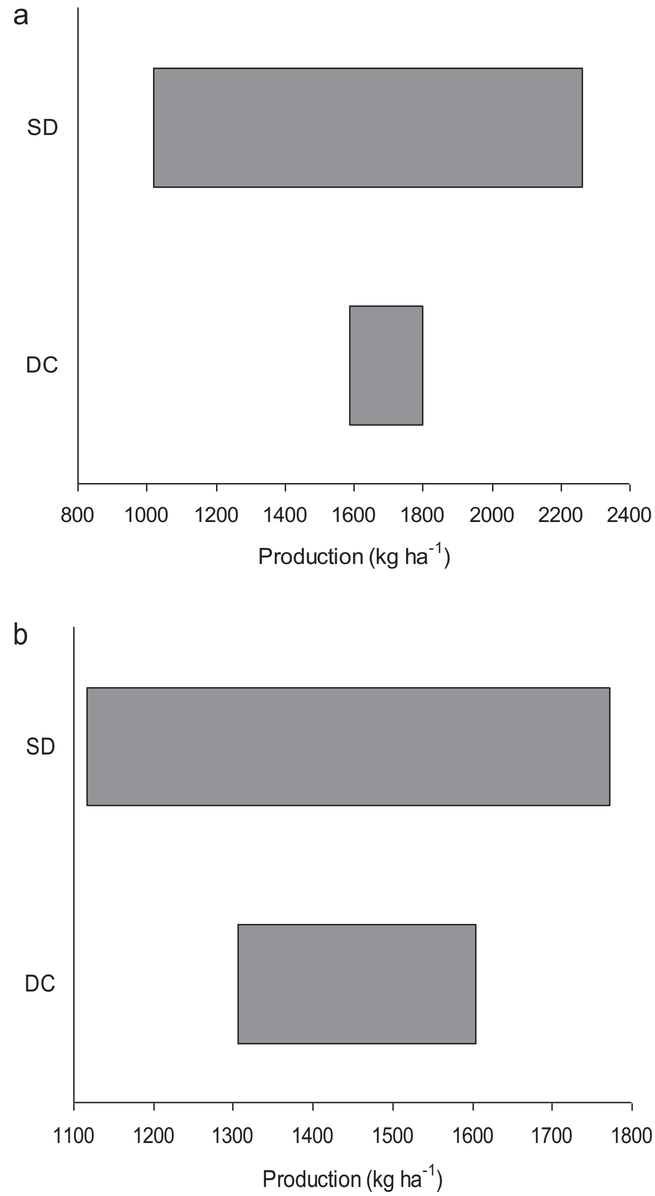

Fig. 7. Sensitivity analysis of shrimp production to water quality and management variables for alternative seeding schedules: (a) Spring cycle and (b) summer cycle. The wider the bar, the higher the sensitivity. *SD* is the stocking density and *DC* is the duration of cultivation.

Multiple regression models are considered predictive, rather than explanatory tools, yet the established functional relationships are in general agreement with reports by other authors regarding the correlations between growth and survival parameters and water quality and management factors (Sadeh et al., 1986; Jackson and Wang, 1998; Wannamaker and Rice, 2000; Eby and Crowder, 2002; Valderrama and Engle, 2002; Ruiz-Velazco et al., 2010a,b). This indicates consistency and reliability in the predictability of the models. Moreover, it was not necessary to study predictors other that those stated (Eq. (4)), after finding that the functional relationships we used were correct, that there was linear relationships between dependent and independent variables, and that there was no evidence of exclusion of significant factors affecting shrimp production.

Maximum shrimp production was consistently predicted by using the highest stocking densities and longest cultivation periods. This coincides with the results obtained by Ruiz-Velazco et al. (2010a,b), when they analyzed intensive production of *L. vannamei* when affected by white spot disease or under normal operating conditions. Sánchez-Zazueta and Martínez-Cordero (2009) analyzed semi-intensive production of *L. vannamei* from the economic perspective and concluded that schemes with lower stocking densities and intermediate cultivation times generated the highest probabilities of achieving superior economic performance. A bio-economic analysis using the stock and multiple regression models presented here should be conducted to determine whether the maximum economic profits could be achieved by using the stocking densities and durations of cultivation that maximized shrimp biomass production.

Stocking density was the most important management variable determining the variability of shrimp production. Sensitivity analyses conducted by Ruiz-Velazco et al. (2010a) and Hernandez-Llamas et al. (2011) have also demonstrated that stocking density is the most important variable influencing intensive commercial production of *L. vannamei* under normal operating conditions or when affected by white spot disease. The influence that stocking density has on production parameters of shrimp has been extensively studied. A negative influence of stocking density on growth and survival has been generally reported. Yet, we did not find evidence that shrimp growth (final weight) was affected by cultivation density, although survival was negatively affected, as in the case reported by Valderrama and Engle (2002).

In a survey of 23 extensive, semi-intensive and intensive farms, Hopkins and Villalon (1992) found that the relationship between final shrimp size and stocking density was barely discernible. Sandifer (1991) analyzed final size of *L. vannamei* for stocking densities ranging from 20 to 200 PL m^{-2} and did not find a tendency of shrimp size to decline as stocking density increased. We are inclined to think that expertise in cultivation management is an important factor that compensates for the potential negative effects of high stocking densities on growth of shrimp.

In our study, higher mortality was associated with increased stocking density. More adverse cultivation conditions are expected in ponds stocked at high densities, resulting in increased mortality and availability of feed for the surviving shrimp. This helps to explain the final size of shrimp in ponds stocked at high densities, which is not different from the final size in ponds stocked at lower densities. Increases in growth rate follow self-thinning of populations of the blue shrimp *Litopenaeus stylirostris* (Pardy et al., 1983; Hernandez-Llamas et al., 1993). Kautsky et al. (2000) propose that high stocking densities is a risk factor for transmission of shrimp diseases. We did not find evidence that differences in mortality in ponds stocked at different densities could be attributed to disease outbreaks.

Sensitivity analysis indicated that final weight of shrimp is the most important zootechnical parameter influencing variability in production. As expected, final shrimp size was directly related to the duration of cultivation. On the other hand, there is no a priori reason to assume that the duration of cultivation could affect the instantaneous mortality rate, yet we found that higher mortality was associated with shorter periods of cultivation. This may be a consequence of increased relative mortality during early stages of cultivation. Detailed population monitoring is necessary to study this.

Small ponds have been recommended for improving shrimp cultivation; it is generally acknowledged that they can be stocked at higher densities, compared with large ponds (Islam et al., 2005; Milstein et al., 2005; Ruiz-Velazco et al., 2010a,b). We did not find evidence that pond size affected growth and mortality of shrimp, yet because of the high stocking densities, the smaller ponds had higher production.

The role of dissolved oxygen on carrying capacity of ponds and shrimp production has been discussed, particularly for intensive production using artificial aeration (Hopkins et al., 1991; Ruiz-Velazco et al., 2010a). Water exchange is the main control of dissolved oxygen in semi-intensive systems and little is known about the relationships between stocking density, dissolved oxygen, and carrying capacity. Using our models, we determined and quantified the relationships between mortality rates, dissolved oxygen, and stocking density. Apparently, there is a causal relationship: high stocking densities – low dissolved oxygen – high mortality. Studies on the carrying capacities of alternative sizes of semi-intensive ponds are needed.

It is well established that increasing pond temperature enhances shrimp growth (Sadeh et al., 1986; Ruiz-Velazco et al., 2010a). We confirmed this relation, but there was no evidence that mortality was influenced by temperature. Temperature was directly correlated with stocking density. We attribute this to the higher stocking densities in small ponds which, in turn, tend to be warmer than large ponds, as suggested by a close-to-significant negative correlation coefficient between temperature and pond size ($P = 0.10$).

We observed that lower dissolved oxygen occurred when high stocking densities and long durations of cultivation were used. This is expected to occur since increasing both management factors result in both, higher shrimp biomass and oxygen demand by shrimp. Accumulation of organic matter in ponds may result in higher oxygen consumption (Milstein et al., 2005). Increased organic matter in ponds where long durations of cultivations were used may also be a factor contributing to explain our results.

The inverse correlation we observed between stocking density and pond size is a consequence of the preference of farmers to stock small ponds at higher stocking densities, compared with large ponds. On the other hand, our results indicate that longer durations of cultivation were needed when high stocking densities were used. This is a consequence of the time required by shrimp to reach harvest size at high densities.

From our results, improved management resulted in increased production and diminished variability. There is no a priori reason to assume that management practices leading to increased production should necessarily produce less variability; however, we found that good management practices produced both benefits. This result is consistent with the findings of Hernandez-Llamas et al. (2011) when they analyzed the variability of shrimp production in intensive commercial farms. Here, we demonstrate the influence of alternative management strategies on variability of semi-intensive shrimp production. Studies with a bio-economic approach for optimal management of risk are necessary.

We conclude that using stock models, multivariate analysis, and a stochastic approach are an effective approach for studying the relationships between production parameters and water quality and management variables and analyzing the variability of semi-intensive shrimp production. The approach can be used for modeling production of other aquaculture species when suitable databases are available.

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References

Chow, S.C., Liu, J.P., 2004. Design and Analysis of Clinical Trials: Concepts and Methodologies, 2nd ed. John Wiley & Sons, Hoboken, NJ.

CONAPESCA (Comisión Nacional de Pesca y Acuacultura), 2010. Anuario Estadístico de Acuacultura y Pesca 2008, http://www.conapesca.sagarpa.gob.mx

Eby, L.A., Crowder, L.B., 2002. Hypoxia-based habitat compression in the Neuse River Estuary: context-dependent shifts in behavioral avoidance thresholds. Canadian Journal of Fisheries and Aquatic Sciences 59, 952–965.

FAO (Food and Agricultural Organization of the United Nations), 2010. El estado mundial de la pesca y la acuicultura 2010. Departamento de Pesca y Acuicultura. FAO, Rome.

Garret, K.A., 1997. Use of statistical tests of equivalence (bioequivalence tests) in plant pathology. Pyhtopatholgy 87, 372–374.

Griffin, W.L., Hanson, J.S., Brick, R.W., Johns, M.A., 1981. Bioeconomic modeling with stochastic elements in shrimp culture. Journal of the World Mariculture Society 12, 94–103.

Hauck, W.W., Anderson, S., 1986. A proposal for interpreting and reporting negative studies. Statistics in Medicine 5, 203–209.

Hernandez-Llamas, A., Hernández-Lizardi, J.L., González-Garibay, M., Magallón-Barajas, F.J., 1993. Growth and survival response of *Penaeus stylirostris* to fertilization, pelleted feed and stocking density in earthen ponds. Aquaculture and Fishery Management 24, 57–69.

Hernandez-Llamas, A., Ruiz-Velazco, J.M.J., Gomez-Muñoz, V.M., 2011. A stochastic approach for analysis of the influence of white spot disease, zootechnical parameters, water quality, and management factors on the variability of production of shrimp *Litopenaeus vannamei* cultivated under intensive commercial conditions. Aquacultural Engineering 45, 66–73.

Hopkins, J.S., Stokes, A.D., Browdy, C.L., Sandifer, P.A., 1991. The relationship between feeding rate, paddlewheel aeration rate and expected dawn dissolved oxygen in intensive shrimp pond. Aquacultural Engineering 10, 281–290.

Hopkins, J.S., Villalon, J., 1992. Synopsis of industrial panel input on shrimp pond management. In: Wyban, J. (Ed.), Proceedings of the Special Session on Shrimp Farming. World Aquaculture Society, Baton Rouge, Louisiana, pp. 138–143.

Islam, M.S., Milstein, A., Wahab, M.A., Kamal, A.H.M., Dewan, S., 2005. Production and economic return of shrimp aquaculture in coastal ponds of different sizes and with different management regimes. Aquaculture International 13, 489–500.

Jackson, C.J., Wang, Y.G., 1998. Modelling growth rate of *Penaeus monodon* Frabicius in intensively managed ponds: effects of temperature, pond age and stocking density. Aquaculture Research 29, 27–36.

Kautsky, N., Ronnback, P., Tedengren, M., Troell, M., 2000. Ecosystem perspectives on management of disease in shrimp pond farming. Aquaculture 191, 145–161.

Milstein, A., Islam, M.S., Wahab, M.A., Kamal, A.H.M., Dewan, S., 2005. Characterization of water quality in shrimp ponds of different sizes and with different management regimes using multivariate statistical analysis. Aquaculture International 13, 501–518.

Mun, J., 2006. Applying Monte Carlo Simulation, Real Options Analysis, Forecasting and Optimization Techniques. John Wiley & Sons, Hoboken, NJ.

Pardy, R., Griffin, W.L., Johns, M.A., Lawrence, A.L., 1983. A preliminary economic analysis of stocking strategies for penaeid shrimp culture. Journal of the World Mariculture Society 14, 49–63.

Poole, R.W., 1974. An Introduction to Quantitative Ecology. McGraw-Hill, New York.

Quinn, G.P., Keough, M.J., 2002. Experimental Design and Data Analysis for Biologists. Cambridge University Press, London, UK.

Ratkowsky, D.A., 1990. Handbook of Nonlinear Regression Models. Marcel Dekker, New York, NY.

Rencher, A.A., 2002. Methods of Multivariate Analysis, 2nd ed. New York, John Wiley & Sons.

Ruiz-Velazco, J.M.J., Hernández-Llamas, A., Gomez-Muñoz, V.M., 2010a. Management of stocking density, pond size, starting time of aeration, and duration of cultivation for intensive commercial production of shrimp *Litopenaeus vannamei*. Aquacultural Engineering 43, 114–119.

Ruiz-Velazco, J.M.J., Hernández-Llamas, A., Gómez-Muñoz, V.M., Magallón, F.J., 2010b. Dynamics of intensive production of shrimp *Litopenaeus vannamei* affected by white spot disease. Aquaculture 300, 113–119.

Sadeh, A., Pardy, C.R., Griffin, W., Lawrence, A., 1986. Uncertainty consideration resulting from temperature variation on growth of *Penaeus stylirostris* in ponds. Texas Journal of Science 38, 159–172.

Sánchez-Zazueta, E., Martínez-Cordero, F.J., 2009. Economic risk assessment of a semi-intensive shrimp farm in Sinaloa, Mexico. Aquaculture Economics and Management 13, 312–327.

Sandifer, P.A., 1991. Further intensification of pond shrimp culture. Shrimp culture in South Carolina. In: Shrimp Culture in North America and the Caribbean. Advances in World Aquaculture. The World Aquaculture Society, Baton Rouge, LA, pp. 84–95.

Valderrama, D., Engle, C.R., 2002. Economic optimization of shrimp farming in Honduras. Journal of the World Aquaculture Society 33, 398–409.

Wannamaker, C.M., Rice, J.A., 2000. Effects of hypoxia on movements and behavior of selected estuarine organisms from the southeastern United States. Journal of Experimental Marine Biology and Ecology 249 (2), 145–163.

Zar, J.H., 2010. Biostatistical Analysis, 5th ed. Prentice Hall, Upper Saddle River, NJ.