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Application of Bayesian surplus production model and traditional surplus production model on stock assessment of the southern Atlantic albacore (*Thunnus alalunga*)

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Bayesian surplus Production model (BSP) and traditional surplus Production models (TSP) were used to evaluate the southern Atlantic albacore (*Thunnusalalunga*) stock. Population parameterswere estimated using CEDA (catch-effort data analysis) and ASPIC (a surplus-production model incorporate covariates) computer software packages. Performance of the BSP model and TSP model were compared by a Bayesian information criterion (BIC). Maximum sustainable yield (MSY) from the TSP model and BSP model were used to verify the MSY estimations by International Commission for the Conservation of Atlantic Tunas (ICCAT). Catch of 2011 (24122 t) was higher than the MSY from BSP (21756t, 23408t), and the relative fishing mortality ratio (F_{2011}/F_{MSY}) of the stock was higher than 1.0, which shows thatthis stock over-exploited. Different harvest strategies were set to assess the risk for this stock, and these estimates were used topredict the biomass and catch in 2025 (B_{2025}, C_{2025}) and other five indexes (B_{2025}/B_{MSY}, B_{2025}/K, P ($B_{2025}> B_{2012}$), P ($B_{2025}> B_{MSY}$), P ($B_{2025}< B_{MSY/4}$)). Evaluated biological reference points (BRPs) from Bayesian model were compared with the results from traditional modeling method on the southern Atlantic albacore (*T. alalunga*) stock, and results showed that the measures should be taken for the sustainable utilization of this fish stock, and the harvest rate of 0.15 seemed tobe the best management measures
[**Keywords:** Bayesian model, Fox model, *Thunnus alalunga*, Southern Atlantic, Risk assessment]

Introduction

Global optimization and Bayesian approaches were used increasingly in assessing and managing fisheries stocks because of their flexibility in incorporating data from different sources[1, 2]. The goodness-of-fit and statistical performance of the Bayesian surplus production model was compared with that of the classical Fox surplus production model[3]. Bayesian models were used to address the temporal variation in population growth rate caused by changes in species composition[4,5]. Variations in environmental variables and measurement errors often created problems for fish stock assessment scientists[6]. Fisheries scientists involved recovery planning in a conservation situation in which a population was currently depleted, it was critical to obtain good quality estimates to estimate the maximum percentage of the harvest rate that could be tolerated[7].

There have been Bayesian stock assessments analyses using population dynamics models[8,9], but none of those analyzes have been compared with classical approach for statistical inference. Bayesian surplus production model was referred as multilevel priors to represent a situation without hierarchical data[2]. Bayesian models have been increasingly used in ecological applications to quantify multiple sources of uncertainty[9]. How- due to their complexity, Bayesian models were computationally very intensive and difficult to fit[10]. The Markov chain Monte Carlo (MCMC) method uses each of the one-dimensional full conditional posterior distribution in turn to generate a sample from the joint posterior distribution of all the unknowns[11, 12]. Most of these models have not yet been subject to extensive evaluation by means of the simulations across the wide ranges of the scenarios/situations to determine their performance relative to that of simpler standard regression models that only are considered as one source of uncertainty.

In this study, the Bayesian model and classical sur--plus production models were used to assess population dynamics on the southern Atlantic albacore (*T. alalunga*) stock. Albacore (*T. alalunga*) is a highly migratory cosmopolitan and temperate fish species of tuna, inhabiting tropical and temperate pelagic waters of all oceans from about 45 - 50N to 30 - 40S[13, 14]. Since the early 2000s the southern Atlantic stock is considered to have big potential for development by ICCAT (International Commission for Conservation of Atlantic Tunas)[15]. But the ISSF (International Seafood Sustainability Foundation) reported that the southern Atlantic albacore (*T. alalunga*) stock is in a mild over fishing state[16], the measures should be taken for the sustainable utilization of this stock in the future. In this study, the estimated maximum sustainable yield (MSY) from Bayesian model and Fox model was used to verify MSY estimates used by ICCAT. The evaluated biological reference points (BRPs) from Bayesian model were compared with the results from traditional modeling method on the southern Atlantic albacore (*T. alalunga*) stock. Different harvest strategies were set to assess the risk for this stock, and these estimates were used to predict the biomass and catch of this albacore (*T. alalunga*) stock. A central advantage of Bayesian modeling over the classification rules of the catch-based methods is the calculation of F/F_{MSY} and B/B_{MSY} in which the probability of different states can also be calculated.

Material and Methods

The data of the southern Atlantic albacore (*T. alalunga*) stock (1975–2011) were used (From International Commission for the Conservation of Atlantic Tunas) in this study[17]. Global population distribution of albacore (*T. alalunga*) and the southern Atlantic stock (area No 12#) are showed (Fig.1). According to ICCAT, a standardized catch per unit effort (CPUE) based on the Chinese Taipei longline fishery (1975–2011) was used as a relative abundance index of the southern Atlantic albacore (*T. alalunga*) stock[17]. For this albacore stock, the total catches in the past 30 years ranged from approximately 15000 t to 40000 t, which was mostly attributed to the longline fisheries[15].

Bayesian surplus production models (BSP) with multilevel priors are called the hierarchical models even when the data are not hierarchically structured[3, 5]. Bayesian state-space model was an extension of the state-space model proposed by Walters and Martell[18]. Walters and Martell demonstrated that state-space models may be not helpful for correcting time series bias for individual stocks[18]. The data available on Atlantic albacore (*T. alalunga*) stock was not stage-structured, and the state-space surplus production models were used here as the basic model structure[1, 2]:

$$E(B_{t+1}) = B_t + G_t - C_t, \quad (1)$$

$$E(I_{i,t}) = q_i B_t, \quad (2)$$

$$G_t = rB_t(\ln(K) - \ln(B_t)), \quad (3)$$

$$r \sim N(\bar{r}, \sigma^2), \quad (4)$$

where B_t, G_t, and C_t are the population abundance, production function and the total catch in year t, and qi is the catchability coefficient for the *i-th* type of relative abundance index I_i. Here, we used the Fox model as the production function, and it was used widely in fisheries and ecology[19, 20]. In the Fox model, r is the population intrinsic growth rate and K is the carrying capacity. Instead of assuming a constant population growth rate in the Fox model, a hierarchically structured prior was used to model the population growth rate. The hierarchical population structure was implied in the model through a multilevel prior of r.

Traditional surplus production models (SPM) are among the major academic models in assessment and management of modern fishery resources due to their simplicity and relatively undemanding data needs[20]. From surplus production models (SPM), we could predict the MSY (maximum sustainable yield) and F_{MSY}, which are still the major goals of fisheries management[20, 21]. There are several forms of surplus production models (SPM) in the literatures. The dynamic equations used in this study were listed below.

$$\frac{U_{t+1}}{U_t} - 1 = r\ln\left(\frac{qK}{U_t}\right) - qE_t, \quad MSY = rKe^{-1},$$

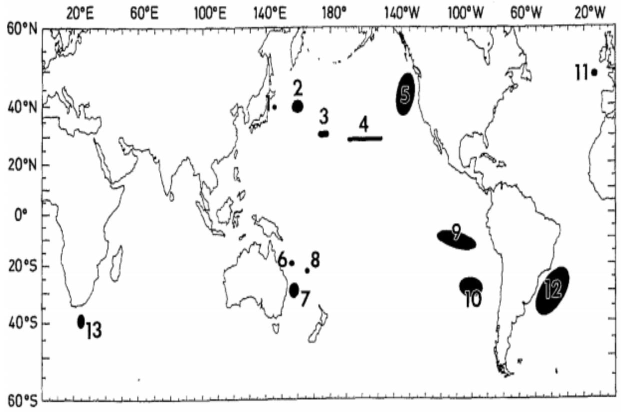

Fig. 1—Map showing catches localities of albacore (*T. alalunga*)

$$f_{msy} = r / q \quad (5)$$

where B_t is the stock biomass, r is the intrinsic population growth rate, K is the carrying capacity, G_e is the catch in equilibrium, f is the effort, q is the catchability coefficient, U_t is the catch per unit effort or abundance index in year t.

The CEDA (Catch-effort data analysis, Hoggarth et al., 2006) software package was used to evaluate the value of parameters[22]. ASPIC (A surplus production model incorporating covariates, Prager, 2005) software package was also used to compare the accuracy of the parameter estimates[23], such as B_1/K,

Table 1—Population parameters (r, K, q) of Fox surplus production models from CEDA and ASPIC

Software package (CEDA / ASPIC)	K	q	r	R_{yield}	R^2
CEDA Fox (non-equilibrium)	378755	3.74E-10	0.434	28519	0.71
ASPIC Fox (non-equilibrium)	387300	4.310E-10	0.390	--	0.86

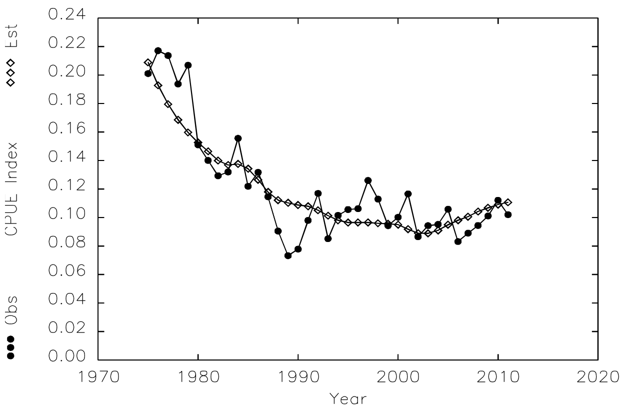

Fig. 2—Observed and predicted catch per unit efforts (CPUE) of the southern Atlantic albacore (*T. alalunga*) stock.

MSY, K, q, F_{MSY}.

Traditional surplus production analyses used standard regression, and treated B_t as an independent variable, G_t as a dependent variable were fraught with estimation problems[20]. The observation error of CPUE was considered as a lognormal distribution and expressed as follows (where U and $U^{\wedge}$ were the observed and predicted CPUEs, respectively):

$$\varepsilon = \mathrm{Log}\left(U\right) - \mathrm{Log}(\hat{U}), \quad (6)$$

$$\hat{U} = \frac{\hat{C}_t}{E_t} = qB_t, \quad (7)$$

Parameter estimates for such relationships provided the basis for setting key values of variables used in fish stock management, such as classes were analyzed Bayesian inferential methods for the state-space model were based on the posterior distribution of parameters σ and states r given the data[10]. To make inferences for θ, one needs to construct a marginal prior distribution of θ by integrating out the states r in $p(Y|\theta)$. For the above Bayesian surplus production model, the likelihood of any set of observation can be represented by the following equation:

$$p\left(D\mathrm{ata}\,|\theta\right) = \prod_{\mathrm{i=1}}^{\mathrm{n}} \frac{1}{I_i\sigma\sqrt{2\pi}} e^{\left(-\frac{\left[Ln(I_i)-Ln(\hat{I}_i)\right]^2}{2\sigma^2}\right)} \quad (8)$$

$$I_i = p_i + \varepsilon_t, \varepsilon_t \subset N(0, \sigma^2), \quad (9)$$

where p $(I|\theta)$ is the likelihood of the data given the parameter vector θ, θ denotes (k, r, σ^2) and I_i and $I_i^{\wedge}$ are the I is observed and predicted recruitment value of the data, respectively. The basic idea behind maximum likelihood is to find the values of the parameters for which the observed data is most likely to occur. In recent years, most reliable fisheries parameter estimations were currently being achieved by using the maximum likelihood (ML) method[20]. However, it was difficult to evaluate $p(\theta, r|Y)$ directly by integration. MCMC (Markov chain Monte Carlo) simulation techniques bypass the need to evaluate the high dimensional integral in $p(\theta, r|Y)$ by generating dependent draws from the posterior distribution $p(\theta, r|Y)$ via Markov chains[24]. For the fitting process, we develop a Bayesian approach via MCMC sampling to make inferences about the Bayesian models[10, 24].

Results

For the albacore stock, we used traditional surplus production (TSP) model (non-equilibrium) to obtain MSY at about (23630t - 27390t), and used the ASPIC model to obtain $B_{2009}/B_{\mathrm{MSY}}$ ratio at about1.18, and $F_{2009}/F_{\mathrm{MSY}}$ ratio at about 1.42 (Fig. 2). The observed and predicted catch per unit efforts (CPUE) of the southern Atlantic albacore (*T. alalunga*) stock are compared (Fig. 2).

We applied CEDA and ASPIC to the catch and standardized CPUE data of southern Atlantic albacore to get information of carrying capacity K, intrinsic growth rate r, and the catchability coefficient q (Table 1). The intrinsic population growth rate r is (0.28 - 0.46), carrying capacity K is (318700 - 390000 t), and catchability coefficient q is (3.44×10^{-10} - 4.88×10^{-10}).

Prior distribution of three parameters were N (0.37, 0.19^2), N (35.4, 17.7×10^4) and N (4.16×10^{-10}, $(2.08\times10^{-10})^2$), respectively. We supposed that N (equal 3) chains of MCMC different initial conditions were estimated and the length (equal 10000), number of parameters (*p*), and the average variance of the chains were obtained. Some sequence of parameter converged, and others were not converged. If the sequences have strong correlation, it was accepted that the Markov chain could be converged (Fig. 3).

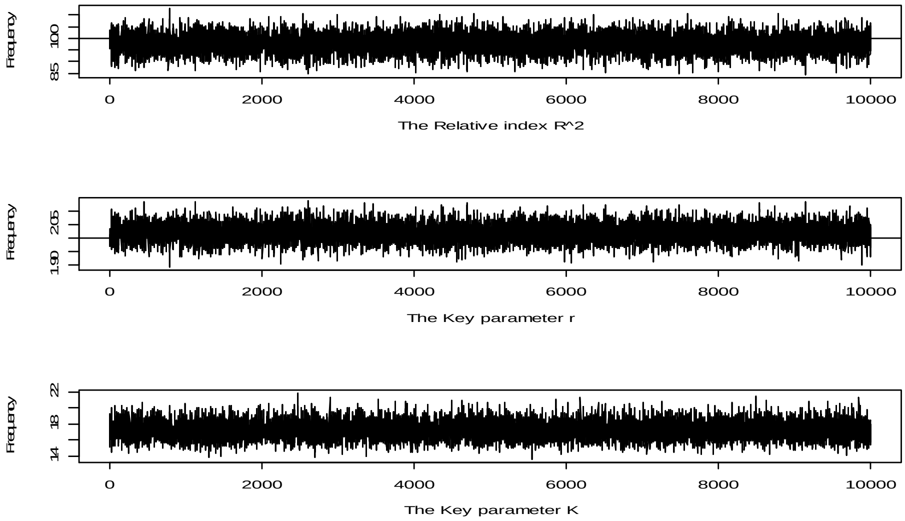

Fig. 3—Plot the convergence of the Markov chains of parameters in the Bayesian estimator.

Table 2—Summary statistics for parameters and biological reference points (BRPs) from Bayesian Model

Bayesian Model	Mean	Median	2.5%quantile	97.5%quantile
r	0.372(0.126)	0.376	0.279	0.465
K (10^4t)	30.55(0.116)	29.90	24.82	38.95
$q(10^{-10})$	4.259 (0.18)	4.270	2.785	5.759
$B_{MSY}(10^4)$	15.28(0.116)	14.95	12.41	19.48
F_{MSY}	0.186(0.126)	0.188	0.140	0.233
$F_{0.1}$	0.167(0.126)	0.169	0.126	0.209

MCMC algorithm was used to compute the posterior distributions of the three parameters. In some cases, the models did not give converge to a stable mixing distribution for at least 10000 runs. We used a burn-in period of 10000 runs, which reduces the effect of starting values on the MCMC estimates. The posterior distributions values and density distributions of *r*, *K* and *q* were showed (Fig. 4).

Bayesian surplus production model was used to estimate the MSY of South Atlantic albacore population (Table 2). The Fox model and the ASPIC estimated the MSY and the ratios of the B_{2009}/B_{MSY} and the F_{2009} /F_{MSY}, and the sensitivity of the model outcomes to the specified priors were tested (Priors were $r \sim N$ (0.37, 0.19^2), $K \sim N$ (35.4, 17.7^2), $q \sim N$ [4.16×10-10, $(2.08\times10\text{-}10)^2$]) .

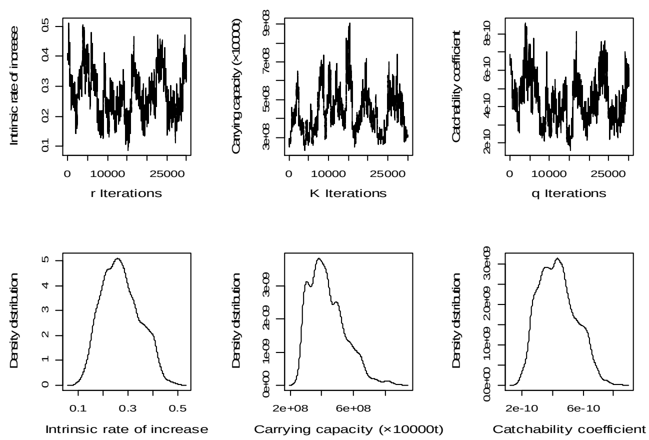

Fig. 4—Plot of posterior distribution values and density distribution for parameters *r*, *K* and *q*.

The estimated maximum sustainable yield (MSY) from Bayesian surplus production (BSP) model and Fox surplus production model (SPM) were used to verify MSY estimates by ICCAT on the South Atlantic albacore stock, and the comparison between MSY and the actual catch in 2011 were presented in this study (Table 3).

Table 3—Summary statistics for MSY and the actual catch in 2011

	ICCAT	Fox Model	BSP Model
MSY_{2011}	(21 500, 28 700)	(23 630, 27 390)	(21 756, 23 408)
C_{2011}	241000	241000	241000

Bayesian models were compared with the Fox surplus production model based on the estimates of parameters. We applied those models to fit the data and used Bayesian information criterion (BIC) to compare the predictions of parameters (Table 4), and then the smaller BIC value indicates the better fit.

Table 4—Model selection criterion (BIC) results of the Bayesian surplus production model and the Fox surplus production model.

	Normal errors	Lognormal errors	Gamma errors
Bayesian surplus production model	14.827	12.847	12.360
Fox surplus production model	15.190	13.739	12.459

Table 5—Risk analysis of Bayesian surplus production model and the Fox surplus production model using harvest coefficient.

Methods and parameters	Different harvest coefficient (from 0.05 to 0.4)							
Fox model	H=0.05	H=0.1	H=0.15	H=0.2	H=0.25	H=0.3	H=0.35	H=0.4
B_{2025} ($\times 10^4$t)	25.10	22.51	18.23	13.84	11.43	8.32	5.63	2.74
C_{2025} ($\times 10^4$t)	1.31	2.23	2.52	2.73	2.58	2.32	1.43	0.80
$B_{2025}/\mathrm{B}_{MSY}$	1.53	1.38	1.12	0.94	0.72	0.52	0.32	0.20
B_{2025}/K	0.80	0.72	0.62	0.46	0.40	0.31	0.18	0.09
BSP	H=0.05	H=0.1	H=0.15	H=0.2	H=0.25	H=0.3	H=0.35	H=0.4
B_{2025} ($\times 10^4$t)	24.58	21.28	17.48	13.97	10.52	7.21	4.18	1.65
C_{2025} ($\times 10^4$t)	1.23	2.13	2.62	2.80	2.64	2.19	1.50	0.70
B_{2025}/B_{MSY}	1.64	1.42	1.16	0.93	0.70	0.48	0.28	0.12
B_{2025}/K	0.82	0.71	0.58	0.47	0.35	0.24	0.14	0.06
$P(B_{2025} > B_{2012})$	0.94	0.87	0.66	0.32	0.14	0.03	0	0
$P(B_{2025} > B_{MSY})$	1	1	0.92	0.39	0.18	0.01	0	0

Risk analysis of Bayesian model and the Fox model were compared under different harvest strategies. We set different harvest strategies to conduct risk assessment for this stock, and we used those two kinds of surplus production models to predict the biomass and catch in 2025 (B_{2025}, C_{2025}) and other five indexes (B_{2025}/B_{MSY}, B_{2025}/K, P ($B_{2025} > B_{2012}$), P ($B_{2025} > B_{MSY}$), P ($B_{2025} < B_{MSY/4}$)) (Table 5)

Discussion

Different methods have been used to estimate MSY of the southern Atlantic albacore (*T. alalunga*) stock, for example Lee and Yeh (2007) used the age structured production model (ASPM) with an estimated MSY 28771 t in base case[25]; ICCAT (2012) used ASPIC to give a range of estimated MSY with 21500 t to 28700t[17]. We estimated the MSY based on TSP model to get the 80% confidence interval of MSY at about 19168t- 25860t. We used Bayesian surplus production model to get an 80% confidence interval of MSY of South Atlantic albacore population at about 21756-23408t. ICCAT (2012) used non-equilibrium production model to obtain the MSY with 23630 to 27390t[17]. The result of Bayesian model was lower than that reported by Lee and Yeh (2007) which was obtained using ASPIC primarily[25]. The estimated MSY from the TSP model was similar with MSY estimates used by ICCAT[17], and the estimated MSY from the Bayesian model was lower than MSY estimates used by ICCAT on the South Atlantic albacore (*T. alalunga*) stock.

Bayesian modeling has been increasingly used in ecological applications to quantify multiple sources of uncertainty[26]. There have been Bayesian stock assessments analyses using population dynamics models[11], but none of those analyzes have been compared with classical approach for statistical inference. Bayesian surplus production model was referred as multilevel priors to represent a situation without hierarchical data[2]. A central advantage of Bayesian modeling over the classification rules of the catch-based methods is the calculation of F/F_{MSY} and B/B_{MSY} in which the probability of different states can also be calculated. Due to their complexity, Bayesian models were computationally very intensive and difficult to fit[10]. Most of these models have not yet been subject to extensive evaluation by means of simulations across wide ranges of scenarios/situations to determine their performance relative to that of simpler standard regression models that only are considered as one source of uncertainty.

Maximum Sustainable Yield (MSY) had been accepted as one of the target biological reference points (BRPs) and it constituted the foundation of federal fishery management policy in the USA[26, 27]. This study estimated the southern Atlantic albacore (*T. alalunga*) stock based on the CPUE data of Chinese Taipei longline fishery. For this albacore stock, the total catches in the past 30 years ranged from approximately 15,000 t to 40,000 t, which was mostly attributed to the Chinese Taipei longline fishery[17]. We evaluated the BRPs by traditional modeling method and the Bayesian model, and risk assessments of those models were compared under different harvest strategies. The Bayesian approach was the most general method for fitting non-linear state-space models, and the Bayesian analysis gave suitable posterior distribution of the estimated parameters[28]. We used BIC to select the best model in this study and the smallest value of BIC indicates the best fit. Results showed that the value of BIC for Bayesian model were lower than the BIC values of the Fox model. A central advantage of Bayesian modeling over the classification rules of the catch-based methods is the calculation of F/F_{MSY} and B/B_{MSY} in which the probability of different states can also be calculated.

In this study, the evaluated biological reference points (BRPs) from Bayesian model were compared with the results from traditional modeling method on the southern Atlantic albacore (*T. alalunga*) stock, and the comparison between MSY_{2011} and C_{2011} were presented in this study. Those performances make us believe that the Bayesian methods are likely to be appropriate for the assessment of the southern Atlantic albacore (*T. alalunga*) stock. In this study, the estimated MSY from Bayesian model and Fox model were used to verify MSY estimates by ICCAT on the South Atlantic albacore stock. Different harvest strategies were set to assess the risk for this stock, and these estimates were used to predict the biomass and catch in 2025 (B_{2025}, C_{2025}) and other five indexes (B_{2025}/B_{MSY}, B_{2025}/K, $P(B_{2025} > B_{2012})$, $P(B_{2025} > B_{MSY})$, $P(B_{2025} < B_{MSY/4})$). The Bayesian modeling provides an extremely compact performance of the exact dynamics population. The methods might present a useful choice for the southern Atlantic albacore (*T. alalunga*) stock assessment.

Conclusion

The study verifies the MSY estimates of albacore (*T. alalunga*) stock to support the management (i.e. setting of MSY) for the south Atlantic albacore stock. The biological reference points (BRPs) of the albacore stock were evaluated and verified by Bayesian surplus production model and Fox surplus production model. The MSY estimates from BSP was lower than those from conventional estimates; the relative biomass ratio or relative fishing mortality ratio from BSP were higher than those from traditional modeling method, and the results showed that the measures for the catches should be taken for the sustainable utilization of this fish stock. This study was based on the CPUE data of Chinese Taipei longline fishery of the southern Atlantic albacore stock. In the future, we plan to conduct further study on quantify multiple sources of uncertainty for this stock.

Acknowledgement

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