博士論文（要約）

Fishery stock assessment in the East China Sea using a multivariate auto-regressive state-space (MARSS) model with spatial distributional information

（空間的分布情報を利用した多変量自己回帰状態空間（MARSS）モデルによる東シナ海の漁業資源評価）

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2017

東京大学農学生命科学研究科水圏生物科学専攻

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CHAPTER 1 General Introduction

本章の内容は、学術雑誌論文として出版する計画があるため公表できない。5 年以内に出版予定。

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CHAPTER 2 Data and data conversion

2.1 Data

2.1.1 Fishery-dependent data

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2.1.2 Fishery-independent data

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2.2 Data conversion

In the time-series analyses, dependence of the variance of states on the levels of the states can generate bias in the estimated results. This “dependence of the variance of states on their levels” is not the spatiotemporal autocorrelation between states (i.e., population densities, which correspond to the observed CPUE data in the present study), but the dependence of fluctuation amplitude of states on their levels. In general, amplitudes of fluctuation of states are larger when the levels of states are higher, and vice-versa (Hayakawa et al., 2007; Nakamura and Ueno, 2002; Fig. 2.7). Additionally, in the present study, Kalman filter algorithm is used in the MARSS model (Holmes et al., 2014), thus, datasets with normal distribution are desirable through the analyses. Then three methods were tested to convert the observed fishery CPUE data Y_t at time t for removing such dependence and securing the normality of the data distribution:

(1) Logarithmic transformation: $Y_t \to \log(Y_t+1)$, where $\log(Y_t+1)$ is the converted data;

(2) Power transformation (Nakamura and Ueno, 2002; Hayakawa et al., 2007): $Y_t \to Y_t^{\mu}$, where Y_t^{μ} is the converted data and μ is the power exponent. Parameter μ was estimated in R software;

(3) Box-Cox transformation (Box and Cox, 1964; Boylan et al., 1982): $Y_t \to ((Y_t+\mu_2)^{\mu_1}-1)/\mu_1$ when $\mu_1 \neq 0$, while $y_t \to \log(Y_t+\mu_2)$ when $\mu_1 = 0$, where $((Y_t+\mu_2)^{\mu_1}-1)/\mu_1$, $\log(Y_t+\mu_2)$ are converted data, and μ_1, μ_2 are parameters. GeoR package in R was used to estimate the parameters μ_1 and μ_2.

A normality test was conducted to choose the most suitable data-conversion method by referring to a histogram and a Q-Q plot to compare the performance of these three methods. Histogram gives an estimate of the probability distribution of a continuous variable; while Q-Q plot is a probability plot, which is a graphical method for comparing two probability distributions by plotting their quantiles against each other (Wilk and Gnanadesikan, 1968). If compared distributions are similar, the points in the Q–Q plot will approximately lie on the line $y = x$ (Henry, 2002). R software was utilized to compare the distribution of fishery CPUE datasets with the normal distribution.

The entire fishery CPUE datasets from 1959 to 2014 of yellow seabream, largehead hairtail, and silver croaker were used for conversion. As stated above, these datasets were collected from the whole operational fishing grids in the ECS.

2.3 Results for data conversion

For the entire fishery CPUE data of yellow seabream, frequency of the leftmost data on the abscissa with the value of 0 did not change by any conversion method, while rest of the data were greatly changed (Fig. 2.8). In the present study, many of the 0s were considered to be derived from fishing grids where yellow seabream are not inhabited, thus, these 0s might be separate values which can be ignored in the results. As a result, comparing with the logarithmic transformation, probability distribution of fishery CPUE data with power and Box-Cox transformation were more approximate to the normal distribution (Fig. 2.8).

Then, Q-Q plot was used to make a further comparison. The regression line of fishery CPUE data with power transformation was closer to the line $y = x$ than the Box-Cox one (Fig. 2.9). Accordingly, power transformation was the most suitable data-conversion method for securing the normality of data distribution.

For the fishery CPUE datasets of largehead hairtail and silver croaker, I got the same conclusions that distribution of data with the power transformation corresponded best to normal distribution (Fig. 2.10-2.13).

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After conducting the power transformation, the dependence of the variance of converted CPUE data on their levels was greatly weakened when compared to that of the raw CPUE data. For yellow seabream, largehead hairtail, and silver croaker, a fishing grid was randomly chosen to show the results obtained, respectively (Fig. 2.14).

Fig. 2.1-Fig. 2.6

これらの図は、学術雑誌論文として出版する計画があるため公表できない。5 年以内に出版予定。

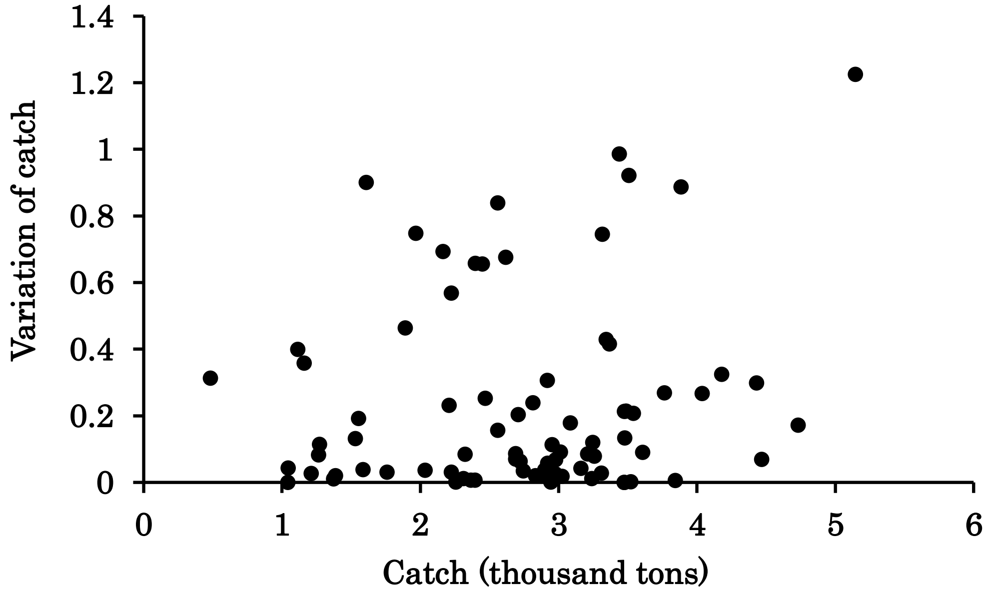

Fig. 2.7 Relation between annual catch and its variation of top shell *Turbo* (*Batillus*) *cornutus* in prefectures along the Pacific coast in Japan. When C_t represents the annual catch at time *t*, $(C_{t+1} - C_t)^2$ represents the variation of catch at time *t*. Redrawn figure of Hayakawa et al., (2007).

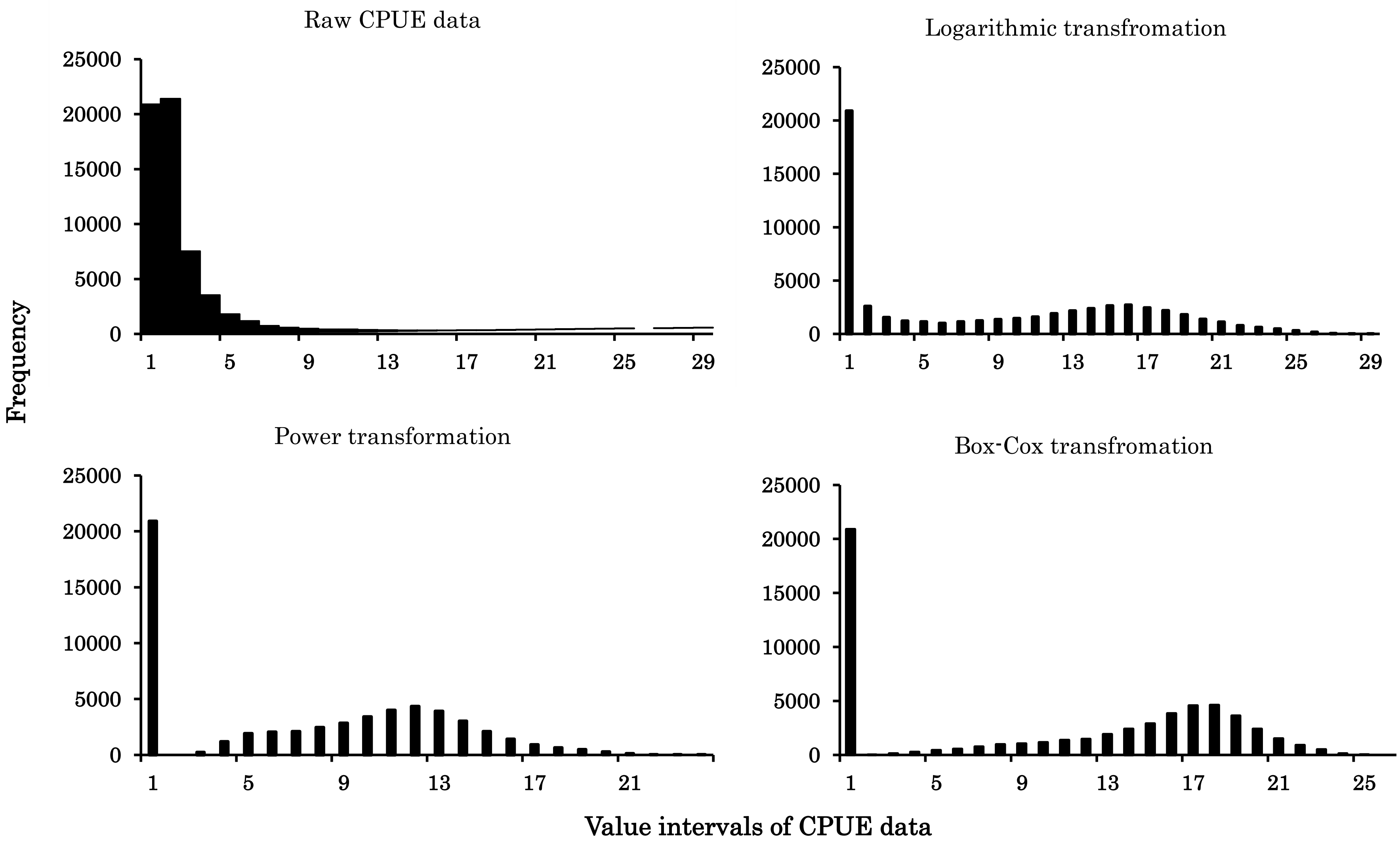

Fig. 2.8 Histogram of the entire raw CPUE data of yellow seabream, with the logarithmic transformed one, the power transformed one and the Box-Cox transformed one, respectively.

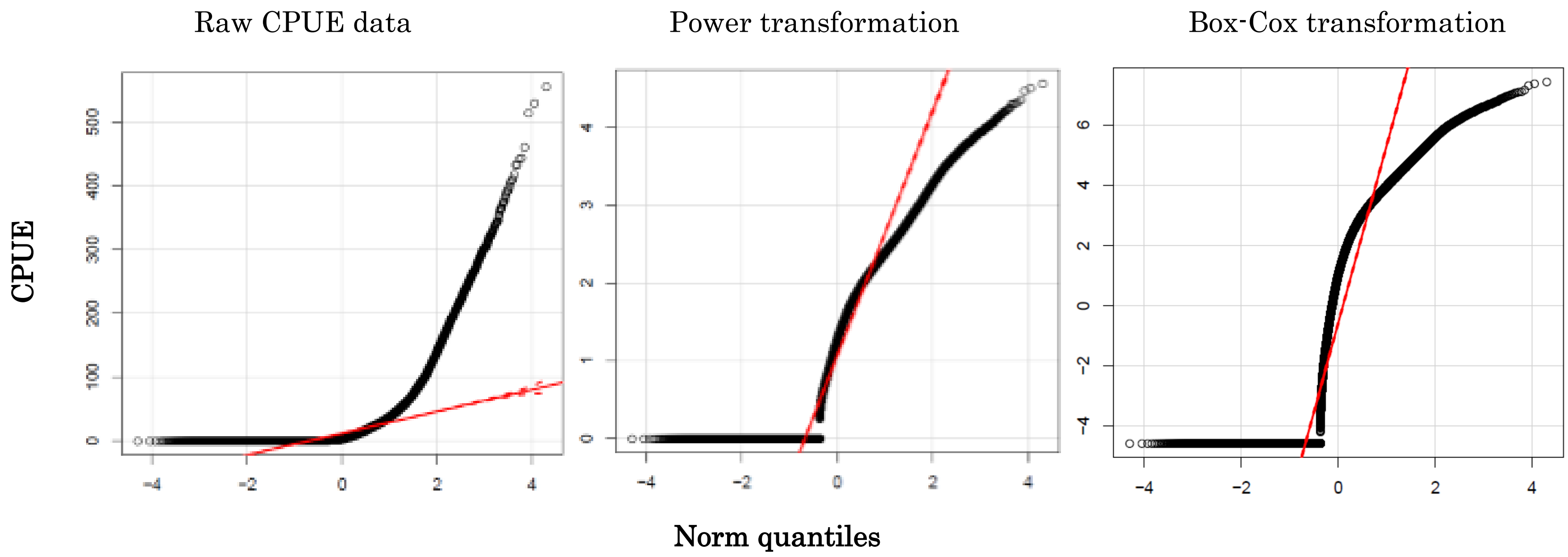

Fig. 2.9 Q-Q plots of the entire raw CPUE data of yellow seabream, with the power transformed one and the Box-Cox transformed one, respectively.

The red line is the regression line of data.

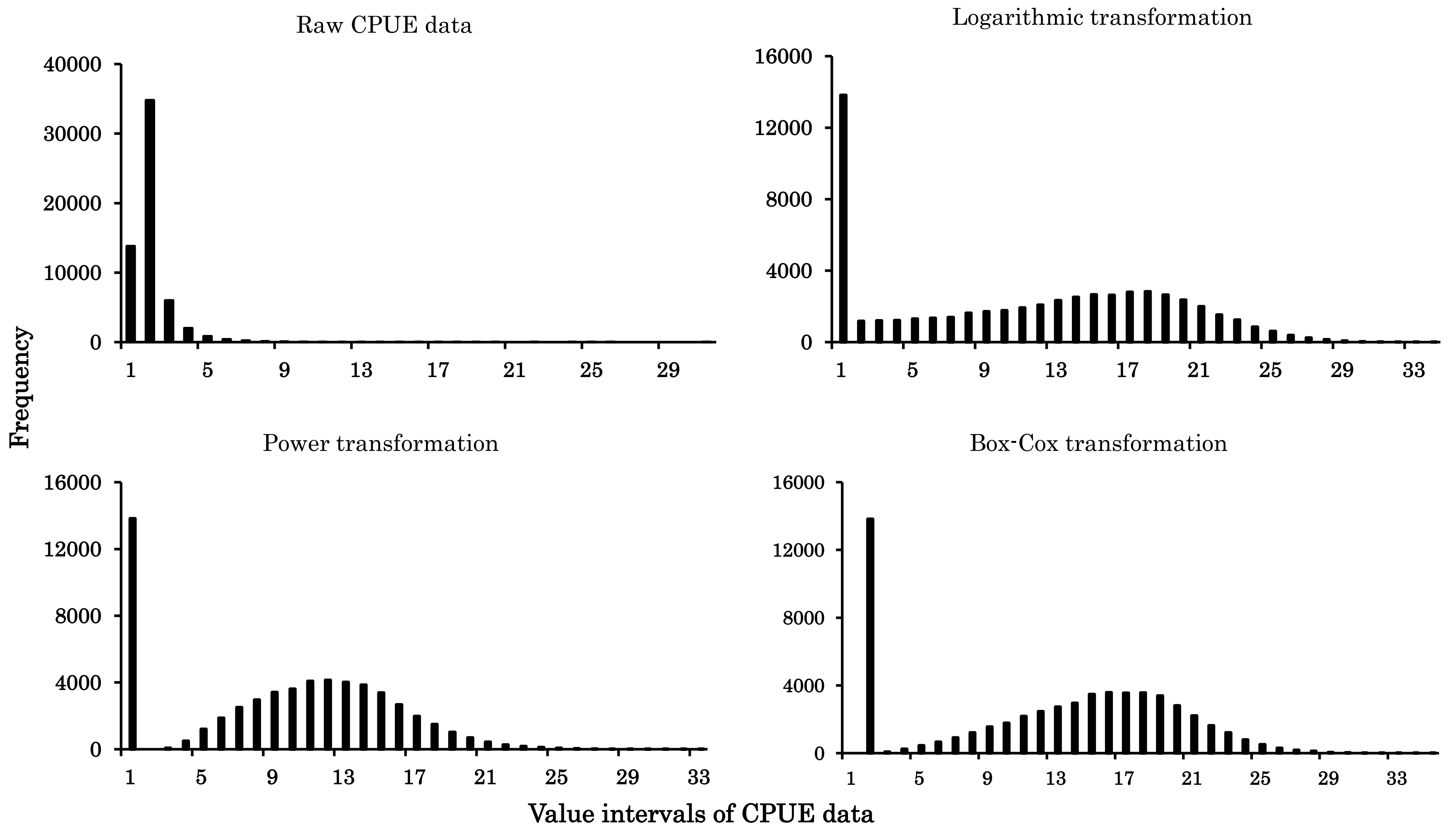

Fig. 2.10 Histogram of the entire raw CPUE data of largehead hairtail, with the logarithmic transformed one, the power transformed one and the Box-Cox transformed one, respectively.

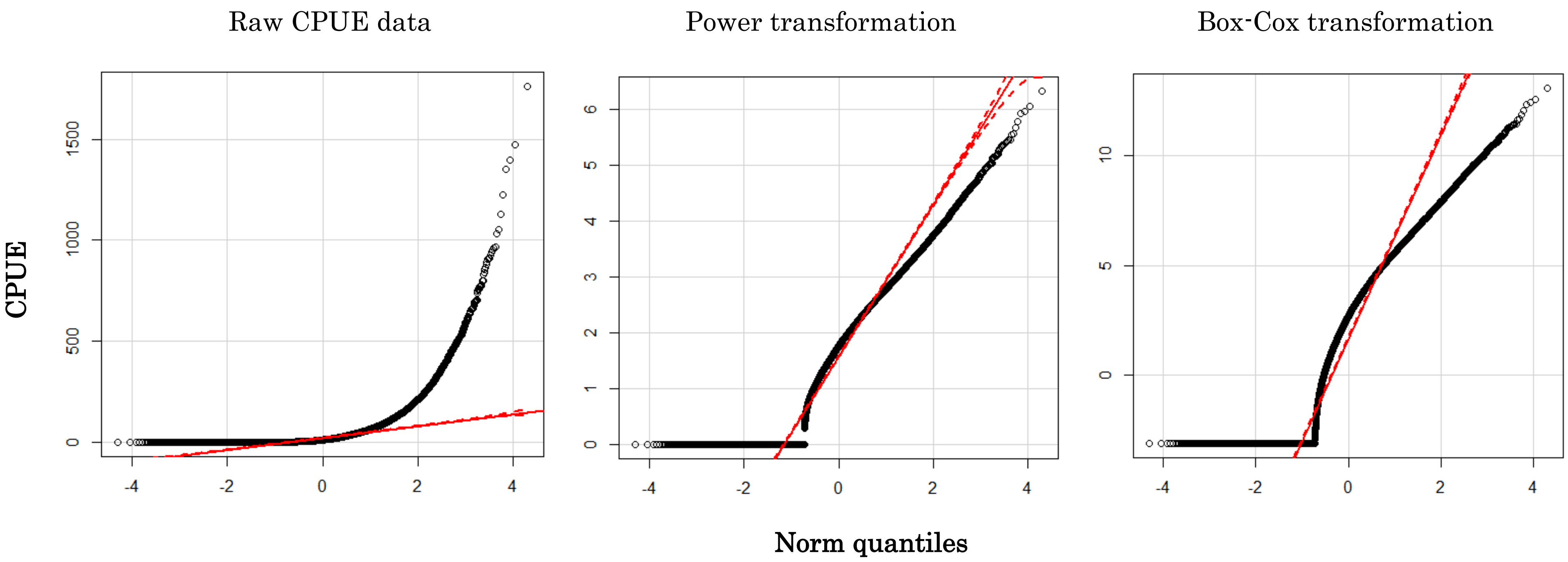

Fig. 2.11 Q-Q plots of the entire raw CPUE data of largehead hairtail, with the power transformed one and the Box-Cox transformed one, respectively. The red line is the regression line of data.

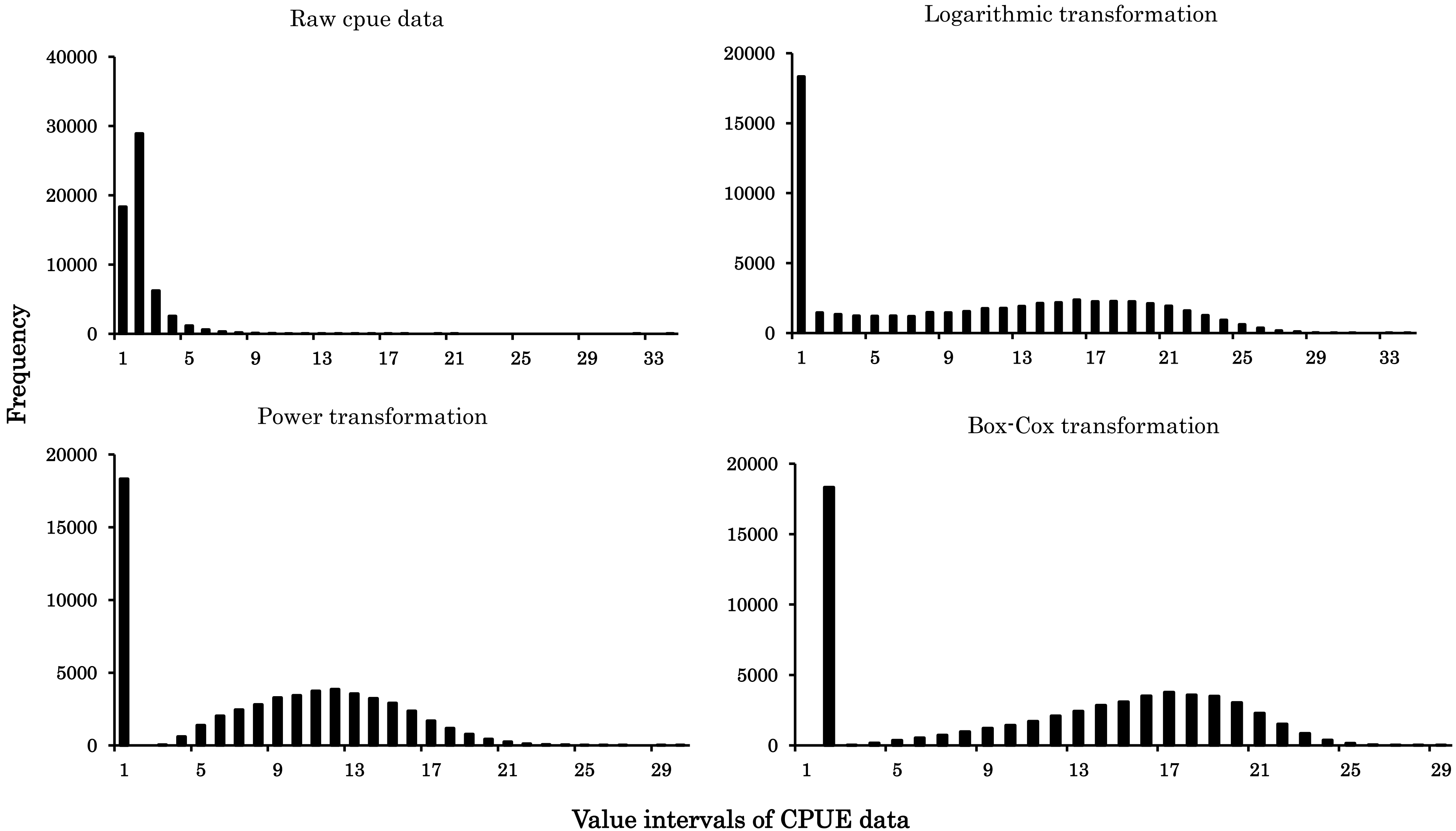

Fig. 2.12 Histogram of the entire raw CPUE data of silver croaker, with the logarithmic transformed one, the power transformed one and the Box-Cox transformed one, respectively.

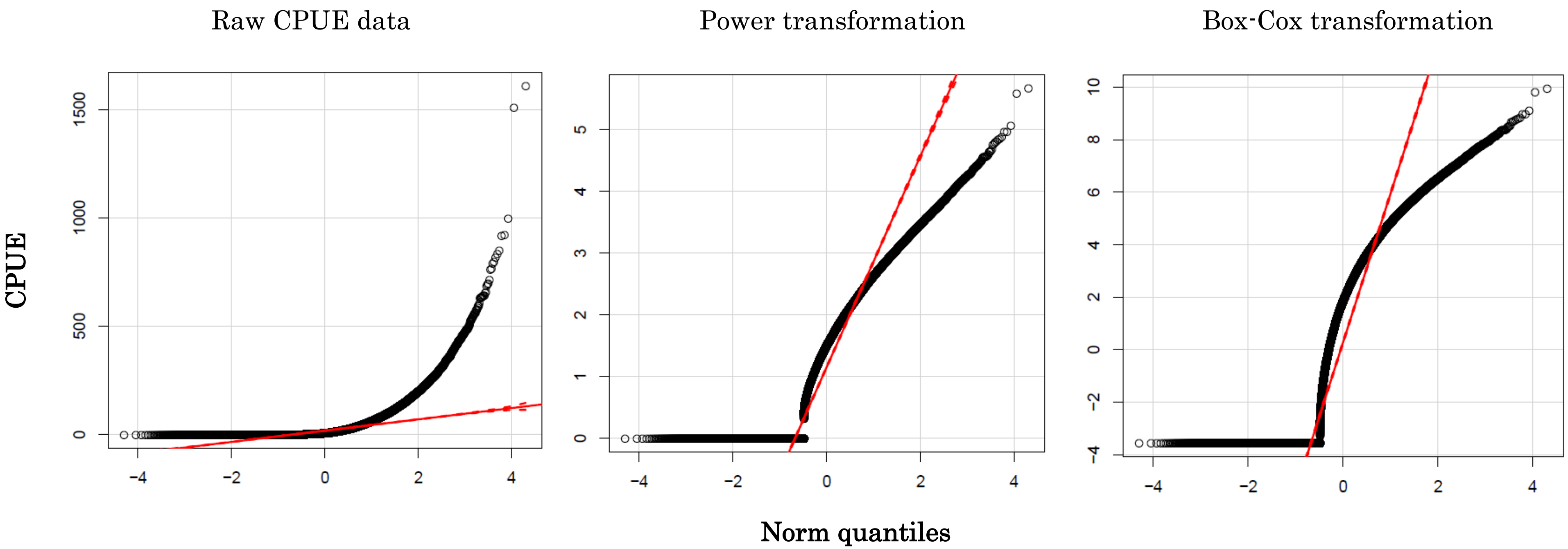

Fig. 2.13 Q-Q plots of the entire raw CPUE data of silver croaker, with the power transformed one and the Box-Cox transformed one, respectively. The red line is the regression line of data.

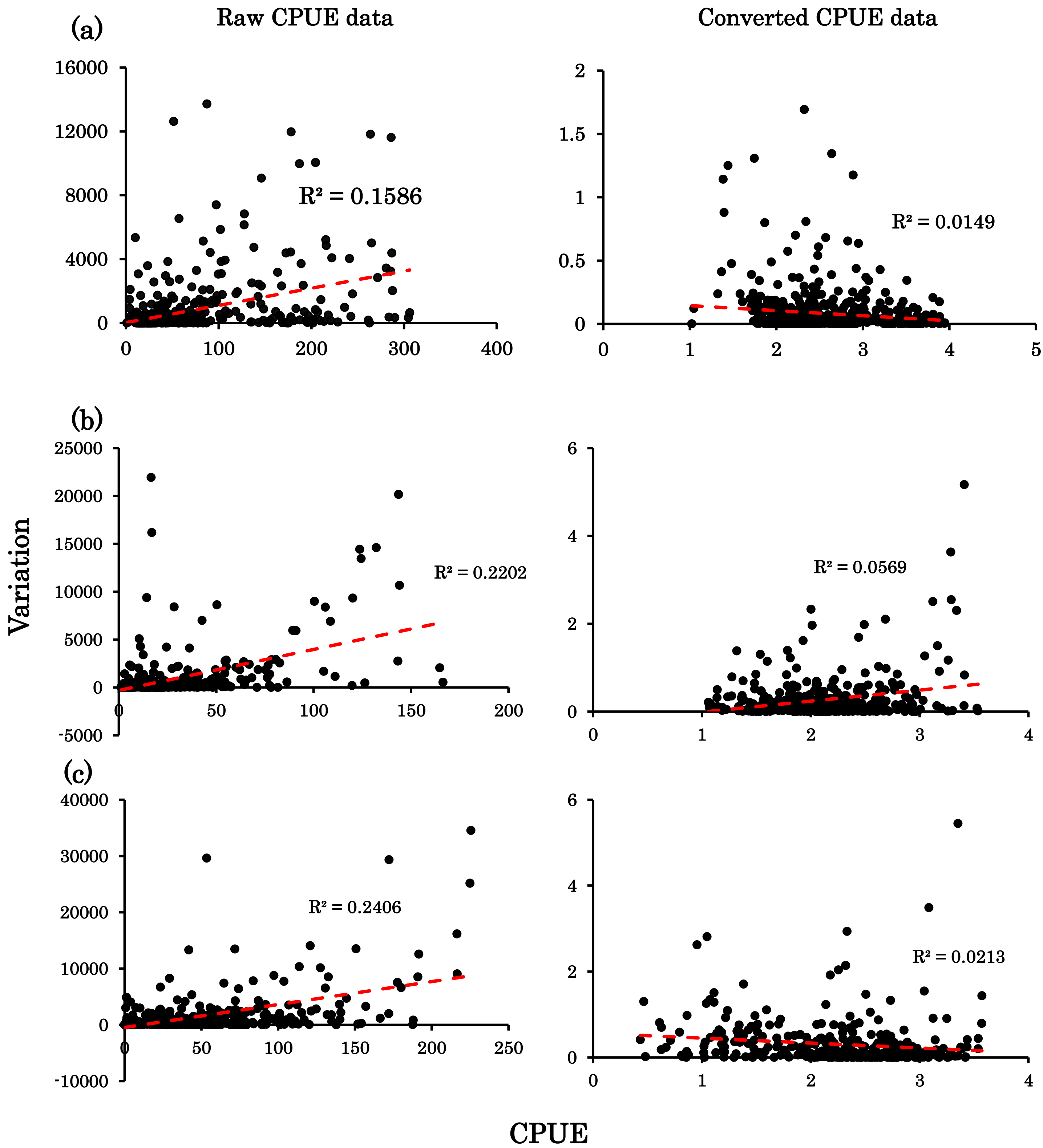

Fig. 2.14 Relations between fishery CPUE and its variation of a random fishing grid for (a) yellow seabream: fishing grid No. 246; (b) largehead hairtail: fishing grid No. 266 and (c) silver croaker: fishing grid No. 270. For comparion, relations for the raw CPUE data were shown on the left side and those for the converted data were shown on the right side. The regression lines of data were in red. CPUE with the value of 0 were removed for plotting. When Y_t represents the CPUE at time *t*, $(Y_{t+1} - Y_t)^2$ represents the variation of CPUE at time *t*.

CHAPTER 3 Development of a practical way of utilizing the MARSS model

この章の内容は、学術雑誌論文として出版する計画があるため公表できない。5 年以内に出版予定。

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3.3.1 Relationship between the number of analyzed fishing grids and the interpolation accuracy

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3.4.2 Relationship between the number of analyzed fishing grids and the analysis time

3.4.3 Method for reducing the analysis time

3.5 Discussions

3.5.1 Interpolation accuracy and analysis time with MARSS

3.5.2 Practical method for reducing analysis time

Fig. 3.1-3.6 の内容は、学術雑誌論文として出版する計画があるため公表できない。5年以内に出版予定。

CHAPTER 4 Application of the MARSS model to CPUE data from trawl fishery

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4.2.1 Selection of the analyzed fishing grids

4.2.2 Estimation of the AIs and CIs

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4.2.4 Calculation of conventional AIs

4.3 Results

4.3.1 Yellow seabream

4.3.2 Largehead hairtail

4.3.3 Silver croaker

4.4 Discussion

4.4.1 Yellow seabream

4.4.2 Largehead hairtail

4.4.3 Silver croaker

4.4.4 Accuracy and precision of AIs

Fig. 4.1-4.12 の内容は、学術雑誌論文として出版する計画があるため公表できない。5 年以内に出版予定。

Chapter 5 Utilization of data from research vessels in MARSS

本章の内容は、学術雑誌論文として出版する計画があるため公表できない。5 年以内に出版予定。

5.1 Introduction

5.2 Materials and methods

5.2.1 Conversion for survey CPUE data

5.2.2 Analysis of fishery and survey data in MARSS

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CHAPTER 6 General discussion

本章の内容は、学術雑誌論文として出版する計画があるため公表できない。5 年以内に出版予定。

Summary

The abundance index (AI) is a representative indicator used to assess the state of fishery resources. Conventional AI is generally calculated by summing the catch per unit of effort (CPUE) weighted by the size of each fishing area. However, CPUE data has many missing values because of the annual changes in operational fishing areas, which can lead to a considerable bias in the estimated AI.

This study uses a multivariate auto-regressive state-space (MARSS) model to estimate and interpolate missing values in spatially arranged, long-term bottom-trawl CPUE datasets for yellow seabream *Dentex hypselosomus*, largehead hairtail *Trichiurus japonicus* and silver croaker *Pennahia argentata* in the East China Sea (ECS) to obtain an unbiased AI.

1. Data and data conversion

This study employed both the fishery-dependent datasets of yellow seabream, largehead hairtail, and silver croaker caught by the Japanese bottom-trawl fishery in the ECS and the fishery-independent datasets of yellow seabream and largehead hairtail caught by the Japanese bottom-trawl survey in the ECS. Many values were missing in the fishery-dependent datasets because of the shrinkage of the operational areas. In time-series analyses, dependence of the state variance on the levels of the states can generate bias in the estimated results. The logarithmic transformation, power transformation, and Box-Cox transformation were tested to convert the observed CPUE data for removing such dependence of variance and securing normality of the data distribution. A normality test was conducted to choose the most suitable data-conversion method by referring to a histogram and a Q-Q plot to compare the performance of the three methods. Power transformation was found to be the most suitable data-conversion method.

2. Development of a practical method of utilizing the MARSS model

First, the converted fishery CPUE dataset of largehead hairtail was used to analyze the relationship between the number of analyzed fishing grids and the interpolation accuracy. Consequently, the interpolation accuracy could be improved by increasing the number of analyzed fishing grids.

Second, the relationship between the number of analyzed fishing grids and the analysis time was determined using the converted fishery CPUE data of 20 neighboring fishing grids for yellow seabream to the normal MARSS model. The analysis times were obtained when the MARSS model was converged for each case. As a result, the time required for the analysis markedly increased with an increasing number of fishing grids included in the analysis.

The "partial Kalman filter" and "reduced EM iterations" methods were developed to reduce the analysis time when a large number of fishing grid datasets were treated simultaneously in the MARSS model. The value of the log-likelihood and the analysis time among the normal MARSS, the "partial Kalman filter", and the "reduced EM iterations" methods were compared to determine the most practical approach. The least required analysis time and a similar performance to the normal MARSS showed that the "reduced EM iterations" method was the most practical approach for analysis.

3. Application of the MARSS model to CPUE data from trawl fishery

The converted fishery CPUE datasets for yellow seabream, largehead hairtail, and silver croaker were applied to the MARSS model using the "reduced EM iterations" method. For each species, the annual shifts in their AIs and their seasonal migrations were addressed. The conventional AIs were also calculated for comparison. Consequently, the MARSS model adequately evaluated the broadening CIs of the estimated AIs when the missing values in the dataset increased in the 2000s; while comparing with the estimated AIs, the AIs calculated by the conventional method showed considerable biases under these conditions.

4. Utilization of data from research vessels in MARSS

The CPUE datasets from both the trawl fisheries and the surveys were applied to the MARSS model for analysis (i.e., "analysis F&S") to improve the reliability of the estimated AI. In comparison, "analysis F" is an abbreviation for the analysis in MARSS when only the fishery CPUE data was utilized. The AIs and 95% CIs estimated by "analysis F&S" were calculated for comparison with those estimated by "analysis F". The values of the estimated AIs and the 95% CIs from "analysis F&S" were similar to those from "analysis F" before 2000, while became lower than those from "analysis F" in the 2000s. The resutls implied that the combined use of data from both the fishery and the research survey in MARSS was successful in improving the abundance estimation accuracy. The survey datasets were useful when the fishery datasets were limited, but they were barely useful when the amount of fishery datasets was large enough in the analyses.

In conclusion, applying the MARSS model using the "reduced EM iterations" method to the large-size CPUE datasets of yellow seabream, largehead hairtail, and silver croaker confirmed the effectiveness of this new practical approach to the CPUE analysis. The MARSS model is available for the evaluation of fishery resources, particularly for fish species with a decreasing number of CPUE data caused by fishery reduction, such as many fish species in the ECS with a low level of abundance; and for species with a changed fishing ground by force (e.g., establishment of the exclusive economic zones or the marine protected areas). Moreover, the MARSS model will become extremely useful when a spatially arranged CPUE dataset is available. Unlike common approaches for CPUE standardization (e.g., generalized linear model and generalized additive model), the MARSS model can flexibly estimate the states and properly interpolate the missing values considering the dynamic temporal (annual and monthly) and spatial effects on the CPUE throughout the analysis. Overall, the countries involved must establish an effective framework for cooperative management and research activities in this area to maintain the sustainable use and proper evaluation of the fishery resources in the ECS. Methods such as the MARSS model can provide a useful platform to improve cooperative activities.

Acknowledgements

This PhD dissertation would not have been completed without the generous assistance from many people. First of all, my deepest gratitude is to my supervising Associate Professor Dr. Takashi Yamakawa, Graduate School of Agriculture and Life Sciences, the University of Tokyo. His support, guidance and encouragement helped me overcome many difficulties throughout my study and enabled me to develop a broadening understanding of fisheries stock assessment. I have been very fortunate to have this wise and kind supervisor in my Doctoral course.

I am very grateful to Professor Dr. Tsuguo Otake, Graduate School of Agriculture and Life Sciences, the University of Tokyo, who has given me many precious advices for my study in the seminar, and encouraged me a lot over these three years. Also, I really appreciate the other member of my doctoral committee, Dr. Kunio Shirakihara, Dr. Kazuhiko Hiramatsu and Dr. Teruhisa Komatsu (Atmosphere and Ocean Research Institute, The University of Tokyo), for providing valuable and helpful comments on my dissertation.

I would like to express my gratitude to Dr. Mari Kuroki, Graduate School of Agriculture and Life Sciences, the University of Tokyo, who is always very graceful and kind to me, and also gives me many precious comment for my study. I think she is a very wonderful woman researcher in her field, and want to be a good researcher like her in the future.

Special thanks must go to the members of the Seikai National Research Institute for providing data on Japanese bottom-trawl fisheries and research survey in the East China Sea, and their precious advice and help. In Particular, the members of Ms. Mari Yoda, Dr. Tohya Yasuda, Dr. Hiroyuki Kurota and Dr. Yoshimasa Aonuma. I also want to thank Dr. Seiji Ohshimo, National Research Institute of Far Seas Fisheries, and Dr. Masa-aki Fukuwaka, Hokkaido National Fisheries Research Institute for their significant advice and helpful suggestions to my study.

I would extent my thanks to all my lab mates. Without their kindness, I couldn't much feel comfortable in the laboratory every day.

Thanks also to my friends who have been always supported my life and encouraged me to look forward.

Last but not least, I am exceedingly grateful to my family, they never stopped encouraging and supporting me all the time. I could not have completed my study without their love and help. Thank you for always believing in me. Thank you all.

以上の方々に、心より感謝を申し上げます。

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