

Nonparametric Kernel Regression Analysis on the Relationship between Marine Capture Fisheries Production and the Price Index Received by Fishermen in the Arafura Sea

Sudarti Dahsan¹, Anatansyah Ayomi Anandari², Andrian Andaya Lestari³, Rudy Agus Gemilang Gultom⁴

^{1,2,3,4}Department of Sensing Technology, Faculty of Defense Science and Technology, Republic of Indonesia Defense University, IPSC Sentul, Citereup District, Bogor Regency, West Java Province, 16810, Indonesia
sudarti.dahsan@tp.idu.ac.id, anatanayomiii@gmail.com, andaya.phd@gmail.com, rudygultom@idu.ac.id



Abstract— The Arafura Sea is known as an area rich in fisheries resources, which is the main source of income for many local Fishermen. The main problem arises due to price and production fluctuations which can significantly affect Fishermen's income. Kernel nonparametric regression analysis was chosen as a research method to overcome the limitations of parametric regression models in capturing complex and nonlinear patterns in these relationships. This research aims to fill this knowledge gap by using a nonparametric kernel regression analysis approach. Thus, it is hoped that this research can provide new insights into the relationship patterns between marine capture fisheries production and price indices, opening the door to increasing the sustainability of the fisheries sector and the welfare of Fishermen in this region. This research is quantitative and uses nonparametric kernel regression data analysis to explore the relationship between marine capture fisheries production and the price index received by Fishermen in the Arafura Sea. Based on nonparametric kernel regression analysis with bandwidth selection methods, such as Cross-Validation, Generalized Cross-Validation, and Mean Squared Error, this research shows variations in estimates of marine capture fisheries production and the price index received by Fishermen in the Arafura Sea. Differences in estimation results between methods reflect different approaches in dealing with the trade-off between model fit to the data and model complexity. Although the results suggest flexible relationships, it is important to remember that conclusions about causal relationships cannot be drawn directly, and this study provides valuable insight into the complex dynamics of factors influencing fisheries production in the region.

Keywords— Arafura Sea; Fisheries Production; Fishermen; Kernel Regression; Price Index

I. INTRODUCTION

The marine capture fisheries sector has a vital role in supporting the economy and providing food resources for people in various regions, including the Arafura Sea [1]. This region is known as an area rich in fisheries resources, which is the main source of income for many local Fishermen. However, as global and local dynamics continue to change, this fisheries sector is faced with a number of challenges that require in-depth understanding for effective management [2]. One critical aspect that needs to be considered is the relationship between marine capture fisheries production and the price index received by Fishermen [3]. Fluctuations in the price index can have a significant impact on the economic well-being of Fishermen, who depend heavily on income from the sale of their catch [4]. Therefore, to improve fisheries resource management and provide supportive policies, it is important to properly understand the dynamic relationship between fisheries production and economic factors such as price indices [5].

Although there have been many studies exploring these aspects, there is still a lack of in-depth understanding, especially in the context of the Arafura Sea. This research aims to fill this knowledge gap by using a nonparametric kernel regression analysis approach. Thus, it is hoped that this research will provide new insights into the relationship patterns between marine capture fisheries production and price indices, opening the door to increasing the sustainability of the fisheries sector and the welfare of

Fishermen in this region [6]. By understanding these dynamics in more detail, this research can make a significant contribution to decision making in fisheries resource management and sustainable economic development in the Arafura Sea.

One statistical approach used to analyze complex relationships like this is nonparametric kernel regression analysis. This technique allows researchers to explore patterns of relationships without having to rely on certain assumptions about the form of the regression function [7]. In the context of this research, we use nonparametric kernel regression analysis to explore the relationship between marine capture fisheries production in the Arafura Sea and the price index received by Fishermen. This research aims to make a significant contribution to understanding the economic dynamics of marine capture fisheries and provide deeper insights for policy makers, Fishermen and other stakeholders. By involving sophisticated analytical methods, it is hoped that this research can provide a solid foundation for better decision making in managing fisheries resources and sustainable economic development in the Arafura Sea region.

II. RESEARCH METHODS

This research is quantitative and uses nonparametric kernel regression data analysis to explore the relationship between marine capture fisheries production and the price index received by Fishermen in the Arafura Sea. This approach was chosen because it allows researchers to identify patterns of relationships without having to rely on certain assumptions about the form of the regression function, providing the necessary flexibility in dealing with the complexity of possible relationships. The data used in this research comes from the Ministry of Maritime Affairs and Fisheries of the Republic of Indonesia and the Central Statistics Agency. This secondary data was chosen because it provides a broad framework and includes relevant information related to fisheries production and price indices received by Fishermen. The quality of the data from these sources is considered reliable and adequate for the desired analysis purposes.

The analysis process begins with data processing, including data cleaning, normalization, and transformations necessary to ensure the accuracy and sustainability of the analysis. Next, kernel nonparametric regression analysis is performed using appropriate statistical algorithms and software. The use of kernels in this analysis allows identifying complex relationship patterns without having to limit ourselves to rigid parametric regression models [8]. The important aspects of this research method are validation and interpretation of results. Validation was carried out to ensure the reliability and accuracy of the findings, while interpretation focused on revealing the implications of the analysis results on the relationship between wild-capture fisheries production and the price index received by Fishermen in the Arafura Sea. This method is designed to provide in-depth and relevant insights for the development of effective policies in supporting the sustainability of the fisheries sector and the welfare of Fishermen in this region.

III. RESULTS AND DISCUSSION

Discussing the results of the analysis carefully, the aim is to understand in depth the complex relationship between marine capture fisheries production and the price index received by Fishermen in the Arafura Sea region. Kernel nonparametric regression analysis is the main tool for exploring correlation patterns without making certain distribution assumptions, thus enabling the discovery of patterns that may be missed by conventional parametric methods [9]. By focusing on this aspect, deeper insights can be revealed regarding the economic dynamics of Fishermen and the factors that influence the price index they receive in the context of marine capture fisheries production in the Arafura Sea. Explore this nonparametric kernel regression analysis to gain a more holistic understanding of the complex economic dynamics involving fisheries production and Fishermen's income in this region.

3.1 Trends in Capture Marine Fisheries Production in the Arafura Sea

In recent years, it has been seen that the trend of marine capture fisheries production in the Arafura Sea has increased significantly. This phenomenon can be attributed to various factors, including growing global demand for fishery products, more effective marine resource management policies, and increasingly sophisticated fishing technology [10]. Changes in the dynamics of the Arafura marine ecosystem also play an important role in directing fisheries production flows. A deep understanding of these trends is crucial in developing sustainable maritime security strategies in the region.

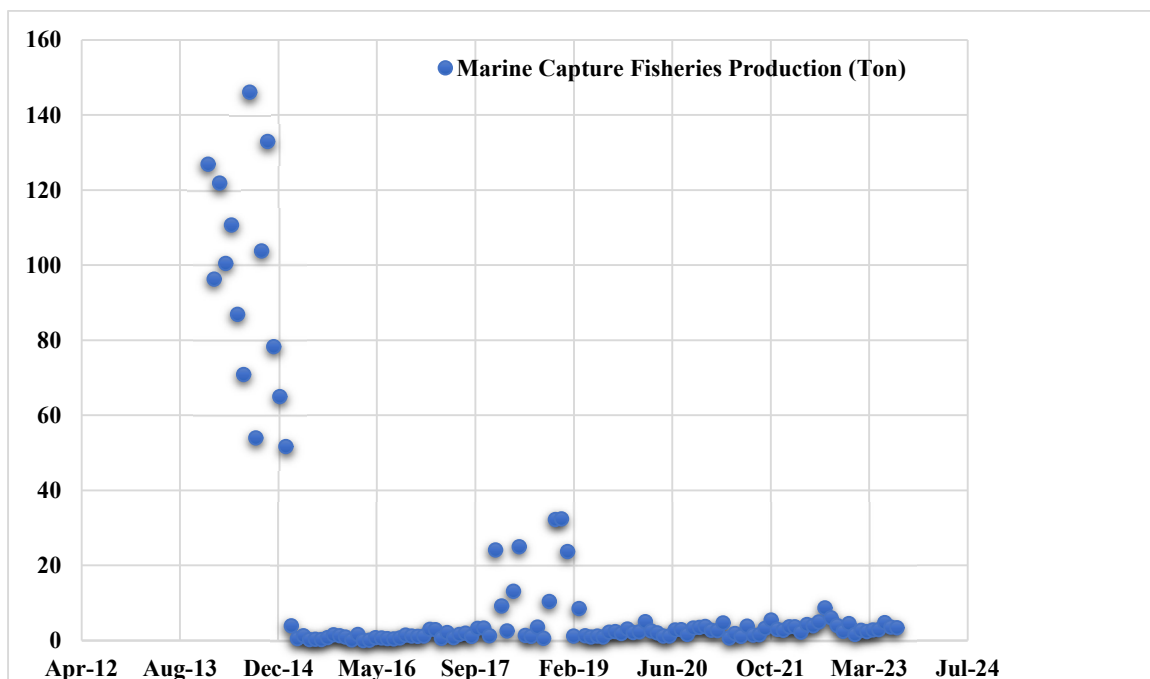


Fig. 1. Graph of Production Trends in Marine Capture Fisheries in the Arafura Sea 2014-2023

Based on monthly fish production data in the Arafura Sea from January 2014 to August 2023, we can see significant variations in marine capture fisheries production trends during that time period. Temporal analysis shows production fluctuations that reflect dynamics in the fisheries sector in this region. At the beginning of the period, especially in January 2014, fish production reached its peak with a value of 126,956,7895 kg. However, since then, there has been considerable variation, with some months experiencing sharp declines, such as in March 2015 and April 2015, where production reached very low levels, namely 3,974.387495 kg and 564.4109118 kg, respectively.

After this period of decline, there was a tendency for production to recover, especially in mid-2015 to early 2016. However, fluctuations continued until mid-2017, when production again showed a significant increase. The period after mid-2017 to mid-2018 recorded relatively stable production levels, before again experiencing a significant increase at the end of 2018. Furthermore, since mid-2018, a significant growth trend has been seen, reaching a peak in December 2020 to February 2021 with production exceeding 3,800 kg. Despite variations after this period, fish production remains relatively high until August 2023.

This temporal analysis provides a clear picture of fluctuations in marine capture fisheries production in the Arafura Sea, and identifies critical periods where production experiences significant decreases or increases [11]. To further understand this trend, a more in-depth study can be carried out regarding external factors that might influence fisheries production, such as climate change, fisheries policies, or other factors that can influence the condition of the aquatic ecosystem.

3.2 Dynamics of the Price Index Received by Fishermen and the Implications for Economic Welfare

The various changes that have occurred in the fisheries sector are crucial for understanding the economic dynamics of Fishermen, especially through analysis of the Price Index Graph Received by Fishermen in the waters of the Arafura Sea [12]. This graph visualizes fluctuations in prices received by Fishermen, reflecting changes in the relative value of their fisheries catch. Through an in-depth understanding of this graph, we can explore the underlying economic implications, understand the challenges fishers face, and detail potential opportunities to improve their economic well-being. Let's investigate this visual image further to gain better insight into the economic reality of Fishermen in the waters of the Arafura Sea.

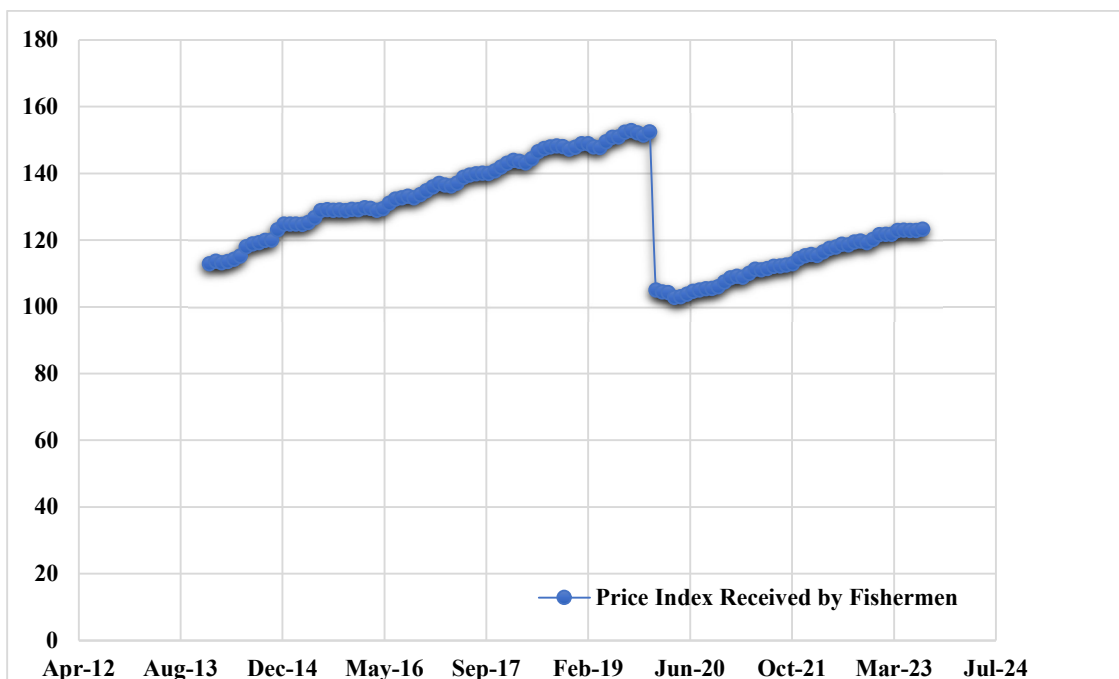


Fig. 2. Price Index Graph Received by Fishermen in 2014-2023

The dynamics of the price index received by Fishermen has a significant impact on their economic welfare. The price index reflects changes in the relative value of various goods and services bought or sold by Fishermen. An increase in the price index received by Fishermen can be a positive indicator, showing an increase in income from the sale of fish or other fisheries commodities. This increase in income can have a positive impact on the economic well-being of Fishermen, allowing them to meet basic needs, such as food, housing, and education [13]. Additionally, increased income can stimulate investment in better fishing equipment, modern technology, or training that can improve their operational efficiency.

However, price index fluctuations can also provide challenges for Fishermen. Increases in input prices such as fuel or equipment costs can reduce the net profits received by Fishermen. In addition, external factors such as climate change, fishing regulations, or changing market demand can influence the dynamics of the price index, which in turn affects Fishermen's income. In this context, it is important to implement policies that support the sustainability of the fisheries sector, increase Fishermen's access to technology and training, and create a stable economic environment [14]. The government and other stakeholders can play a role in forming policies that take into account the dynamics of the price index, so that they can make a positive contribution to the economic welfare of Fishermen.

Economic welfare has a central role in the lives of Fishermen and has a direct impact on various aspects of their lives [15]. Fundamentally, economic prosperity creates the basis for fulfilling Fishermen's basic needs, including food, housing, education and health [16]. Stable and adequate income allows Fishermen to provide a decent life for their families, creating a healthy and productive environment [17]. Apart from that, economic prosperity opens the door to Fishermen's access to adequate health services. With sufficient income, they can access medical care, provide for their family's health needs, and respond to emergencies without facing excessive financial hardship [18]. Good economic prosperity also supports the education of Fishermen's children, opening up opportunities to improve educational levels and paving the way to a brighter future.

The importance of economic well-being is also reflected in the ability of Fishermen to invest in better fishing equipment and modern technology [19]. Sufficient income allows them to improve and increase production capacity, which in turn can increase catches and operational efficiency [20]. This not only provides direct benefits for Fishermen, but also supports the sustainability of the fisheries sector as a whole. Apart from practical aspects, economic welfare also has an impact on the psychological and social aspects of Fishermen's lives [21]. Financial security creates a sense of stability and self-confidence, which can improve

mental well-being and overall quality of life. Therefore, efforts to improve the economic welfare of Fishermen must be a priority, involving supportive policies, training and development of relevant infrastructure.

3.3 Relationship Patterns of Fisheries Production and Price Index

Kernel nonparametric regression analysis is a statistical method used to model the relationship between independent variables and response variables without making special assumptions about the functional form of the relationship [22]. The general goal of nonparametric kernel regression analysis is to investigate the relationship between independent variables and response variables without following a specific mathematical model [23]. This provides greater flexibility in understanding data patterns that traditional parametric regression models may not be able to capture. This analysis is often used for data exploration, identifying complex patterns, and understanding dynamics that may be hidden in the data [24]. Assuming the predictor and response variables are random variables, then $m(x)$ can be described as:

$$\begin{aligned}
 m(x) &= \int_{-\infty}^{\infty} yf(y|x)dy \\
 &= \int_{-\infty}^{\infty} y \frac{f(x,y)}{f_x(x)} dy
 \end{aligned}
 \tag{1}$$

By using the kernel density estimator $f(x,y)$ and $f_x(x)$ as follows

$$\hat{f}(x,y) = \frac{1}{nh_x h_y} \sum_{i=1}^n K_x\left(\frac{x-X_i}{h_x}\right) K_y\left(\frac{y-Y_i}{h_y}\right)
 \tag{2}$$

$$\hat{f}_x(x) = \frac{1}{nh_x} \sum_{i=1}^n K_x\left(\frac{x-X_i}{h_x}\right)
 \tag{3}$$

The Nadaraya Watson estimator obtained is the weighted average of Y_i

$$\hat{m}(x) = \sum_{i=1}^n W_i(x) Y_i
 \tag{4}$$

The effectiveness of the weight function $W_i(x)$ of the kernel smoother is determined by the Kernel K and the bandwidth sequence h . So the accuracy of estimating the regression curve $m(x)$ does not only depend on bandwidth [25]. In this research, using the Generalized Cross Validation (GCV) method is one of the references in selecting the optimal bandwidth (h) in nonparametric regression. GCV is formulated using the following equation

$$\hat{Y}_i = \sum_{j=1}^n W_j(X_i) Y_j
 \tag{5}$$

with

$$W_j(X_i) = H_{ij}$$

Data analysis using kernels allows using multiple bandwidths and selecting the best estimator based on a qualitative assessment of the estimation results [26]. Comparing estimated calculations is also possible with m estimates according to the minimum average MSE (Mean Square Error) criteria.

$$MSE(\hat{m}) = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{m}(x_i))^2
 \tag{6}$$

Another way is also to use CV (Cross Validation) values.

$$CV(h) = n^{-1} \sum_{j=1}^n \left[\frac{Y_j - \widehat{m}_h(X_j)}{1 - H_{jj}(h)} \right]^2 \tag{7}$$

Next is the GCV method in kernel regression which is a method for selecting optimal bandwidth by minimizing the GCV function.

$$GCV(h) = \frac{n^2 MSE}{\left[n - \sum_{j=1}^n H_{jj} \right]^2} \tag{8}$$

The following is the optimum bandwidth output using the CV method.

TABLE 1. OUTPUT BANDWIDTH METODE CV

No	h	CV
[1,]	1	833.4609
[2,]	2	884.8581
[3,]	4	892.3483
[4,]	3	892.6266
[5,]	5	901.7155
[6,]	6	917.5867
[7,]	7	935.5511
[8,]	8	952.6124
[9,]	9	967.3107
[10,]	10	979.3039

Based on the table above, the h opt is 1 with a minimum CV of 833.4609. In the context of nonparametric kernel regression analysis, bandwidth is a very important parameter because it controls the extent of influence of each data point on the overall prediction [27]. Choosing the optimal bandwidth is crucial in ensuring the model provides accurate and robust results.

In your research results, the h opt (optimum bandwidth) found is 1, and this indicates that in this situation, a bandwidth of 1 gives the best results. With a minimum Cross-Validation (CV) value of 833.4609, it can be concluded that the nonparametric regression model with a bandwidth of 1 has good performance in generalizing patterns from the data without being too affected by noise or small fluctuations in the dataset. In addition, a minimum CV value indicates that a model with a bandwidth of 1 has a low error rate, so that prediction results tend to be more accurate and reliable. In other words, this model can well capture the relationship pattern between marine capture fisheries production and the price index received by Fishermen in the Arafura Sea. To visualize the data estimation results based on the optimum h value, they are as follows:

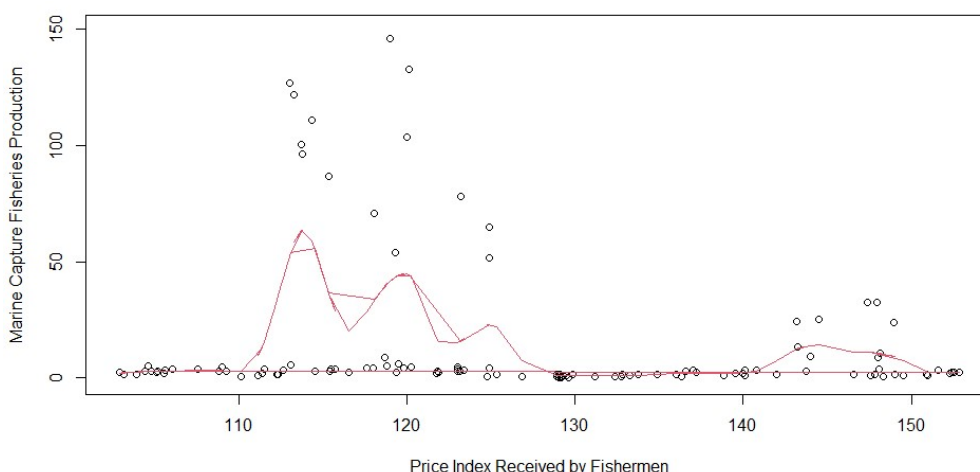


Fig. 3. Best Kernel Nonparametric Regression Model with Minimum CV

Next, using the GCV method, the output for optimum bandwidth is obtained as follows

TABLE 2. OUTPUT BANDWIDTH METODE GCV

No	h	GCV	MSE
[1,]	4	911.6413	826.9256
[2,]	1	913.5712	640.7053
[3,]	5	917.1848	847.1006
[4,]	3	918.1713	808.3254
[5,]	2	923.8066	766.4097
[6,]	6	930.3358	869.6483
[7,]	7	946.2483	892.1449
[8,]	8	961.7127	912.5712
[9,]	9	975.1362	929.9431
[10,]	10	986.0899	944.1543

From the table, it can be seen that the optimal bandwidth value (h_{opt}) produced using the GCV method is 4, with a minimum GCV value of 911.6413 and an MSE of 826.9256. This shows that in the context of nonparametric kernel regression analysis using the GCV method, a bandwidth of 4 provides the best performance with a minimal error rate.

It should be noted that GCV is used as a bandwidth selection criterion because it aims to minimize the trade-off between model fit to the data and model complexity [25]. In other words, optimal bandwidth selection with GCV tries to strike a good balance between advantages and disadvantages of model complexity. The recorded MSE value also provides an idea of how well the model can generalize patterns from the data. In this case, the low MSE indicates that the model with bandwidth 4 has good ability in estimating the relationship between marine capture fisheries production and the price index received by Fishermen in the Arafura Sea. The estimation results using the kernel approach are as follows which are visualized in the scatterplot image between the actual data and the estimated data.

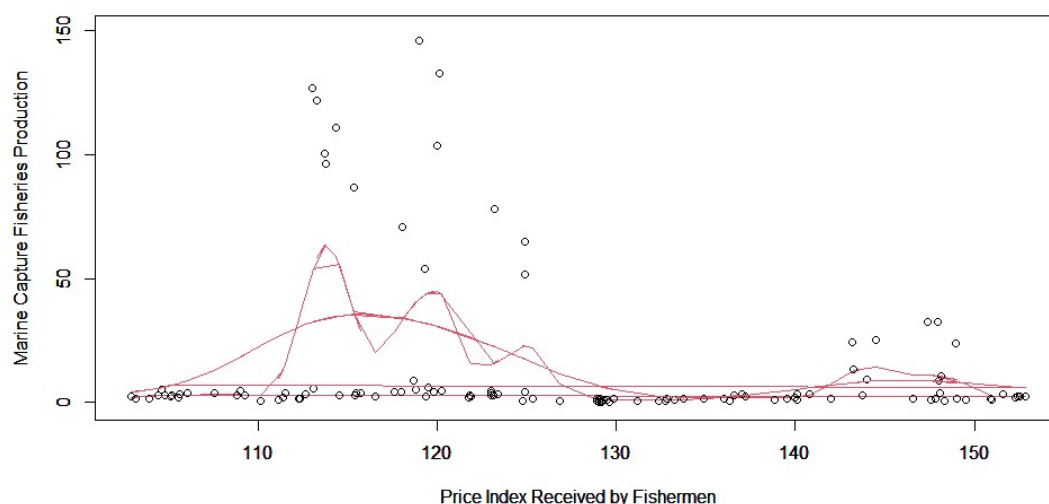


Fig. 4. Best Kernel Regression Model with Minimum GCV

Apart from the CV and GCV methods, there are also other methods that can be used to determine optimal bandwidth, namely the MSE value. Basically, the principle of CV and GCV is to create a function that minimizes the MSE value of the estimated model.

TABLE 3. BANDWIDTH ESTIMATION RESULTS WITH THE SMALLEST MSE

No	h	GCV	MSE
[1,]	0.1	1907.924	206.9383
[2,]	0.2	1700.191	412.1837
[3,]	0.3	1409.659	491.2718
[4,]	0.4	1230.357	530.4144
[5,]	0.5	1109.932	553.1196
[6,]	0.6	1027.674	570.6936
[7,]	0.7	973.7953	587.574
[8,]	0.8	940.7953	604.9669
[9,]	0.9	922.4319	622.8318
[10,]	1	913.5712	640.7053

The optimal bandwidth value using the MSE method obtained by h_{opt} is 0.1 with a GCV of 1907.924 and a minimum MSE of 206.9383. From the table, it can be seen that the optimal bandwidth value (h_{opt}) produced using the MSE method is 0.1, with a GCV value of 1907.924 and a minimum MSE of 206.9383. This shows that, in the context of nonparametric kernel regression analysis using the MSE method, a bandwidth of 0.1 provides the best performance with a minimal error rate.

It is important to understand that MSE is used as a bandwidth selection criterion because it aims to measure how well the model can reproduce known observational data. In other words, selecting a bandwidth that minimizes MSE reflects an attempt to achieve a high level of accuracy and precision in the regression model.

In addition, the comparison between GCV and MSE values shows that in this case, the minimum MSE value does not always reflect the minimum GCV value. This highlights the importance of considering multiple methods in determining optimal

bandwidth, as each can provide a different perspective regarding the balance between model fit to the data and model complexity. Then to visualize the data obtained are as follows:

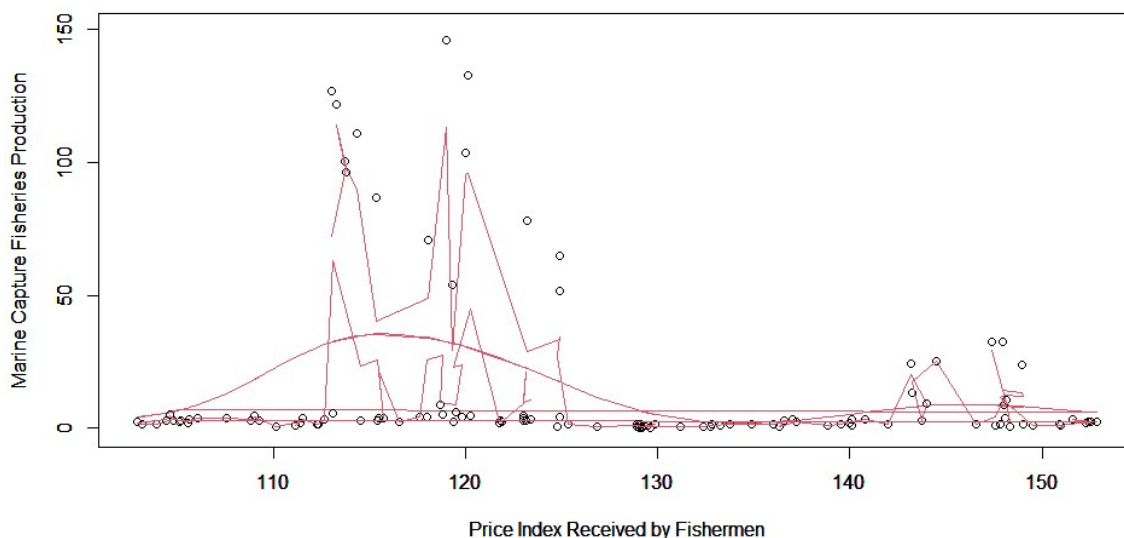


Fig. 5. Best Kernel Regression Model with Minimum MSE

Based on the three methods that have been used, a comparison of the estimated results of marine capture fisheries production in the Arafura Sea was obtained based on the kernel regression model with the CV, GCV and MSE methods, namely as follows:

TABLE 4. COMPARISON OF ESTIMATION RESULTS

Month	Average Fish Production Per Month (Tons)	Price Index Received by Fishermen	CV Estimates	GCV Estimation	MSE Estimation
Jan-22	2.80	115.43	34.85	35.46	25.85
Feb-22	3.75	115.74	28.86	35.52	3.78
Mar-22	3.72	115.46	34.22	35.47	21.40
Apr-22	2.29	116.54	20.16	35.35	2.29
May-22	4.36	117.61	28.30	34.49	4.36
Jun-22	3.97	117.95	32.55	34.09	25.84
Jul-22	4.98	118.81	40.61	32.84	27.63
Aug-22	8.76	118.70	39.80	33.02	9.73
Sep-22	6.10	119.51	44.34	31.60	8.96
Oct-22	4.10	119.83	44.95	30.97	24.02
Nov-22	2.53	119.36	43.76	31.88	23.04
Dec-22	4.61	120.26	43.69	30.07	44.61
Jan-23	1.73	121.73	17.04	26.58	2.25
Feb-23	2.78	121.79	16.28	26.43	2.35
Mar-23	2.45	121.86	15.51	26.25	2.43

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Apr-23	2.86	123.01	14.99	23.08	9.12
May-23	2.99	123.12	15.49	22.76	21.21
Jun-23	4.85	123.03	15.08	23.02	10.62
Jul-23	3.66	123.02	15.03	23.05	9.84
Aug-23	3.45	123.38	16.79	22.00	10.62

Table 4 presents a comparison of the results of estimates of marine capture fisheries production in the Arafura Sea based on kernel regression models using the Cross-Validation (CV), Generalized Cross-Validation (GCV), and Mean Squared Error (MSE) methods. In each row of the table, there is data on average fish production per month (in tons), the price index received by Fishermen, as well as production estimates using these three methods.

This comparative analysis provides insight into how the three methods provide different production estimates for each month within a certain time span. It is worth noting that this comparison can provide a more holistic view of kernel regression model performance by considering variations in bandwidth selection. For example, in January 2022, the estimated marine capture fisheries production using the CV, GCV, and MSE methods is 34.85, 35.46, and 25.85 tons, respectively. This difference reflects how the choice of bandwidth evaluation method can affect the estimation results. Likewise, in the following months, this pattern of differences can be seen.

Additionally, note that production estimates can vary significantly from month to month, and these differences can be caused by variations in observed data. This analysis can help in evaluating the model's fit to actual data and provide insight into the extent to which the model can provide consistent and accurate estimates. It is important to note that choosing the most appropriate method depends on the characteristics of the data and the research objectives. Some methods may place greater emphasis on prediction accuracy, while others may focus more on model generalization.

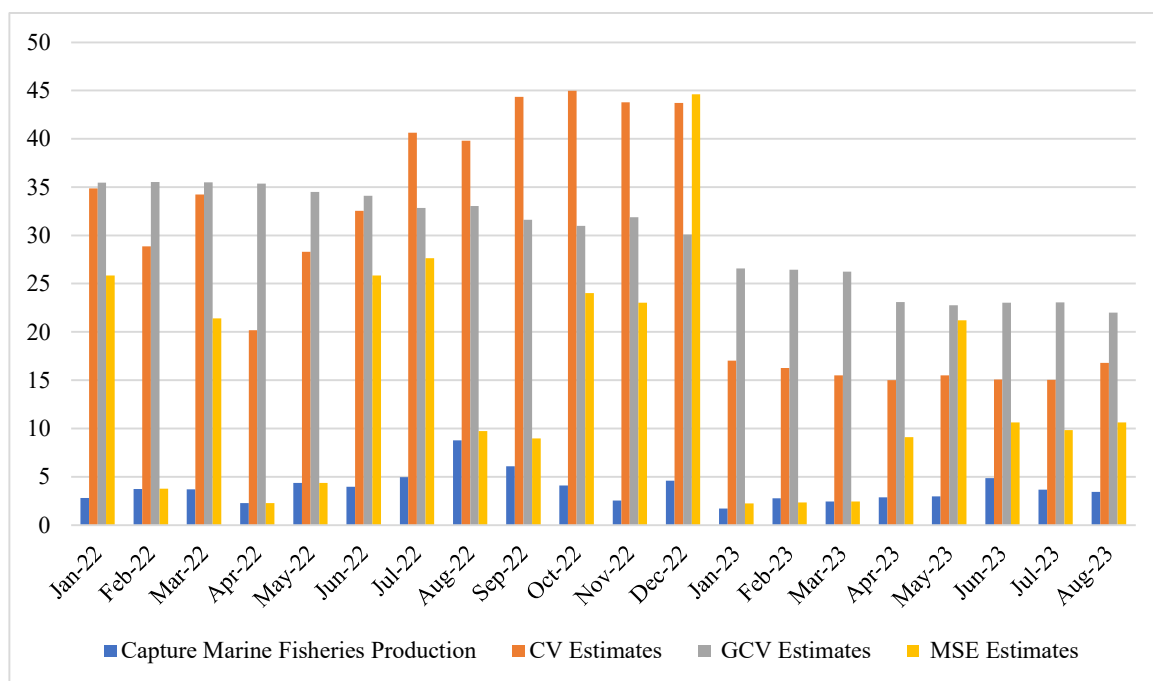


Fig. 6. Best Regression Model

The comparison graph of estimates of marine capture fisheries production in the Arafura Sea using the Cross-Validation (CV), Generalized Cross-Validation (GCV), and Mean Squared Error (MSE) methods shows significant variations in the estimation

results for each month. In this graph, the differences between the estimated production values of the three methods can be clearly seen, providing a deeper understanding of how the choice of bandwidth evaluation method can affect the analysis results. These comparison curves provide an informative picture regarding the relative performance of the three methods in estimating the relationship between monthly fish production and the price index received by Fishermen during the specified research period.

3.4 The Relationship between Capture Marine Fisheries Production and the Price Index Received by Fishermen in the Arafura Sea

Based on the research results that have been presented, the relationship between marine capture fisheries production and the price index received by Fishermen in the Arafura Sea is evaluated using kernel nonparametric regression analysis with various bandwidth selection methods, such as Cross-Validation (CV), Generalized Cross-Validation (GCV), and Mean Squared Error (MSE). Of these three methods, each provides a different estimate of marine capture fisheries production for each month within a certain time period. The comparison results show variations in production estimates, and these differences may result from the choice of different bandwidth evaluation methods.

Cross-Validation (CV), Generalized Cross-Validation (GCV), and Mean Squared Error (MSE) methods are used to determine optimal bandwidth, which in turn affects the model's flexibility in capturing relationship patterns. The variation in results between methods reflects different approaches in dealing with the trade-off between model fit to the data and model complexity. For example, if we focus our attention on January 2022, we can see that the estimated marine capture fisheries production using the CV method is 34.85 tons, GCV is 35.46 tons, and MSE is 25.85 tons. These differences illustrate variations in the way the three methods capture and interpret the relationship between fisheries production and the price index for that month.

Furthermore, looking at the estimation results for the following months, we can see how fluctuations in fisheries production in the Arafura Sea are related to changes in the price index received by Fishermen. In certain months, there may be clearer patterns or more complex relationships, reflected in differences in estimation results between methods. In general, this research provides an overview of how the factors that influence marine capture fisheries production are related to the price index received by Fishermen in the Arafura Sea. The results of nonparametric kernel regression analysis provide flexible estimates of the relationship pattern between the independent variable (price index) and the dependent variable (fishery production).

Differences in estimates between method can indicate the level of complexity of the relationship between fisheries production and price index. In addition, the choice of method can influence the level of generalization of the model to new data and the extent to which the model can provide accurate predictions. It is important to note that conclusions about causal relationships or causal influences cannot be drawn directly from this analysis. However, the research results provide valuable insight into the dynamics between marine capture fisheries production and the price index received by Fishermen in the Arafura Sea, and reflect the complexity in determining the factors that influence fisheries production in the region.

IV. CONCLUSION

This research uses nonparametric kernel regression analysis to investigate the relationship between marine capture fisheries production and the price index received by Fishermen in the Arafura Sea. This method provides flexibility in modeling relationships without having to make special assumptions about the functional form of the relationship. Three bandwidth selection methods, namely Cross-Validation (CV), Generalized Cross-Validation (GCV), and Mean Squared Error (MSE), are used to determine optimal bandwidth and provide different production estimates. The results of the analysis show that estimates of marine capture fisheries production vary between method, especially in certain months. These differences illustrate how each method captures the complexity of the relationship between fisheries production and price indices.

Although differences in estimates provide a deeper understanding of the dynamics of this relationship, it is important to remember that causal conclusions or causal relationships cannot be drawn directly. However, this research provides valuable insight into the complexity of factors influencing fisheries production in the Arafura Sea. Awareness of production fluctuations and their impact on Fishermen's welfare can be the basis for developing better policies to support the sustainability of the fisheries sector in this region. By combining the results of the three bandwidth selection methods, this research provides a richer and more holistic picture of the relationship between marine capture fisheries production and the price index received by Fishermen in the

Arafura Sea. This understanding can help the government and stakeholders to develop more effective strategies for managing fisheries resources and improving the economic welfare of Fishermen in the region.

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