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Analysis of Unmet Need for Health Services Based on the Percentage of Public Health Complaints with a Kernel Estimator Approach

Marisa Rifada[1]*, Dita Amelia[1], Jeny Praesti Setyaningrum[1], Niswah Septiandini[1], Yovita Karin Kalista[1], Shabrina Nareswari Dwitya[1]
[1]Department of Mathematics, Airlangga University, Indonesia
marisa.rifada@fst.unair.ac.id

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ABSTRACT

Healthcare services are a fundamental need that governments must guarantee to ensure optimal health outcomes for all citizens. However, many individuals still face significant barriers in accessing necessary healthcare services. This quantitative research employs a spatial analysis to examine the unmet need for health services based on public health complaints, utilizing a nonparametric regression approach with Kernel estimator. The Kernel estimator method was chosen for its flexibility in capturing unstructured data patterns, allowing the analysis to better reflect real-world conditions. The study uses health complaint data from the Central Bureau of Statistics, covering 38 provinces in Indonesia in 2024. However, data from 4 provinces were incomplete, so only 34 provinces were included in the analysis. The independent variable is the percentage of public health complaints, while the dependent variable is the percentage of unmet healthcare needs. A Gaussian kernel function was applied for nonparametric regression, identified as the optimal method based on the lowest Generalized Cross Validation (GCV) value of 1.052939 at a bandwidth of 0.33. The model demonstrates high predictive accuracy, with an R^2 of 82.44% and a Mean Squared Error (MSE) of 30.7%. These findings provide actionable insights for targeting healthcare disparities and improving service accessibility.

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A. INTRODUCTION

Healthcare services are a fundamental need that must be guaranteed by the government so that every community can achieve the best level of health. Access to healthcare plays an important role in improving physical, mental health, and overall quality of life (Fatharani, 2024). However, the reality in the field shows that many people still face challenges in accessing healthcare services when needed. This situation is known as unmet need. Unmet need in the health context refers to a condition where a person or group of people do not get the health services they should get or only receive services that are not up to standard (Watrianthos & Suryadi, 2023). Based on information from the National Socio-Economic Survey (Susenas) conducted by Statistics Indonesia in 2022, more than 27% of Indonesia's population who experienced health complaints did not access healthcare services. The most frequently cited reasons were feeling that their complaints did not require medical attention, cost issues, and long distances to healthcare facilities. This mismatch indicates that the healthcare system has not been able to reach all layers of society equitably (Badan Pusat Statistik, 2023).

Research indicates that unmet need is influenced by demographic factors, socioeconomic status, health perceptions, and accessibility to medical services. Research conducted by Chong et al. (2022) indicates that limited access to healthcare facilities, absence of healthcare facilities that meet standards, unaffordable treatment costs, social stigma related to certain conditions or diseases, and low awareness and information about health and available services have a significant impact on the likelihood of unmet need occurring. Research has also shown similar findings in other contexts. For example, Choi & Kim (2021) found that among older Korean women, inconvenient transportation was the primary reason for unmet healthcare needs (38.4%), followed by financial burden (28.4%) and mild symptoms (16.8%). In the United States, Syed et al. (2013) in their systematic review documented that transportation barriers such as rescheduled or missed appointments, delayed care, and missed medication disproportionately affect low-income and underserved populations, leading to poorer health outcomes. This shows that unmet need emerges from complex interactions between various structural and cognitive factors.

The reason for using the percentage of community health complaints in analyzing unmet need is because health complaints can be considered as an early sign that someone needs medical services (Pan et al., 2022; Vahedi et al., 2021). Ideally, when someone feels unwell, they will seek treatment. But in reality, not everyone who is sick goes to healthcare facilities. This indicates that there are unmet needs. By looking at how many people complain of illness but do not seek treatment, we can determine how large the gap is between need and access to healthcare services (Ko, 2016). This figure provides a real picture of the barriers faced by the community, ranging from costs, distance, to the assumption that their illness does not need medical treatment. Therefore, this data is important for evaluating the extent to which healthcare services can reach the community, and as a basis for designing more appropriate policies.

Previous research modeled unmet need using a truncated spline nonparametric regression approach, using factors such as family planning officer coverage, family planning service locations, percentage of poor families, and household head education level (Sholicha et al., 2018). However, this approach has not fully captured healthcare service needs from the perspective of direct community experience. In fact, health complaints experienced by the community daily can be a real indicator of the extent to which healthcare services meet existing needs (Maslyankov & Hernández, 2024). Therefore, this research uses a different approach by making the percentage of health complaints the basis for analyzing unmet need. The kernel estimator method was chosen because it can capture unstructured data patterns more flexibly, so the resulting analysis is expected to better reflect real conditions in the field (Chamidah & Rifada, 2016; Lestari et al., 2018, 2019).

To analyze the unmet need phenomenon spatially based on health complaints, a method capable of capturing complex data patterns without certain distributional assumptions is needed. One suitable method is the Nonparametric Regression method using Kernel Estimator. Kernel estimator is one of estimation methods in local smoothing (Chamidah & Rifada, 2016), where the estimation of biresponse semiparametric regression model for longitudinal data using local polynomial kernel estimator has been proven effective in handling complex healthcare data structures (Lestari et al., 2022; Utami et al., 2025). Kernels do not require certain distribution assumptions in their analysis (Azizatin & Retnaningsih, 2016). Kernel regression assigns weights to data points based on their proximity to the point of estimation effectively capturing intricate data structures and potentially yielding lower prediction errors (Mardianto et al., 2025). This approach is used to estimate the distribution function of data nonparametrically, and is very useful in identifying geographical patterns of complaint concentrations that are not accompanied by access to healthcare services (Mardianto et al., 2019) The Kernel Estimator method is effective in mapping healthcare service needs in urban and rural areas, because it can detect hidden local patterns in aggregate data. The kernel estimator method is used because it is highly recommended for estimating nonparametric regression functions (Lestari et al., 2022), particularly for analyzing ordinal categorical data where traditional parametric approaches may not be suitable, as demonstrated through local maximum likelihood estimation techniques (Rifada et al., 2021). Through this method, areas with unmet service need levels can be identified more clearly, so the results can be utilized to develop more targeted health programs or interventions.

This nonparametric estimation-based mapping approach enables identification of areas that have high concentrations of unmet need but are not optimally served by the healthcare system. Identifying these geographic disparities is essential, as it allows policymakers to direct interventions more effectively toward underserved populations (Pangwoh et al., 2024). This is important because policy interventions can be directed more specifically to areas with the highest needs. Previous studies have shown that spatial analysis using nonparametric methods provides a more flexible and accurate understanding of service gaps, especially in public health planning (Guo et al., 2023; Li et al., 2024), making such approaches increasingly relevant in addressing health inequities. This research also contributes to achieving the Sustainable Development Goals (SDGs), particularly Goal 3: "Good Health and Well-being," and Goal 10: "Reduced Inequalities". With a more comprehensive understanding of unmet need patterns and distribution, health program planning becomes more data-based and socially justice-oriented.

Using the Kernel Estimator approach, this research attempts to describe the distribution of areas that have unmet healthcare service needs (unmet need), based on the precentage of community health complaints. This mapping is expected to serve as a foundation for the government, especially policymakers in the health sector, to determine which areas need more attention. For example, areas with high complaint concentrations but low access to services can be prioritized for additional healthcare facilities, provision of medical personnel, or strengthening health education and promotion. In addition, this approach also provides a deeper picture of service inequality, so it can help in formulating more equitable and just health policies.

B. METHODS

1. Data and Data Sources

Secondary data is used in this study, which is data obtained indirectly from official sources. This study uses data from the Central Bureau of Statistics (bps.go.id) which covers 38 provinces in Indonesia in 2024. However, only 34 provinces were analyzed because data from the other 4 provinces were not available or incomplete. The data used consists of two variables, namely the percentage of public health complaints as the predictor or independent variable (X), and the percentage of unmet need for health services by province as the response or dependent variable (Y). The percentage of public health complaints represents the proportion of individuals in the total population who reported experiencing health problems within a specific reference period. Meanwhile, the percentage of unmet need is calculated by dividing the number of individuals who experienced health complaints that interfered with daily activities but did not seek outpatient care, by the total population, and expressing the result as a percentage (%). This study uses a nonparametric regression method with a kernel estimator to analyze the relationship between the two variables without assuming a particular form of relationship.

2. Research Methodology

This study employs a nonparametric regression approach using kernel smoothing techniques to explore the relationship between variables without imposing apredetermined functional form. The analysis utilizes the R software based on locpol and KernSmooth packages, which offer essential tools for implementing local polynomial fitting and kernel-based smoothing, enabling the model to flexibly adapt to data structures and patterns. The analysis steps used in this research are:

a. Research data collection.
b. Perform descriptive analysis of variable characteristics and data plot visualization.
c. Determine the most optimal bandwidth value using the GCV (Generalized Cross Validation) method with several kernel functions: Gaussian, Triweight, Triangle, Epanechnikov, Quartic, and Cosine, with selection based on the minimum GCV value and the resulting plot display.
d. Determine the best kernel function based on the minimum GCV value from various alternative kernel functions used.
e. Perform the estimation process using kernel estimator based on the combination of optimum bandwidth and best kernel function obtained from the previous stage.
f. Display observation plots and estimation results to evaluate the level of model fit to the data.
g. Compose conclusions based on modeling results and analysis.

C. RESULT AND DISCUSSION

1. Descriptive Statistics

The relationship between the response variable and the predictor variables can be examined through scatter plot analysis. In this study, the resulting scatter plots reveal no discernible pattern, indicating that the data is well-suited for analysis using nonparametric regression methods. The scatter plots illustrating the relationship between the predictor variables and the response variable are presented as shown in Table 1.

Table 1. Descriptive Statistics

Variable	N	Mean	Variance	Minimum	Maximum
X	34	24.815	33.601	13.220	38.880
Y	34	5.087	1.804	2.040	8.40

Based on descriptive analysis of the Table 1 on the percentage of health complaints (X) and unmet need for health services (Y), it is known that there are 34 observations for each variable. The average percentage of health complaints is 24.815 with a variance of 33.601, while the average unmet need for health services is 5.087 with a variance of 1.804.

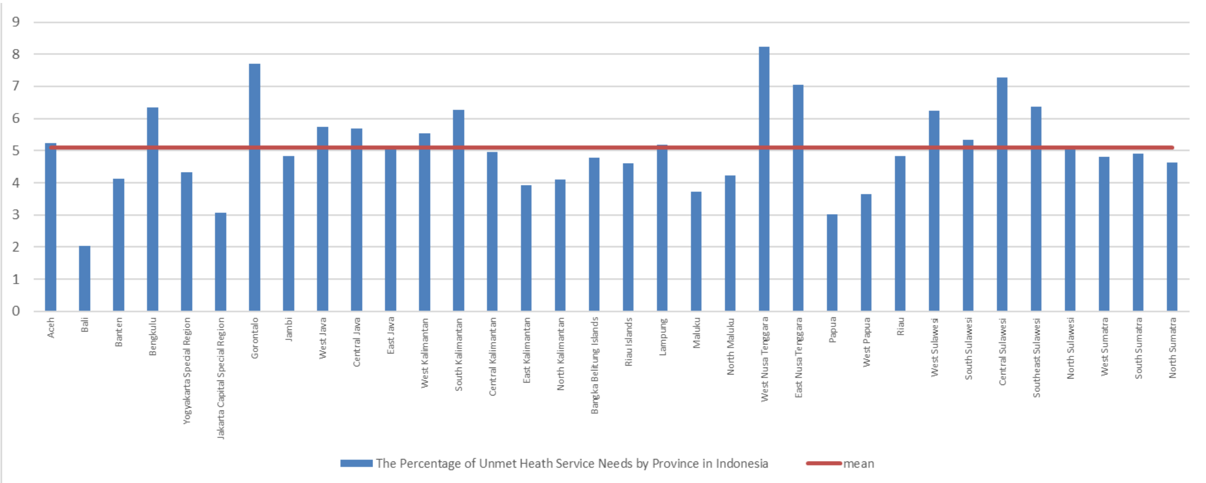

Figure 1. The Percentage of Unmet Heath Service Needs by Province in Indonesia

Based on the graph of the Figure 1, it can be seen that there are 12 provinces that exceed the national average. Bali Province has the lowest health Unmet Need, which is 2.040 percent, while the province with the highest health Unmet Need is West Nusa Tenggara with 8.240 percent.

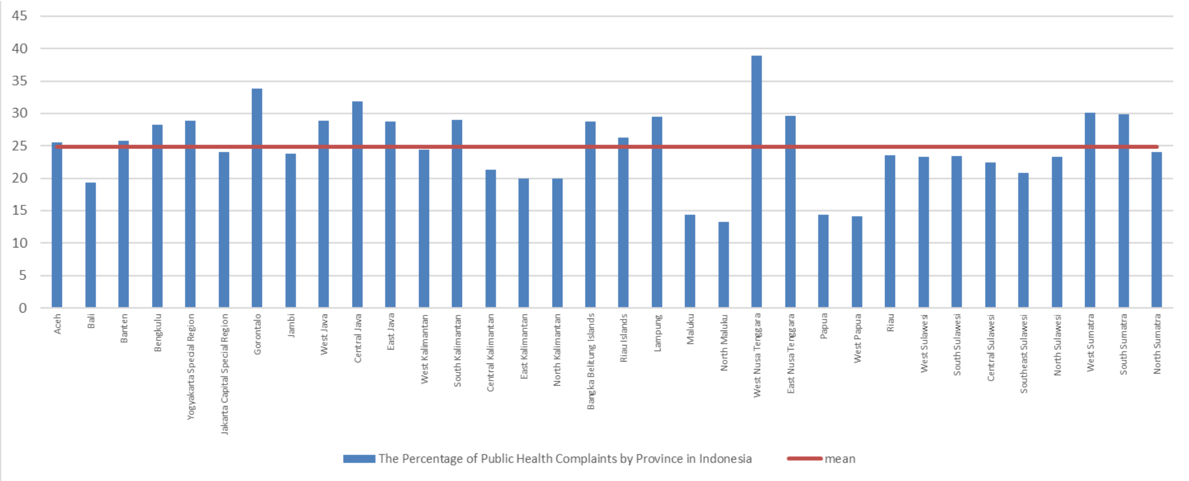

Figure 2. The Percentage of Public Health Complaints by Province in Indonesia

Based on the graph of the Figure 2, it can be seen that there are 16 provinces that exceed the national average. West Nusa Tenggara Province has the highest percentage of health complaints with a value of 38.880 and the lowest percentage of health complaints is North Maluku Province with 13.220.

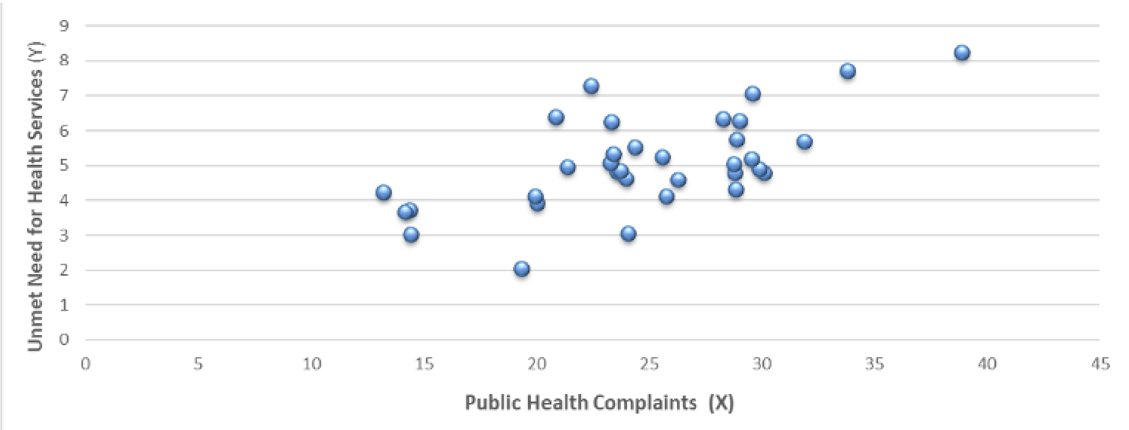

Figure 3. Scatter Plot

Based on Figure 3, it shows a plot between the percentage of health complaint values (X) and unmet need for health services (Y). Based on the data, it is known that the plot is spread out and does not describe a particular linear or polynomial form. Therefore, a nonparametric approach is suitable for use in the data analysis stage.

2. Optimal Bandwidth Determination with GCV

a. Gaussian

For the Gaussian kernel, optimal bandwidth search was conducted by examining GCV values in the bandwidth range of 0.20 to 0.50. From the results obtained, the lowest GCV value was found at bandwidth 0.33, which is 1.052939. This means that at this point, the model produces the most balanced distribution estimation, neither too smooth nor too rigid. The Gaussian Kernel estimation plot can be seen in Figure 4 below.

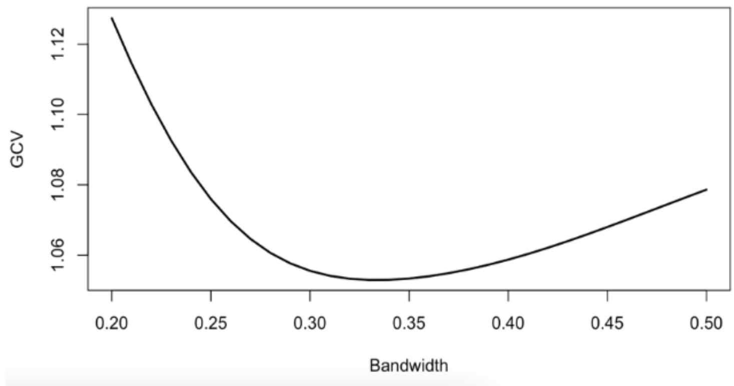

Figure 4. GCV Value Plot based on Bandwidth using Gaussian Kernel

The GCV value decreases consistently from bandwidth 0.20 until reaching the minimum point at 0.33, then increases again afterwards. This shows that bandwidth 0.33 is the most optimal value in producing a balance between smoothness and accuracy in estimation. The graph shows the typical U-shape pattern of the GCV process, which indicates that bandwidth selection greatly affects estimation performance. If the bandwidth is too small, the model becomes too sensitive to data (overfitting), while if it is too large, important patterns in the data can be lost (underfitting).

b. Triweight

For the Triweight kernel, optimal bandwidth search was conducted by examining GCV values in a certain bandwidth range. From the results obtained, the lowest GCV value was found at bandwidth 20.68, which is 1.548573. This means that at this point, the model produces the most balanced distribution estimation, neither too smooth nor too rigid. The Triweight Kernel estimation plot can be seen in Figure 5 below.

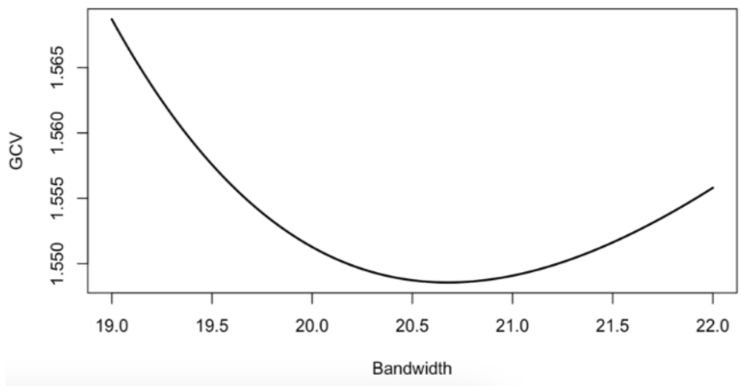

Figure 5. GCV Value Plot based on Bandwidth using Triweight Kernel

The GCV value decreases consistently until reaching the minimum point at bandwidth 20.68, then increases again afterwards. This shows that bandwidth 20.68 is the most optimal value in producing a balance between smoothness and accuracy in estimation.

c. Triangle

For the Triangle kernel, optimal bandwidth search was conducted by examining GCV values in the bandwidth range of 15.00 to 16.00. From the results obtained, the lowest GCV value was found at bandwidth 15.54, which is 1.210324. This means that at this point, the model produces the most balanced distribution estimation, neither too smooth nor too rigid. The Triangle Kernel estimation plot can be seen in Figure 6 below.

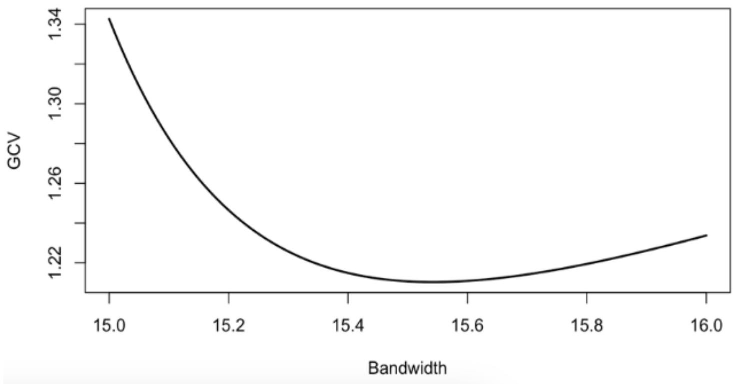

Figure 6. GCV Value Plot based on Bandwidth using Triangle Kernel

The GCV value decreases consistently from bandwidth 15.00 until reaching the minimum point at 15.54, then increases again afterwards. This shows that bandwidth 15.54 is the most optimal value in producing a balance between smoothness and accuracy in estimation.

d. Epanechnikov

For the Epanechnikov kernel, optimal bandwidth search was conducted by examining GCV values in the bandwidth range of 16.00 to 17.00. From the results obtained, the lowest GCV value was found at bandwidth 16.42, which is 1.221432. This means that at this point, the model produces the most balanced distribution estimation, neither too smooth nor too rigid. The Epanechnikov Kernel estimation plot can be seen in Figure 7 below.

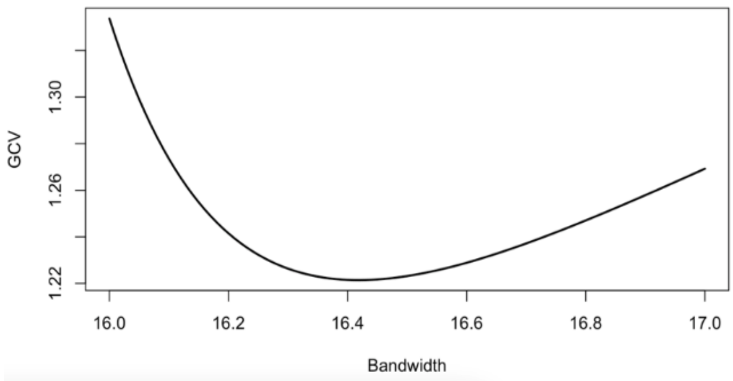

Figure 7. GCV Value Plot based on Bandwidth using Epanechnikov Kernel

The GCV value decreases consistently from bandwidth 16.00 until reaching the minimum point at 16.42, then increases again afterwards. This shows that bandwidth 16.42 is the most optimal value in producing a balance between smoothness and accuracy in estimation.

e. Quartic

For the Quartic kernel, optimal bandwidth search was conducted by examining GCV values in the bandwidth range of 17.50 to 18.50. From the results obtained, the lowest GCV value was found at bandwidth 17.97, which is 1.237911. This means that at this point, the model produces the most balanced distribution estimation, neither too smooth nor too rigid. The Quartic Kernel estimation plot can be seen in Figure 8 below.

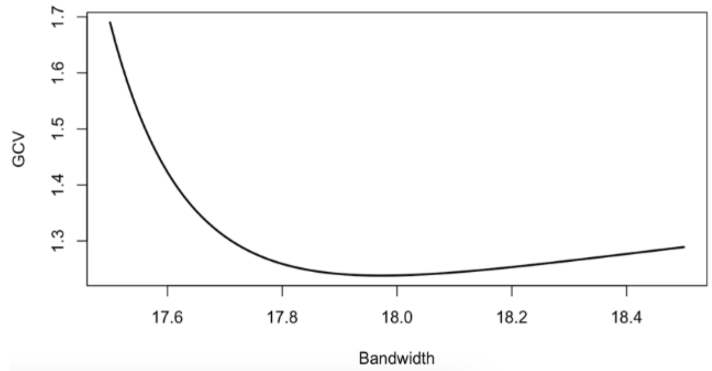

Figure 8. GCV Value Plot based on Bandwidth using Quartic Kernel

The GCV value decreases consistently from bandwidth 17.50 until reaching the minimum point at 17.97, then increases again afterwards. This shows that bandwidth 17.97 is the most optimal value in producing a balance between smoothness and accuracy in estimation.

f. Cosine

For the Cosine kernel, optimal bandwidth search was conducted by examining GCV values in the bandwidth range of 15.00 to 16.00. From the results obtained, the lowest GCV value was found at bandwidth 15.41, which is 1.206715. This shows that at this point, the model provides the most balanced distribution estimation, neither too smooth nor too rigid. The Cosine Kernel estimation plot can be seen in Figure 9 below.

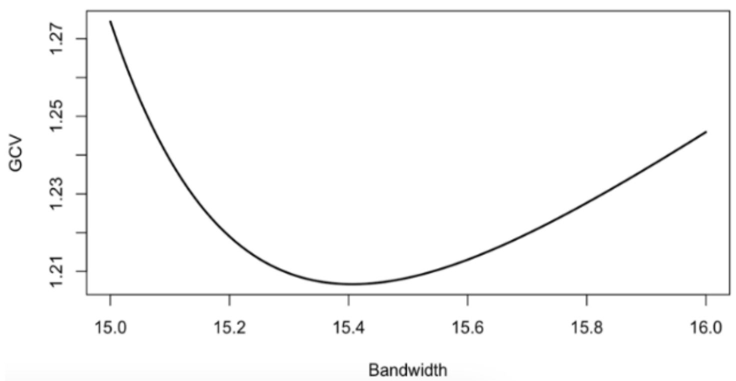

Figure 9. GCV Value Plot based on Bandwidth using Cosine Kernel

The GCV value decreases consistently from bandwidth 15.00 until reaching the minimum point at 15.41, then increases again afterwards. This pattern shows that bandwidth 15.41 is the most optimal value to achieve a balance between smoothness and accuracy in data distribution estimation.

3. Determine the Best Method

Determining the best kernel function method can be done by comparing each Generalized Cross Validation (GCV). GCV is proportional to Mean Square Error (MSE). This means that the kernel function with the smallest GCV value also tends to produce a minimum MSE value, so that the most optimal kernel method with the minimum GCV can approach the data pattern. The following are the minimum GCV results for each kernel function, as shown in Table 2.

Table 2. Comparison of Minimum GCV and Bandwidth

Kernel Functions	The minimum GCV	Bandwidth
Gaussian	1.052939	0.33
Triweight	1.548573	20.68
Triangle	1.210324	15.54
Epanechnikov	1.221432	16.42
Quartile	1.237911	17.97
Cosine	1.206715	15.41

Based on the results of the Table 2 the minimum GCV value of 1.052939 is obtained when using the Gaussian kernel function with a *bandwidth* value of 0.33. Thus, the Gaussian kernel function is the best method that can provide the most accurate estimate compared to the other kernel functions in this study.

4. Estimation Result

From the analysis results that have been obtained, the Gaussian Kernel estimator model can be written as follows.

$$\hat{g}(x) = \frac{\sum_{i=1}^{34} \frac{1}{\sqrt{2\pi}} exp\left(-\frac{1}{2}\left(\frac{x-x_i}{0,33}\right)^2\right) y_i}{\sum_{i=1}^{34} \frac{1}{\sqrt{2\pi}} exp\left(-\frac{1}{2}\left(\frac{x-x_i}{0,33}\right)^2\right)} \quad (1)$$

The best method was obtained using the Gaussian kernel function. This selection is based on the minimum Generalized Cross Validation (GCV) value of 1.052939 and the optimum bandwidth of 0.33. With these parameters, the following estimation results were obtained, as shown in Figure 10.

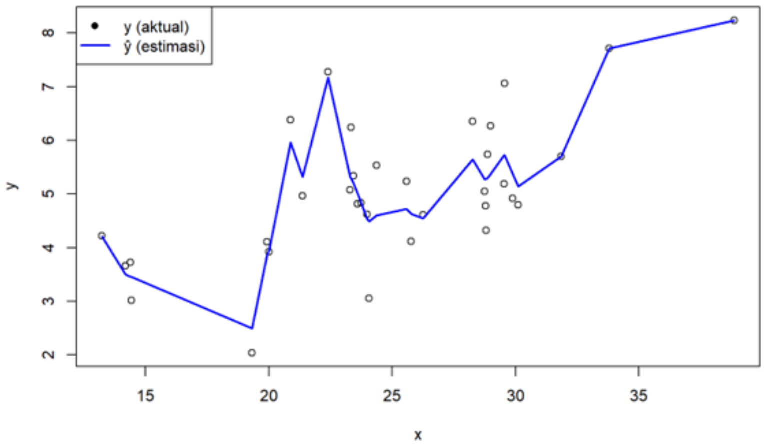

Figure 10. Plot Estimated Values based on Observation Values

The estimation results of Figure 10 using the kernel function show a less smooth line, with a jagged pattern and sharp changes in direction, indicating that the bandwidth used may be too small. However, the coefficient of determination (R^2 =0.8244). The Mean Square Error (MSE) value of 30.7% indicates an acceptable level of prediction error, so the model is considered quite reliable even though the visualization is not optimal.

D. CONCLUSION AND SUGGESTIONS

Based on descriptive analysis in this study, the average percentage of health complaints was 24.815 and the average unmet need for health services was 5.087. The data indicate that 12 provinces exceed the national average for the percentage of unmet need, and 16 provinces exceed the national average for public health complaints in Indonesia. The province with the highest percentage of health complaints and unmet need for health services is West Nusa Tenggara. Based on the scatter plot, it is known that the plot spreads and does not describe a certain linear or polynomial shape.

Based on the results of the above analysis, the best method is obtained using the Gaussian kernel function with a minimum Generalized Cross Validation (GCV) of 1.052939 and an optimum bandwidth value of 0.33. The kernel estimator model with the kernel function used still produces a less smooth estimation line due to the selection of a bandwidth that is too small. The R^2 value of the model is 82.44% and the Mean Squared Error (MSE) is 30.7%. For future research, researchers suggest using a wider range of health complaint data both in terms of area and time, as well as considering other factors such as accessibility, availability of medical personnel, and socioeconomic conditions that also affect unmet need for health services. This study contributes to the understanding of healthcare disparities in Indonesia by providing insights into spatial patterns of unmet healthcare needs, enabling policymakers to better target interventions and improve healthcare accessibility.

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