Available online at http://scik.org
Commun. Math. Biol. Neurosci. 2022, 2022:28
https://doi.org/10.28919/cmbn/7213
ISSN: 2052-2541

ON THE USE OF GENERALIZED ADDITIVE MODELS IN THE IMPACT OF COVID-19 ON HUMAN MOBILITY USING MOBILE POSITIONING DATA IN DKI JAKARTA, INDONESIA

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Abstract: This paper presents a mobility indicator derived from anonymized and aggregated mobile positioning data. The mobility indicator captures insights into the mobility patterns of the human in DKI Jakarta and it is expected to inform responses against the Covid-19. As an application, the indicator is used to study the impact of Covid-19 on mobility in DKI Jakarta. It is found that daily cases of Covid-19 and physical distancing interventions significantly reduces the level of mobility. This finding will support policymakers in formulating the best data-driven approaches for coming out of Covid-19 pandemic and determining future scenarios in case of new outbreaks.

Keywords: Covid-19; mobile positioning data; mobility.

2010 AMS Subject Classification: 93A30, 62-07.

1. INTRODUCTION

The recent global outbreak of The Coronavirus Disease 2019 (Covid-19) disease is causing a lot

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Received January 29, 2022

of fear and panic among people in the world [1]. The Covid-19, caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), rapidly expanded throughout the world during the first quarter of 2020, reaching pandemic status on 11 March [2]. Covid-19 is spreading human suffering worldwide; that is what we should all be focused on [3]. As of March 31, 2020, the Covid-19 is affecting over 200 countries and over 700,000 individuals [4].

In response to the Covid-19 pandemic, countries have sought to control SARS-CoV-2 transmission by restricting population movement through social distancing interventions, thus reducing the number of contacts [5]. One of the key lessons learned from the COVID-19 pandemic has been the pivotal role of human behavior, specifically mobility and mixing in spreading infection [6]. In order to study mobility under Covid-19, to evaluate the efficiency of mobility restriction policies, and to facilitate a better response to future crisis, we need to understand all possible mobility data sources at our disposal [7].

In this paper, we characterize the relationship between transmission through daily cases of Covid-19, physical distancing interventions (PSBB) and mobility in DKI Jakarta. This research focuses on studying mobility to DKI Jakarta in Jabodetabek metropolitan area. We assign that area because two reasons. First, DKI Jakarta as the nation's capital of Indonesia has a pull factor for people to do activity in that province. Around 1,2 million people from Bodetabek (the surrounding area from DKI Jakarta Province) do their main activity in DKI Jakarta [8]. Second, DKI Jakarta was recorded as the province with the highest cases of Covid-19 in 2020.

Mobility data represent an important proxy measure of social distancing [5]. In 2019, BPS-Statistics Indonesia has developed an algorithm Anchor Mobility Data Analytic (AMDA) to identify the home and work location of the mobile phone subscribers on their mobile phone footprint. The accuracy of AMDA reaches 88.7% for home locations and 70.4% for work locations at the regency level. BPS-Statistics Indonesia collaborated with Telkomsel which is the biggest Mobile Network Operator (MNO) in Indonesia with around 60% market share [9]. MNO share anonymised and aggregated mobile positioning data. These data would provide mobility patterns of subscribers and would serve the following purposes in the fight against Covid-19 [2]:

- “understand the dynamics of the Covid-19 daily cases using historical matrices of mobility flows;
- quantify the impact of physical distancing measures (PSBB) on mobility;
- feed models to estimate mobility based on PSBB interventions and daily cases of Covid-19.”

2. DATA

2.1 Mobile Positioning Data (MPD)

Mobile positioning means tracing the location coordinates of mobile phones. There are different frameworks for positioning, for instance, handset-based, network-based, or GPS-based [10]. Mobile positioning has two types that are passive and active positioning. Active mobile positioning is mobile tracing data in which the location of the mobile phone is determined (asked) with a special query using a radio wave. In order to ask about the location of certain phones, a special environment and permit from the phone holder are required. Moreover, passive MPD is automatically stored in the log files (billing memory; hand-over between network cells, home location register, etc.) of the mobile operator [11]. The easiest method for passive mobile positioning is a ‘billing log” that is recorded for called activities. Any active use of a mobile phone (call and SMS in and out, GPRS, etc.) is deemed to be call activity.

Passive mobile positioning data is normally collected to the precision of network cells. Every cell has a certain geographical coverage area and unique identity code and therefore this method is called Cell ID. Mobile operators can aggregate anonymous geographical data from the log file, such as location points or movement vectors [10]. Thereafter, the subscriber’s location is obtained from the location aggregation of Base Transceiver Station (BTS) [12]. Passive mobile positioning data is used to get the objectives in this research.

Mobile phone data have been used to study mobility patterns in cities. Since home and workplace are the most important places in people’s lives and define the structure and activity patterns of the city, identifying home and work locations is much interesting [13]. The most important step for the application of mobile phone data in official statistics: identifying where someone lives, that is, detecting their home location [14]. Determining the home and work location of subscribers is a crucial thing in mapping human mobility through MPD.

2.2 Daily Mobility Indicators

This study uses the result of AMDA for establishing a daily mobility indicator. The mobility indicator is constructed by the home and work location of subscribers. The Mobility indicator is a data product that aggregates mobile position data in the form of Origin-Destination Matrix (ODM) [2].

Let $\boldsymbol{M}$ is an ODM or home-work location matrix where row is represent location of subscriber's home and column is represent the location of the subscriber's work at 13 regencies in Jabodetabek. The subscribers' movement is recorded between regency so that the sum of the diagonal elements of $\boldsymbol{M}$; tr($\boldsymbol{M}$)= $\sum_{i=1}^{13} m_{i.i} = 0$.

$$\boldsymbol{M} = \begin{vmatrix} m_{1.1} & m_{1.2} & m_{1.3} & m_{1.4} & m_{1.5} & \cdots & m_{1.13} \\ m_{2.1} & m_{2.2} & m_{2.3} & m_{2.4} & m_{2.5} & \cdots & m_{2.13} \\ m_{3.1} & m_{3.2} & m_{3.3} & m_{3.4} & m_{3.5} & \cdots & m_{3.13} \\ m_{4.1} & m_{4.2} & m_{4.3} & m_{4.4} & m_{4.5} & \cdots & m_{4.13} \\ m_{5.1} & m_{5.2} & m_{5.3} & m_{5.4} & m_{5.5} & \cdots & m_{5.13} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ m_{13.1} & m_{13.2} & m_{13.3} & m_{13.4} & m_{13.5} & \cdots & m_{13.13} \end{vmatrix}$$

The average mobility indicator is computed based on formula considering in-flow and out-flow of the population [15]. Mathematically, the mobility indicator is described by formulating sum of internal, inwards, and outwards mobility for the geographic area [2]. Let $\boldsymbol{M}$ is seen as partitioned matrix. A partitioning of matrix $\boldsymbol{M}$ into four submatrices could be indicated symbolically as follows:

$$\boldsymbol{M} = \left|\begin{array}{ccccc|cc} m_{1.1} & m_{1.2} & m_{1.3} & m_{1.4} & m_{1.5} & \cdots & m_{1.13} \\ m_{2.1} & m_{2.2} & m_{2.3} & m_{2.4} & m_{2.5} & \cdots & m_{2.13} \\ m_{3.1} & m_{3.2} & m_{3.3} & m_{3.4} & m_{3.5} & \cdots & m_{3.13} \\ m_{4.1} & m_{4.2} & m_{4.3} & m_{4.4} & m_{4.5} & \cdots & m_{4.13} \\ m_{5.1} & m_{5.2} & m_{5.3} & m_{5.4} & m_{5.5} & \cdots & m_{5.13} \\ \hline \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ m_{13.1} & m_{13.2} & m_{13.3} & m_{13.4} & m_{13.5} & \cdots & m_{13.13} \end{array}\right| = \begin{vmatrix} \boldsymbol{M_{11}} & \boldsymbol{M_{12}} \\ \boldsymbol{M_{21}} & \boldsymbol{M_{22}} \end{vmatrix}$$

where

- $\boldsymbol{M_{11}}$ is matrix describing subscriber's movement within DKI Jakarta Province
- $\boldsymbol{M_{12}}$ is matrix describing subscriber's movement out form DKI Jakarta Province
- $\boldsymbol{M_{21}}$ is matrix describing subscriber's movement in to every regency at DKI Jakarta Province
- $\boldsymbol{M_{22}}$ is matrix describing subscriber's movement in Bodetabek. That matrix is not the scope of this research

The mobility indicator is computed by formula as follows:

$$I_m = \frac{sum(\boldsymbol{M_{11}}) + sum(\boldsymbol{M_{12}}) + sum(\boldsymbol{M_{21}})}{total\ subscriber\ in\ DKI\ Jakarta} x100$$

$$= \frac{\sum_{i=1}^{5}\sum_{j=1}^{5} m_{i.j} + \sum_{i=i}^{5}\sum_{j=6}^{13} m_{i.j} + \sum_{i=6}^{13}\sum_{j=1}^{5} m_{i.j}}{total\ subscriber\ in\ DKI\ Jakarta} x100$$

2.3 Daily Cases Data of Covid-19 in DKI Jakarta

This study uses daily Covid-19 case data in DKI Jakarta which is available on the official website of the DKI Jakarta Provincial Government (corona.jakarta.go.id/id). The period covered was from the 11th March 2020 until 27th October 2020, excluding weekends and national holidays.

The data used is daily Covid-19 case data with a median size for the previous seven days. The median size is used because it takes into account the results of research related to the incubation period of Covid-19. [16] explained that the estimated median incubation period distribution of Covid-19 was 7.76 days (95% confidence interval (CI): 7.02 to 8.53). [17] explained that the median Covid-19 incubation period was 8.3 (90% CI, 7.4 – 9.2) days for all patients, 7.6 (90% CI, 6.7 – 8.6) days for younger adults, and 11.12 (90% CI, 9.0 – 13.5) days for older adults. Moreover, [18] explained that the incubation period of COVID-19 follows a Weibull distribution and has a median of 5.8 days with a bootstrap 95% CI: 5.4–6.7 days. The median incubation period was estimated at 4.0 days (95% CI: 3.5–4.4) for cases aged under 30, 5.8 days (95% CI: 5.6–6.0) for cases aged between 30 and 59, and 7.7 days (95% CI: 6.9–8.4) for cases aged greater than or equal to 60.

3. METHOD

In this section, we are going to introduce Generalized Additive Models (GAMs) which use to fit the data. GAMs are a nonparametric extension of Generalized Linear Models (GLMs) [19]. GAMs are statistical models that can be used to estimate trends as smooth functions of time. GAMs use automatic smoothness selection methods to objectively determine the complexity of the fitted trend, and as formal statistical models, GAMs, allow for potential complex, nonlinear trends, a proper accounting of model uncertainty, and the identification of periods of significant temporal change [20]. GAMs extend GLMs by replacing the linear predictor $\eta = \sum_1^p \beta_j X_j$ with an additive predictor of the form $\eta = \sum_1^p s_j(X_j)$, the $s_j(.)'$s are unspecified functions that are estimated using a scatterplot smoother, in an interative procedure we call the local scoring algorithm [21]. The GAMs replaces $\sum X_j \beta_j$ with $\sum f_j(x_j)$ where f_j is an unspecified ('nonparametric') function, this function is estimated in a flexible manner using a scatterplot smoother and the estimated function $\hat{f}_j(x_j)$ can reveal possible nonlinearities in the effect of the x_j [22].

If $g(.)$ is the link function between μ and the additive predictor then the additive model can be written as

$$g(\mu) = \alpha + \sum_{j=1}^{p} f_j(x_j) \tag{1}$$

We write $g(\mu) = \eta(X)$ and as such express μ as the inverse link function of $\eta: \mu = g^{-1}(\eta)$ [23]. The idea is to specify a basis for each function and choose an appropriate set of basis functions, B_{jt}, so that the j^{th} smooth function can be represented as

$$f_j(x_j) = \sum_{t=1}^{k_j} B_{jt}(x_j)\beta_{jt} \tag{2}$$

where β_{jt} are coefficients to be estimated and k_j is a number of basis function [24]. A basis is a set of functions that collectively span a space of smooths that, we hope, contains the true $f_j(x_j)$ or a close approximation to it. The functions in the basis are known as basis functions, and arise from a basis expansion of a covariate [20].

A crucial step in applying GAMs is to select the appropriate level of the 'smoother' for a predictor [25]. The backfitting algorithm serves a baseline method for estimating $\alpha, f_1, \ldots, f_p$ in the GAMs, regardless of the smoothing method used to estimate $f_j(.)$, the algorithm can be outlined as follows [23]:

1. Contruct initial values $\alpha^0 = g\left(\frac{\sum y_i}{n}\right), f_1^0 = \cdots = f_p^0 = 0$
2. At iteration k, contruct the dependent variable

$$z_i = \eta_i^k + (y_i - \mu_i^k)\left(\frac{\partial \eta_i}{\partial \mu_i}\right)_k \tag{3}$$

Fit a weighted additive model to z_i using weights

$$w_i = \left(\frac{\partial \mu_i}{\partial \eta_i}\right)_k^2 (V_i^k)^{-1} \tag{4}$$

where V_i^k is the variance of y_i at μ_i^k. Use the new estimates $f_1^{k+1} = \cdots = f_p^{k+1}$ to obtain updates η_i^{k+1} and μ_i^{k+1}.

3. Test for convergence
4. Repeat step 2 as necessary.

4. RESULTS

4.1 Pattern of Commuter Rate

Figure 1 shows time varying curve from rate of commuter and rate of daily cases of Covid-19 in DKI Jakarta. Based on Figure 1, at the beginning of the emergence of the Covid-19 cases in DKI Jakarta, it was seen that the mobility of the subscriber in DKI Jakarta was still high, around 17%, or out of 100 subscribers of DKI Jakarta there were 17 people who carried out mobility either between or within of the DKI Jakarta area. However, that condition changed after President Joko Widodo issued a policy for productive activities (work, study, and worship) at home to suppress the spread of the Covid-19 virus. The policy was delivered by the president on March 16, 2020 [26].

Since March 17, 2020 (at Day 4) there has been a significant decline in the commuting rate to the level of 6%. This also happened in line with the increase in daily cases of Covid-19 in DKI Jakarta. Furthermore, the commuting rate increased after day 50 although at the same time there was also an increase in Covid-19 cases. However, the commuting rate again decreased significantly when the level of Covid cases reached the level of 10 cases out of 100,000 residents of DKI Jakarta.

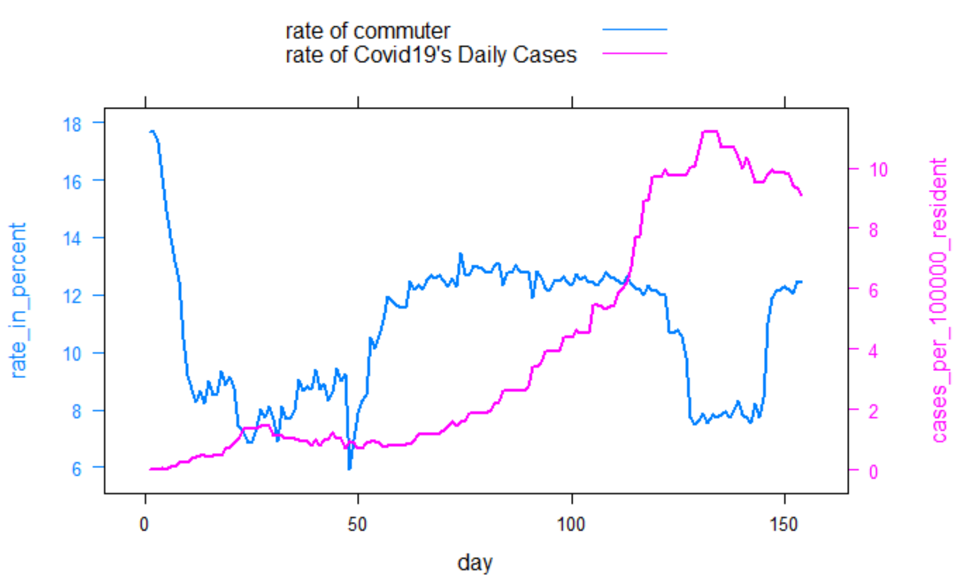

Figure 1. Rate of Commuter and Daily Cases of Covid-19 in DKI Jakarta

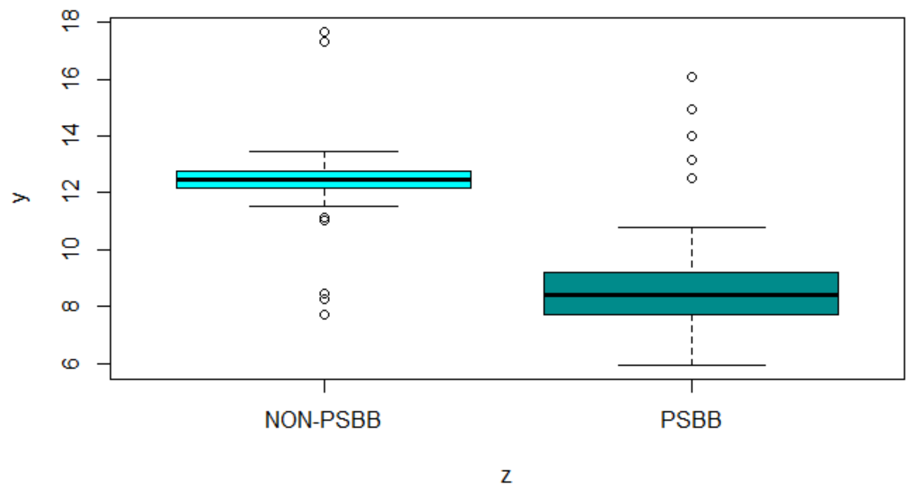

Figure 2. Boxplot of Commuter Rate (y) by Status of PSBB (z) in DKI Jakarta

Figure 2 shows the data distribution of commuter rate by status of PSBB. Based on Figure 2, the median commuter rate during NON-PSBB is around 12%. On the other hand, the median commuter rate during the PSBB is around 8%. This means that there is a decrease in human mobility either between or within when the PSBB policy is implemented in DKI Jakarta.

If we look at all variables simultaneously, it appears that there is no a certain pattern that can describe the relationship between the three variables. Figure 3 shows a nonlinear relationship between Covid-19 cases, status of PSBB, and human mobility as seen from the commuter level.

Based on Figure 3, at the beginning of the Covid-19 pandemic that hit Indonesia, especially DKI Jakarta, there was about one case per 100,000 human and at the same time, there was also a significant decline in the commuting rate, from 18% to 7%, or a decrease of more than 50%. This decline was due to government policies limiting human mobility (PSBB).

Furthermore, humans began to adapt to the conditions of this pandemic along with the easing of human mobility restrictions (NON-PSBB). The return trip rate was up about 12% despite the rising Covid-19 case rate.

The 12% rate continues to hold or is stable even though Covid-19 cases have increased to a level of 9 cases per 100,000 residents. However, this pattern has changed with the re-implementation of the PSBB policy or when the increase in Covid-19 cases was getting higher to the level of more than 10 cases per 100,000 residents. The commuter rate has fallen back to almost the same as conditions at the beginning of the pandemic, namely at a level of around 7%.

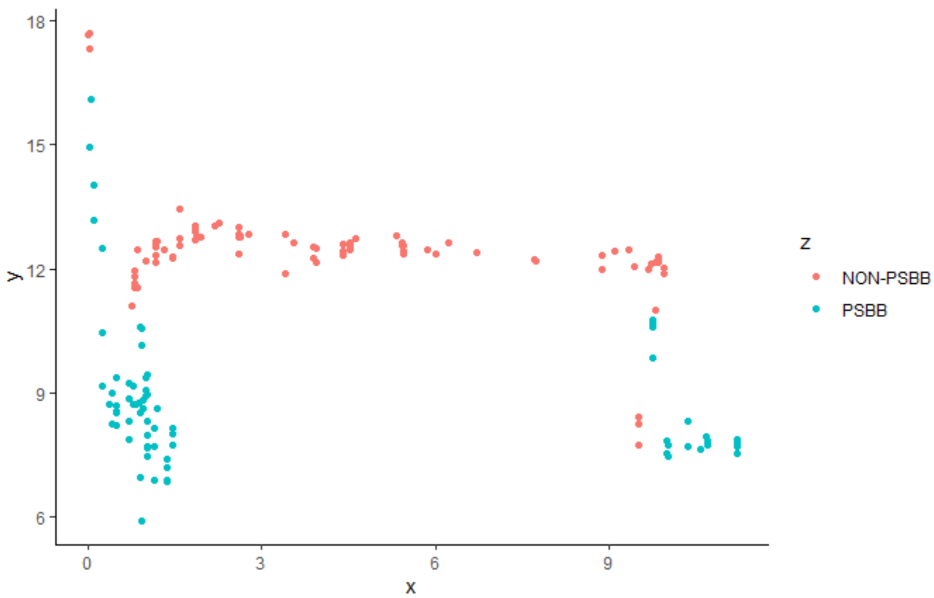

Figure 3. Scatter plot of Commuter Rate (y) and Daily Cases rate of Covid-19 (x) by Status of PSBB (z) in DKI Jakarta

4.2 Generalized Additive Model

In this section, we are going to model the data that has been shown in Figure 3 with model GAMs. The GAMs model is used to predict human mobility (commuter rate) based on PSBB status and daily Covid-19 case rates. Table 1 shows the results of the estimated parameters of the GAMs model. Based on Table 1, both the PSBB status and the daily Covid-19 case rate significantly affect human mobility in DKI Jakarta. This is in line with research that has been carried out related to mobility and Covid-19. We have detected dramatic changes in mobility due to Covid-19, both within the US and globally [27].

If viewed partially, the implementation of the PSBB policy in DKI Jakarta made the average commuter rate decrease by 3.6059 % points (ceteris paribus). Furthermore, the value of edf (effective degrees of freedom) in smooth terms represents the complexity of the smooth. In typical OLS regression the model edf is equivalent to the number of predictors/terms in the model. When viewed from the R-sq value, 79.9% of the variation from the commuter rate is influenced by changes in the PSBB status and the daily rate of Covid-19 cases in DKI Jakarta.

Table 1. Parameter Estimates and Significance

<table>
<tr><td colspan="5">Parametric coefficients:</td></tr>
<tr><td>Variable</td><td>Estimate</td><td>Standard Error</td><td>t value</td><td>Pr(>| t |)</td></tr>
<tr><td>(Intercept)</td><td>12.4493</td><td>0.1418</td><td>87.79</td><td><2e-16</td></tr>
<tr><td>z-PSBB</td><td>-3.6059</td><td>0.2405</td><td>-14.99</td><td><2e-16</td></tr>
<tr><td colspan="5">Approximate significance of smooth terms:</td></tr>
<tr><td>smooth function</td><td>edf</td><td>Ref.df</td><td>F</td><td>p-value</td></tr>
<tr><td>$f(x)$</td><td>8.37</td><td>8.889</td><td>19.9</td><td><2e-16</td></tr>
<tr><td colspan="5">basis function:</td></tr>
<tr><td>B_1:</td><td>-6.4863583</td><td>B_6:</td><td colspan="2">-11.864703</td></tr>
<tr><td>B_2:</td><td>22.5894452</td><td>B_7:</td><td colspan="2">0.9537909</td></tr>
<tr><td>B_3:</td><td>4.3344037</td><td>B_8:</td><td colspan="2">-18.9130478</td></tr>
<tr><td>B_4:</td><td>-15.1338098</td><td>B_9:</td><td colspan="2">-16.4363968</td></tr>
<tr><td>B_5:</td><td>4.4637354</td><td></td><td colspan="2"></td></tr>
<tr><td>R-sq. (adj):</td><td>0.799</td><td>Deviance explained:</td><td colspan="2">81.1%</td></tr>
</table>

Figure 4 shows the predictive value of human mobility (commuter rate) according to daily Covid-19 cases with smooth terms of 8.37. Blue shadows show confidence intervals at the mean value of a commuter rate at the level of certain cases of Covid-19.

Based on Figure 4, the GAM plots when PSBB is applied (the right side) are in a lower position than when PSBB is not applied (the left side). This means that PSBB has a significant impact on human mobility. This is also a supporting fact for Figure 2 which has been described previously.

This plot shows that the commuter rate of a 10 cases per 100,000 residents in DKI Jakarta, when PSBB is not applied, is about 12%, all else being equal. Moreover, the commuter rate of a 10 cases per 100,000 residents in DKI Jakarta, when PSBB is applied, is about 8%, all else being equal. This fact is also in line with previous research in Europe. The indicator of Mobility is used to study the impact of COVID-19 confinement measure on mobility in Europe and It is found that a large proportion of the change in mobility patterns can be explained by these measures [2].

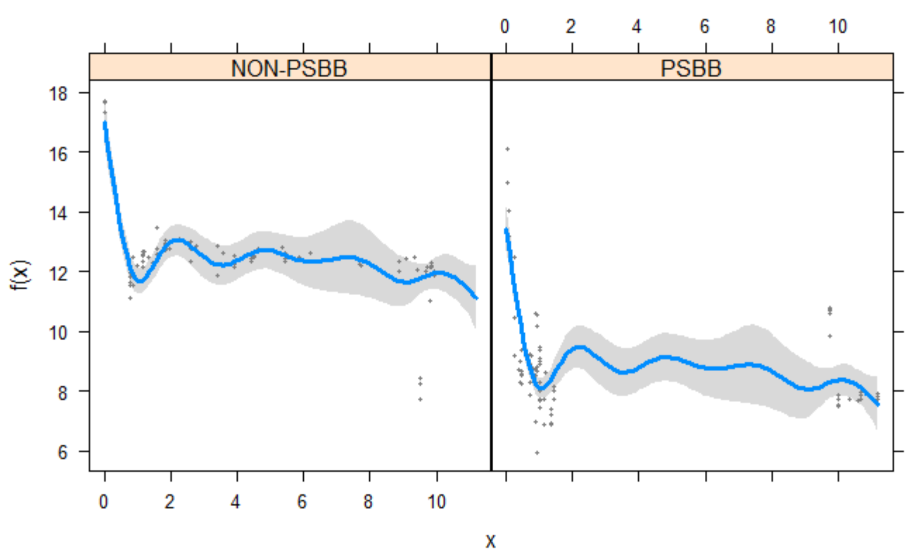

Figure 4. GAMs plot with Standard Errors with Mean

Figure 5 is shown to see the quality of the formed model. Quality is seen from the model residuals. There are four plots in Figure 5. Each of these gives a different way of looking at model residuals. On the top-left is a Q-Q plot, which compares the model residuals to a normal distribution. A well-fit model's residuals will be close to a straight line. On bottom left is a histogram of residuals. We would expect this to have a symmetrical bell shape. On top-right is a plot of residual values. These should be evenly distributed around zero. Finally, on the bottom-right is plot of response against fitted values. A perfect model would form a straight line. We don't expect a perfect model, but we do expect the pattern to cluster around the 1-to-1 line. Based on Figure 5, the model formed is quite good with the criteria of a Q-Q plot that is close to a straight line and a histogram of residuals, most of which are close to zero.

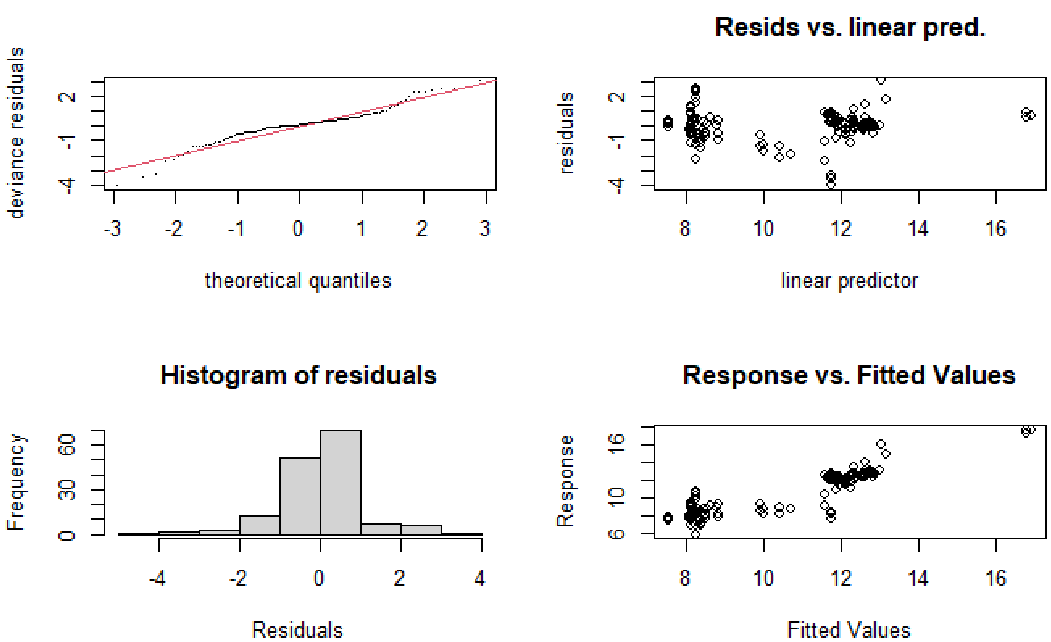

Figure 5. GAMs residuals

5. CONCLUSION

The study describes a mobility indicator based on anonymized and aggregated mobile positioning data. The indicator is then used to assess the impact on mobility based on the daily cases of Covid-19 and physical distancing interventions (PSBB) in DKI Jakarta. This later analysis shows that the daily cases of Covid-19 and (PSBB) explain up to 79.9% of the mobility patterns. Moreover, PSBB significantly reduces the level of mobility by around 3.6%. This study can be expanded to other areas of observation because mobile positioning data is also available for other regencies in Indonesia.

CONFLICT OF INTERESTS

The author(s) declare that there is no conflict of interests.

REFERENCES

[1] J.D.G. Ankamah, E. Okyere, S.T. Appiah, S. Nana-Kyere, Nonlinear dynamics of COVID-19 SEIR infection model with optimal control analysis, Commun. Math. Biol. Neurosci. 2021 (2021), Article ID 13. https://doi.org/10.28919/cmbn/5095.

[2] C. Santamaria, F. Sermi, S. Spyratos, S.M. Iacus, A. Annunziato, D. Tarchi, M. Vespe, Measuring the impact of COVID-19 confinement measures on human mobility using mobile positioning data. A European regional analysis, Safe. Sci. 132 (2020), 104925. https://doi.org/10.1016/j.ssci.2020.104925.

[3] R. Baldwin, B. Weder, Economics in the time of Covid-19, Centre for Economic Policy Research Press, 2020.

[4] World Health Organization, Novel coronavirus (2019-nCoV) situation reports, Mar. 2020.

[5] P. Nouvellet, S. Bhatia, A. Cori, et al. Reduction in mobility and COVID-19 transmission, Nat. Commun. 12 (2021), 1090. https://doi.org/10.1038/s41467-021-21358-2.

[6] M.S. Andersen, A.I. Bento, A. Basu, et al. College openings in the united states increased mobility and COVID-19 incidence, medRxiv 2020.09.22.20196048, (2020). https://doi.org/10.1101/2020.09.22.20196048.

[7] R. Pérez-Arnal, D. Conesa, S. Alvarez-Napagao, et al. Comparative analysis of geolocation information through mobile-devices under different COVID-19 mobility restriction patterns in Spain, Int. J. Geo-Inf. 10 (2021), 73. https://doi.org/10.3390/ijgi10020073.

[8] BPS, Statistics of Jabodetabek commuter; Result of Jabodetabek commuter survey 2019. Jakarta: BPS.

[9] A.R.S. Nugroho, A.R.M.N.S.P. Munaf, et al., Home and work identification process using mobile positioning data. Conference of European Statisticians, Expert Meeting on Statistical Data Collections, 27 – 30 September 2021.

[10] R. Ahas, S. Silm, O. Järv, E. Saluveer, M. Tiru, Using mobile positioning data to model locations meaningful to users of mobile phones, J. Urban Technol. 17 (2010), 3–27. https://doi.org/10.1080/10630731003597306.

[11] R. Ahas, A. Aasa, A. Roose, Ü. Mark, S. Silm, Evaluating passive mobile positioning data for tourism surveys: An Estonian case study, Tourism Manage. 29 (2008) 469–486. https://doi.org/10.1016/j.tourman.2007.05.014.

[12] P.D. Prabawa, H.T. Soblia, et al., The use of mobile positioning data (MPD) to delineate metropolitan area in Indonesia: Case study in Cekungan Bandung. 2020 Asia-Pacific Statistics Week, 15 – 19 June 2020.

[13] L. Tongsinoot, V. Muangsin, Exploring Home and Work Locations in a City from Mobile Phone Data, in: 2017 IEEE 19th International Conference on High Performance Computing and Communications; IEEE 15th International Conference on Smart City; IEEE 3rd International Conference on Data Science and Systems (HPCC/SmartCity/DSS), IEEE, Bangkok, 2017: pp. 123–129. https://doi.org/10.1109/HPCC-SmartCity-DSS.2017.16.

[14] M. Vanhoof, F. Reis, T. Ploetz, Z. Smoreda, Assessing the quality of home detection from mobile phone data for official statistics, J. Official Stat. 34 (2018), 935–960. https://doi.org/10.2478/jos-2018-0046.

[15] N. Zamyatina, R. Goncharov, Population mobility and the contrasts between cities in the Russian Arctic and their southern Russian counterparts, Area Develop. Policy. 3 (2018) 293–308. https://doi.org/10.1080/23792949.2018.1500863.

[16] J. Qin, C. You, Q. Lin, T. Hu, S. Yu, X.-H. Zhou, Estimation of incubation period distribution of COVID-19 using disease onset forward time: A novel cross-sectional and forward follow-up study, Sci. Adv. 6 (2020), eabc1202. https://doi.org/10.1126/sciadv.abc1202.

[17] T. Kong, Longer incubation period of coronavirus disease 2019 (COVID‐19) in older adults, Aging Med. 3 (2020), 102‐109. https://doi.org/10.1002/agm2.12114.

[18] J. Dai, L. Yang, J. Zhao, Probable longer incubation period for elderly COVID-19 cases: Analysis of 180 contact tracing data in Hubei Province, China, Risk Manag. Healthc. Policy. 13 (2020), 1111–1117. https://doi.org/10.2147/RMHP.S257907.

[19] T.W. Yee, N.D. Mitchell, Generalized additive models in plant ecology, J. Veget. Sci. 2 (1991) 587–602. https://doi.org/10.2307/3236170.

[20] G.L. Simpson, Modelling palaeoecological time series using generalised additive models, Front. Ecol. Evol. 6 (2018), 149. https://doi.org/10.3389/fevo.2018.00149.

[21] T. Hastie, R. Tibshirani, Generalized additive models, Stat. Sci. 1 (1986), 297-310. https://doi.org/10.1214/ss/1177013604.

[22] T. Hastie, R. Tibshirani, Generalized additive models for medical research, Stat. Meth. Med. Res. 4 (1995), 187–

196. https://doi.org/10.1177/096228029500400302.

[23] J.M. Grego, Generalized additive models, in: A.H. El‐Shaarawi, W.W. Piegorsch (Eds.), Encyclopedia of Environmetrics, 1st ed., Wiley, 2012. https://doi.org/10.1002/9780470057339.vag007.pub2.

[24] N. Pya, S.N. Wood, A note on basis dimension selection in generalized additive modelling, ArXiv:1602.06696 [Stat]. (2016). http://arxiv.org/abs/1602.06696.

[25] A. Guisan, T.C. Edwards, T. Hastie, Generalized linear and generalized additive models in studies of species distributions: setting the scene, Ecol. Model. 157 (2002), 89–100. https://doi.org/10.1016/S0304-3800(02)00204-1.

[26] Kompas. (2020). https://nasional.kompas.com/read/2020/03/16/15454571/jokowi-kerja-dari-rumah-belajar-dari-rumah-ibadah-di-rumah-perlu-digencarkan?page=all

[27] M.S. Warren, S.W. Skillman, Mobility changes in response to COVID-19, ArXiv:2003.14228 [Cs]. (2020). http://arxiv.org/abs/2003.14228.