Robust and Non-Robust Analysis of Semivariogran Isotropic in Crime Data by Changing Sill, Case Study: Bandung's Theft Data

K.N. Sari, U.S. Pasaribu, and R. Trismayangsari

***Abstract*—Research in criminality is sufficiently developed but mathematical statistics analysis has little role in this field. In Indonesia, this research is mostly done in descriptive statistics and simple modeling. The population development has an effect on social and economy. Consequently, the crime rate increases with the compliance of people's living needs. In this research, we focus on analyzing criminal loss caused by theft. The loss is modeled by an isotropic semivariogram model. Here, we consider the non-robust Matheron model and the robust Cressie-Hawkins and Dowd models to analyze semivariogram of the crime. The best model is determined from the variance of loss and statistics of experimental semivariogram such as mean, first quartile, median, and third quartile. Data with enough high loss has candidate of sill that is first and third quartile of experimental semivariogram. We apply the analysis to Bandung's theft data and corresponding model is exponential with a range of 4.45 kilometers. Through this model, we can predict theft having significant losses at the range of 4.45 kilometers. This information can be a recommendation for the police to raise awareness for locations around 4.45 kilometers from the location of theft.**

***Index Terms*—Cressie-Hawkins, Crime, Dowd, Loss Value, Matheron, Range, Sill, Theft**

I. Introduction

A crime is defined as an act that breaches the criminal laws of an authority (such as a state or country). Crimes can be carried out against individuals, organizations, the state or involve the destruction of property [1]. Everyone has the same chance to experience the consequences of a crime such as theft. The necessities of life that must be obtained and the difficulty of getting job make some people will do anything even to commit a crime. Crime is one of interesting social problems to discussed and studied further. It is proved by there were some researches about crime since 19 century. In 1983, Guerry analyzed the distribution of crimes according to the poverty, the lack in education and the density of population of the departments but he concluded that these variables are not directly causes of crime occurrence [2]. Moreover, there are some researches about crimes used some method such as variogram, Poisson Kriging, self-exciting point, fuzzy time series, time series modeling, spatial model, regression, and binomial negative.

Car-related thefts in Estonia, Latvia, and Lithuania in 2000 was analyzed used variogram to inform about the scales of variation in offense, social, and economic data. Area-to-area and Area-to-point Possion Kriging were used to filter the noise caused by the small number problem [3]. In 2011, Mohler *et al*. proposed self-exciting point processes can be adapted for the purpose of crime modeling and were well suited to capture the spatial-temporal clustering patterns observed in crime data. The results of their research was illustrated how crime hotspot maps can be improved using the self-exciting point process framework [4]. Shrivastav and Ekata used fuzzy time series for forecasting of crime. Here, the historical data of crime incidents (cases of murder in Delhi City) was used to build an test their model. This model could be used as a tool for effective crime prevention strategies [5]. They also modeled historical crime data for forecasting of crime in India. The result show that ARIMA(1,1,1) was the best model [6]. In 2015, spatial with GIS techniques was used to analyze factor responsible for spread of crime activities in Akure, Nigeria. GIS technique is a tool for detecting crime pattern, occurrence, prediction, and commensurate measures [7]. In Indonesia, the research of crime had not developed yet, the data of crime only explore by showing the descriptive statistics so the historical crime data have been explored optimally. Development of mathematical statistics also have not role much in crime analysis. In Bandar Lampung, the crime rate based on the police department's record is presented by a quantitative approach (2007-2011). The peak of crime rate reached 24.2 in 2009. The crime rate of theft had a fairly crime rate compared to other types of crimes such as: murder, fraud, torture, gambling, extortion, and rape [8]. Meanwhile, Delia analyzed causes of fear of crime on theft case among housewives. She used regression to determine four factors that caused the fear of crime. Those factors were knowledge about

Manuscript received November 1, 2019. This research was supported in part by the Programme of Research and Community Service (P3MI) for Institut Technology Bandung in 2019.

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crime, vulnerability becomes victim of crime, the state of the neighborhood, and perseption of law system. The Regression model represented that these four factors significantly influence with fit model of 54.2% [9].

In this research, spatial analysis is used to explore Bandung's theft data. Bandung is the capital of West Java province in Indonesia. Since the Dutch colonial period, Bandung has strong link and economic dependence with Jakarta, the capital of Indonesia. As the population grew, Bandung became a tourist destination and an exclusive resort area for plantation owners and business people from Batavia. This introduces the first wave of cultural industry in the city with the European lifestyle cafes, restaurants, shops, and art-deco hotels. This led to Bandung being named "Paris van Java" [10]. Moreover, Bandung is one of the most populated cities in the world, especially: Cicadas, Kiaracondong, and Bandung kulon. The density of population reached 13,000 per square kilometers. The map of West Java province, Indonesia is presented in the Fig. 1. The population development has an effect on social and economy. Consequently, the crime rate increases with the compliance of the people's living needs. One of the most common crime types in the city is theft.

Fig. 1. The map of Bandung city as the capital of West Java Prvince.

Locations of theft in Bandung have a relationship and affect each others. The relationship between location of crime can be described by semivariogram model. A random variable for this case is loss value that caused by theft. The goal of this research is to determine the best model that represent the spread of loss value. This model is expected to provide an overview the spread of crime and give recomendation for police to develop a strategy for prevention the crime in the near future. The main problem is estimating the parameter model semivariogram and using robust and non-robust semivariogram model that match with characteristics of the data.

The organization of the paper as follow: we present a non-robust Matheron model in Section II part A. The two robust models Cressie-Hawkins and Dowd are explained in Section II part B. We apply the above models to Bandung's theft data as given in Section III.

II. Semivariogram Modeling

A. Non-robust Semivariogram

Let $\{Z(s_1), Z(s_2), ..., Z(s_n)\}$ be a sequence of random variables with loss locations $\{s_i, s_i \in D \subseteq R^m\}$ where m is dimensional space. The spatial relationship between those random variables can be described by a variance of the difference between pair of locations that separated by h. The variance is called semivariogram and can be written as

$$\gamma(h) = \mathbf{Var}\left[Z(s_i+h)-Z(s_i)\right] = \frac{1}{2}\mathbf{E}\left[Z(s_i+h)-Z(s_i)\right]^2 \qquad (1)$$

If the realization of $Z(s_i)$, $i = 1,2,...,n$ are available then experimental semivariogram $\hat{\gamma}(h)$ can be calculated. In 1965, Matheron formulated

$$\hat{\gamma}(h) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)}\left[z(s_i+h)-z(s_i)\right]^2 \qquad (2)$$

where $z(s_i)$ and $z(s_i+h)$ are a value of location s_i and s_i+h respectively and $N(h)$ is the number of location pairs that separated by h. This estimator is unbiased but not robust. Genton (1998) points out that the Matheron estimator has a null breakdown point and an unbounded influence function. Notice that nowdays the robustness of an estimator is often evaluated through its breakdown point and its influence function [11].

That $\hat{\gamma}(h)$ can be fitted by several semivariogram models. There are ten models such as: nugget effect, spherical, exponential, power functions, Gaussian, cubic, hole effect, cardinal sine, prismato-magnetic, and prismato-gravimetric [12]. However, this paper uses the three semivariogram models: exponential, Gauss, and cubic. Semivariogram of the exponential model is given by

$$\hat{\gamma}(h) = C_0 + C\left(1-\exp\left(-\frac{h}{a}\right)\right) \qquad (3)$$

where C_0, C, and a are parameters model.

This model is commonly used in mining because its infinite range is associated with a continuous process [13]. However, this model is widely applied in hydrology [14]. For example in mining, this model was used to observe spatial correlations of uranium deposits in Novazza, Italy. Brallier and Chemung also modeled the potential gas production produced by 1216 gas wells from rock and sandstone deposits in Devonian, Barbour, West Virginia by an exponential model [15]. In hydrology, this model can describe the water content in wells with a certain depth on the aquifers of Santa Peter's sandstone and Mount Simon in Northern Illinois [16].

Semivariogram of Gauss model is given by

$$\hat{\gamma}(h) = C_0 + C\left(1 - \exp\left(-\left(\frac{h}{a}\right)^2\right)\right) \tag{4}$$

where C_0, C, and a are parameters model.

This model has a tendency of parabolic behavior for the semivariogram value around the origin point (h = 0). This indicates that the regional variable has quite a small difference. Gauss models are widely used in petroleum geostatistics. While semivariogram of cubic model is given by

$$\hat{\gamma}(h) = \begin{cases} C_0 + C\left(7\left(\frac{h}{a}\right)^2 - 8.75\left(\frac{h}{a}\right)^3 + 3.5\left(\frac{h}{a}\right)^5 - 0.75\left(\frac{h}{a}\right)^7\right), h \le a \\ C_0 + C \qquad , h > a \end{cases} \tag{5}$$

The equation of this model is similar to the spherical model. The characteristic of this model is the rapid rise of the semivariogram value for close range parameter, then flat for farter distance from the range. This model can represent spatial correlations of metal deposits, such as iron and bauxite deposits in France, uranium deposits in Canada, copper deposits in Chile, laterite nickel deposits in New Caledonia, phosphate in Africa, and gold deposits in South Africa [13].

All models always have three parameters say C_0 (nugget effect), C (partial sill), and a (range). In practice, C_0+C is a constant value for semivariogram where there is no correlation between two separation locations, a represents maximum h where two separation locations still have spatial correlation, while C_0 represents microvariability in addition to random measurement error [17]. Thereafter, C_0+C and a are estimated by least square method. The best estimator obtained by minimize Sum Square of Error (SSE) between experimental and the semivariogram model. The best model was chosen based on the minimum of SSE.

Based on semivariogram model, we can estimate the value of an unobserved location by Kriging. The value of that location is formulated by linear combination of all observed location. Equation of Kriging can be written as

$$\hat{Z}(s_0) = \sum_{i=1}^{n} \lambda_i Z(s_i) \tag{6}$$

where s_0 and s_i are unobserved and observed location respectively, $Z(s_i)$ is random variable in i location and λ_i is Kriging weight on i location. In addition to estimate unobserved location, Kriging also used to validate the semivariogram model. One of method that used is Jacknife Kriging. This method was done by take one observed location and estimated the value and repeat the steps until all observations were estimated. Therefore, SSE Kriging $\sum_{i=1}^{n}(z(s_i) - \hat{z}(s_i))^2$ is calculated for determining the best semivariogram model.

B. Robust Semivariogram

There are two robust estimator for semivariogram will used in this papers that are Cressie-Hawkins and Dowd estimator. Formulation of Cressie-Hawkins is

$$\hat{\gamma}_{CH}(h) = \frac{1}{2}\frac{1}{(N(h))^4}\frac{1}{Ch}\left(\sum_{i=1}^{N(h)} \left|z(s_i + h) - z(s_i)\right|^{1/2}\right)^4 \tag{7}$$

where $Ch = 0.457 + \frac{0.4941}{N(h)} + \frac{0.045}{N(h)}$. Using the set of power transformations proposed by Box and Cox, Cressie-Hawkins found that the fourth root of χ_1^2 has a skewness and kurtosis 0.08 and 2.48 respectively (compared with 0 and 3 for the Gaussian or normal distribution). Formulation of Dowd is

$$\hat{\gamma}_D(h) = \frac{2.198}{2}\left(\textbf{median}\left(\left|z(s_i + h) - z(s_i)\right|\right)\right)^2 \tag{8}$$

Median can be applied to transformed differences location to bring them back to the correct scale and adjusted for bias. Beside that median is ordered statistics that robust with value is too big or small [18].

III. Case Study

The theft data obtained from *Kasat Reskrim Polrestabes* Bandung. There are fourteen thefts from March, 4-10 in 2016. The locations of the theft divided three Bandung's regions that are West, East and Central. Loss value that caused by theft is 21% above 100 million rupiah and 79% between 2-100 million rupiah. The procedure to analyze the data is shown at the flowchart in the Fig. 2. This figure explain the step to find best model of three semivariogram approaches and Kriging method.

From the Fig. 3 seen that the theft happened in East and Central Bandung. There are two thefts in East Bandung and others in Central Bandung. It shows that Central Bandung has rate of crime rate is higher than others. The distribution of theft is shows in the Fig. 3. While, the descriptive statistic of loss value that caused by theft is described in the Table 1. From the Table 1, mean of loss value in this case around 33 million rupiah. While, the variance of loss value is very large with the difference between minimum and maximum value is 113 million rupiah. The Fig. 4(a) show that there is not outlier but it can be said the variability of loss wide enough. It conduce the distribution is not symmetry as seen in the skewness value. Positive skewness means almost all of the data has small value. Negative kurtosis shows that the data has heterogeneous of loss value.

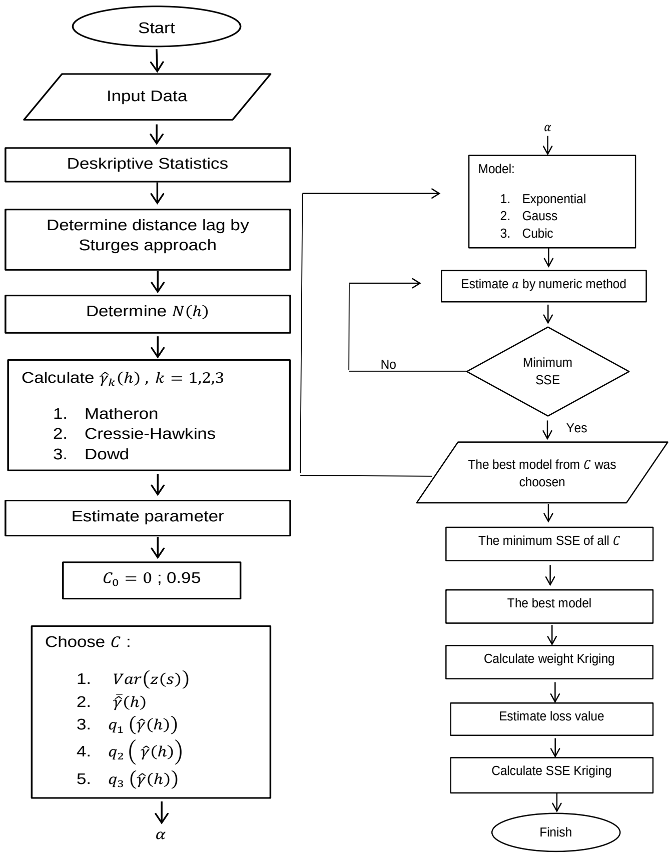


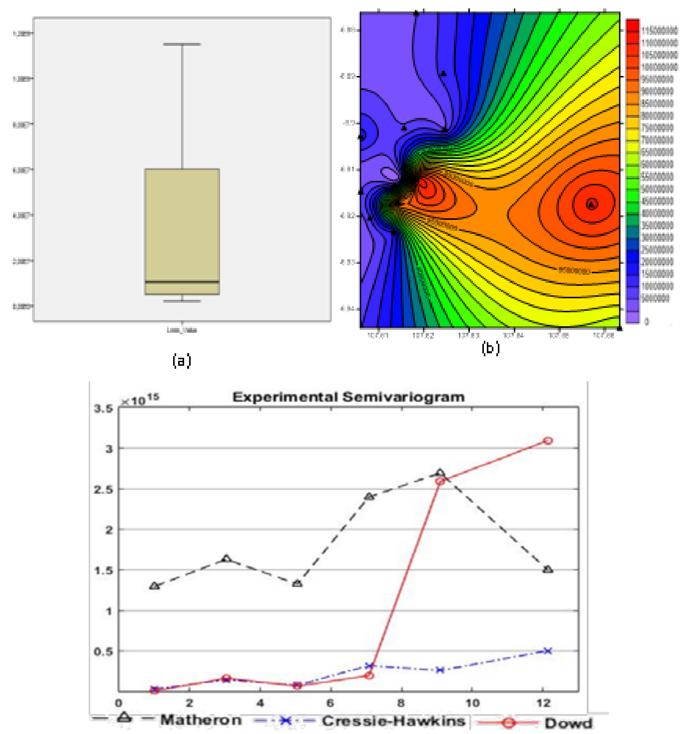
Fig. 2. Flowchart to find best model of three semivariogram approaches and Kriging method.

Fig. 3. Thefts location in Bandung. There are two symbols that have meanings theft in Central and East Bandung respectively. The circle mean the highest of loss value.

The contour map shows that there is a directional influence on the loss value. The highest loss is located in East Bandung. Therefore, the loss value decreases to the west direction. There are two locations have the higest value of loss. That locations are showed by red colour in the legend.

TABLE I
DESCRIPTIVE STATISTICS OF LOSS

Central Data (x10^6)		Variability Data (x10^6)	
Minimum	2	Sum	469
25th percentile (q_1)	4.96	Range	113
50th percentile (q_2)	10.5	Variance	36,020,000
Mean	33.477	Std.Deviation	43.506
75th percentile (q_3)	70.110	Skewness	1.263x10^{-6}
Maximum	115	Kurtosis	-0.178x10^{-6}



(c)

Fig. 4. (a) The box-plot of loss value, (b) The contour map of loss value with the horizontal and vertical axis are coordinate of location, and (c) The experimental semivariogram with the horizontal axis is lag distance h and the vertical axis is $\hat{\gamma}(h)$. The experimental semivariogram $\hat{\gamma}(h)$ are making by three approaches (Matheron, Cressie-Hawkins, and Dowd).

From Fig. 4(c), there are three semivariogram approaches that will used to model loss value as described above. Those approaches are used because the data has some big loss value. The Fig. 4(c) shows that the three semivariograms has the same pattern from lag one until lag four. Although scale of $\hat{\gamma}_M(h)$ quite different than the others semivariogram. There is something unique from $\hat{\gamma}_D(h)$ on two last lags. There is a significant increment from lag four to six. It causes the semivariogram does not look stationary. Here, $\hat{\gamma}_{CH}(h)$ look stationary than the others semivariogram.

After $\hat{\gamma}(h)$ is obtained, several semivariogram models can be fitted to $\hat{\gamma}(h)$. First, the parameters of models must be estimated. There are some candidate of C such as $Var(z(s))$

(c)

and statistic of $\hat{\gamma}(h)$. The statistics of $\hat{\gamma}(h)$ are $\bar{\hat{\gamma}}(h)$, $q_1(\hat{\gamma}(h))$, $q_2(\hat{\gamma}(h))$, and $q_3(\hat{\gamma}(h))$. The results of estimator for each parameter are presented in TABLE II. In the TABLE II(a) shows that only $\hat{\gamma}_M(h)$ has $C_0 \neq 0$. This appropriate with the graphic of $\hat{\gamma}(h)$ which begin not in zero value. In $\hat{\gamma}_M(h)$, sill, range, and SSE are directly proportional for each model. The smaller value of sill has the closer range estimates compared to the others. Selection of the best model is based on the minimum of SSE. Therefore, $q_1(\hat{\gamma}(h))$ was chosen as the sill value. From that parameter, there are two models which has minimum SSE. The best models are exponential and cubic. However, the best model for $\hat{\gamma}_M(h)$ is exponential. This model has the simplest equation. Also, the SSE of exponential and cubic models are not much different. Then, the best model of $\hat{\gamma}_M(h)$ is

$$\hat{\gamma}_M(h) = 9.5\times10^{14} + 1.3139\times10^{14}\left(1-\exp\left(-\frac{h}{4.45}\right)\right) \tag{9}$$

In the TABLE II(b) and (c) show that value of sill and range are directly proportional but the SEE value is the opposite. The smaller of sill value result the highest of SSE value. So, the value of $q_3(\hat{\gamma}(h))$ for C is minimizing the SSE of both semivariograms. Based on the minimum of SSE, the model for $\hat{\gamma}_{CH}(h)$ is the same with $\hat{\gamma}_M(h)$. For the same reason, the best model $\hat{\gamma}_D(h)$ is Gauss. Finally, the model of $\hat{\gamma}_{CH}(h)$ and $\hat{\gamma}_D(h)$ are

$$\hat{\gamma}_{CH}(h) = 3.6110\times10^{14}\left(1-\exp\left(-\frac{h}{5.75}\right)\right) \tag{10}$$

$$\hat{\gamma}_D(h) = 2.7106\times10^{15}\left(1-\exp\left(-\left(\frac{h}{8.9}\right)^2\right)\right) \tag{11}$$

TABLE II
THE MODEL RESULTS OF EXPERIMENTAL SEMIVARIOGRAM BY CHANGING SILL VALUEE OF $\hat{\gamma}(h)$ FOR EACH APPROCHES; (A) MATHERON, (B) CRESSIE-HAWKINS, AND (C) DOWD

No	Model	C_0 (x10^15)	C (x10^15)	a	SSE (x10^30)
1	Exp	0.95	$Var(z(s))$ 1.8930	9.50	1.4108
	Gauss			8.00	1.9772
	Cubic			19.85	2.0241
2	Exp		$q_1(\hat{\gamma}(h))$ 1.3139	4.45	1.2501**
	Gauss			4.80	1.2714
	Cubic			11.5	1.2378*
3	Exp		$\bar{\hat{\gamma}}(h)$ 1.8032	8.70	1.3895
	Gauss			7.30	1.8657
	Cubic			17.75	1.9229
4	Exp		$q_2(\hat{\gamma}(h))$ 1.5618	6.55	1.3227
	Gauss			5.80	1.5271
	Cubic			13.35	1.5290
5	Exp		$q_3(\hat{\gamma}(h))$ 2.4677	14.55	1.5100
	Gauss			11.60	2.3863
	Cubic			28.15	2.3420

(a)

No	Model	C_0	C (x10^15)	A	SSE (x10^30)
1	Exp	0	$q_1(\hat{\gamma}(h))$ 0.0610	0.75	0.3000
	Gauss			1.25	0.3000
	Cubic			3.15	0.3000
2	Exp		$\bar{\hat{\gamma}}(h)$ 0.2178	2.8	0.1090
	Gauss			4.05	0.1200
	Cubic			9.95	0.1030
3	Exp		$q_2(\hat{\gamma}(h))$ 0.1974	2.45	0.1230
	Gauss			3.65	0.1200
	Cubic			9.25	0.1190
4	Exp		$q_3(\hat{\gamma}(h))$ 0.3611	5.75	0.0570**
	Gauss			6.35	0.0420
	Cubic			15.40	0.0410*

(b)

No	Model	C_0	C (x10^15)	a	SSE (x10^30)
1	Exp	0	$q_1(\hat{\gamma}(h))$ 0.0481	0.80	15.7050
	Gauss			1.40	15.7040
	Cubic			3.55	15.7040
2	Exp		$\bar{\hat{\gamma}}(h)$ 1.0145	3.75	8.3610
	Gauss			5.60	7.6800
	Cubic			13.70	7.5900
3	Exp		$q_2(\hat{\gamma}(h))$ 0.1742	1.50	14.1317
	Gauss			2.85	14.3100
	Cubic			9.25	14.3100
4	Exp		$q_3(\hat{\gamma}(h))$ 2.7106	10.50	5.1170
	Gauss			8.90	2.9790**
	Cubic			21.00	2.9810

(c)

**) model is chosen
*) model with the minimum SSE

The model and parameters of three semivariograms are presented in TABLE III. It shows that $\hat{\gamma}_{CH}(h)$ and $\hat{\gamma}_M(h)$ almost have the same value of range than $\hat{\gamma}_D(h)$. Furthermore, $\hat{\gamma}_M(h)$ and $\hat{\gamma}_D(h)$ also have similar value of C and SSE. There are something unique between $\hat{\gamma}_{CH}(h)$ and $\hat{\gamma}_D(h)$. Both of models have different C, a, and SSE value but similar SSE Kriging value. In the Fig. 5, the graph of $\hat{\gamma}_M(h)$

and the model are not really appropiate. The model is appropiate on first and second of distance lags. This characteristic is similar to $\hat{\gamma}_D(h)$. The semivariogram value of two last lag on $\hat{\gamma}_D(h)$ increase so the model is trying reach that values. It result two lags in the middle have quite gap between $\hat{\gamma}_D(h)$ and the model. Of the three graphs, $\hat{\gamma}_{CH}(h)$ and the model looks more appropiate visually. The difference between the model and $\hat{\gamma}_{CH}(h)$ is not too much different. The selection of a good semivariogram approach can be seen from the data characteristics.

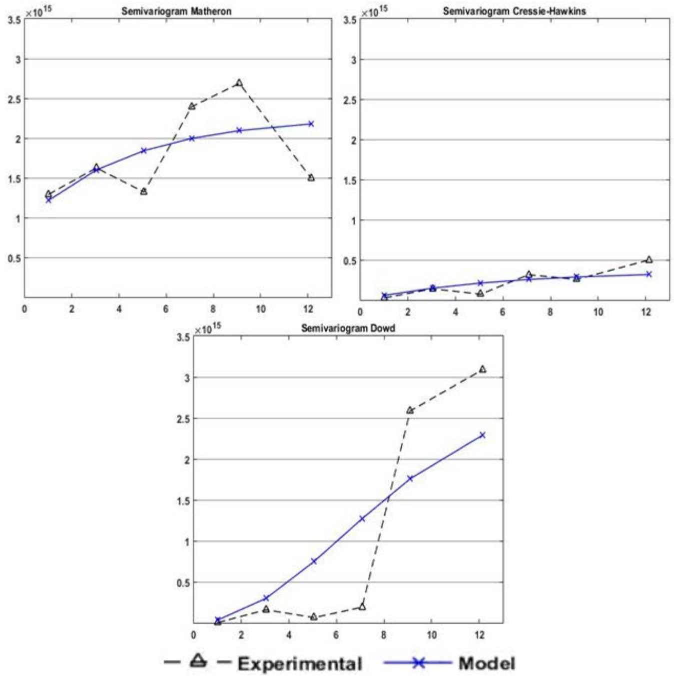


Fig. 5. The semivariogram model of Matheron, Cressie-Hawkins, and Dowd. The selected model is fitted to experimental semivariogram respectively. The horizontal axis is lag distance (*h*) and the vertical axis is semivariogram value.

TABLE III
THE BEST MODEL OF SEMIVARIOGRAM MATHERON, CRESSIE-HAWKINS, AND DOWD WITH THE PARAMETERS VALUE AND SSE KRIGING

Semiv.	Model	C_0 (x10^{15})	C (x10^{15})	a	SSE (x10^{30})	SSE Kriging (x10^{17})
Matheron	Exp	0.95	1.3139	4.45	1.2501	2.8729
CH		0	0.3611	5.75	0.0570	22.3890
Dowd	Gauss		2.7106	8.90	2.9790	22.1800

From the TABLE III, the estimator of C for each semivariogram are 25th percentile and 75th percentile. The results of range parameter reach 4.45 until 8.90 kilometers. This parameters show the influence area of theft.

IV. DISCUSSION AND CONCLUSION

The parameter C for loss value data of $\hat{\gamma}_M(h)$ is $q_1(\hat{\gamma}(h)) = 1.3139 \times 10^{15}$ and a reaches 4.45 kilometers. While, the parameter C for $\hat{\gamma}_{CH}(h)$ and $\hat{\gamma}_D(h)$ are $q_3(\hat{\gamma}(h))$. That value are 0.3611×10^{15} and 2.7106×10^{15} respectively. The value of a for both semivariograms respectively are 5.75 and 8.9 kilometers. The best semivariogram models for the data of thefts are exponential and Gauss. This models have more simpler form then cubic model. From the three parameters, a give the important information for the distance range of the theft. In this case radius of a around 5 kilometers. That means the theft with the same value of loss can be occurs within radius of 5 kilometers.

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