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A Spatial Analysis of Subgrade Density Value of Cisumdawu Hihgway (KM 10+700 – 12+000)

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ABSTRACT

Uniformity of subgrade density value is very necessary, including in Cisumdawu highway. Spatial analysis with geostatistical computation was applied to predict and map subgrade density value. Geostatistical method used was kriging method based on semivariogram model. The data collected were a sandcone test from 2 zones of dry density value at last layer of compaction. Results of spatial measurements showed that existing values have spatial correlation with diversity influenced by distance and type of distribution, also direction of data distribution from subsgrade density. Zone 1 reached level of compatibility of 99.5% and Zone 2 of 99.4%. Mapping value of subgrade density was influenced by normal data distribution, distance between samples and spread pattern. Selection of semivariogram model showed standard deviation value in zone 1 of 0.0025 and zone 2 of 0.004, it indicates accuracy could meet confidence level of 95%. This result was expected to provide accurate evaluation of subgrade compaction work.

Keywords: *Subgrade density, spatial variability, geostatistic, kriging*

ABSTRAK

Keseragaman nilai kepadatan tanah dasar sangat diperlukan dalam memenuhi kriteria perkerasan jalan, khususnya jalan bebas hambatan Cisumdawu. Analisis spasial dengan pendekatan geostatistika digunakan untuk memprediksi dan memetakan nilai kepadatan tanah dasar. Metode geostatistika yang digunakan adalah metode kriging berdasarkan model semivariogram. Data yang digunakan adalah data hasil uji sandcone pada 2 zona nilai kepadatan kering pada lapisan terakhir pemadatan. Hasil analisis spasial menunjukkan bahwa nilai kepadatan memiliki korelasi spasial dengan keragaman yang dipengaruhi jarak dan tipe sebaran, serta arah sebaran data kepadatan tanah dasar. Zona 1 mencapai tingkat kecocokan sebesar 99,5% dan zona 2 sebesar 99,4%. Pemetaan nilai kepadatan tanah dasar dipengaruhi oleh data yang terdistribusi normal, jarak antar sampel dan pola penyebarannya. Pemilihan model semivariogram memberikan nilai standar deviasi pada zona 1 sebesar 0,0025 dan zona 2 sebesar 0,004, hal ini menunjukkan bahwa ketelitian yang memenuhi tingkat kepercayaan 95%. Hasil analisis ini diharapkan dapat memberikan gambaran evaluasi pekerjaan pemadatan tanah dasar secara akurat.

Kata kunci: *kepadatan tanah dasar, variabilitas spasial, geostatistik, kriging*

PENDAHULUAN

The weight of a road is held by the subgrade level of the soil; thus, the soil will have a bigger chance to get damaged when it is weak. It is then necessary to meet the density criteria of the soil.

In relation to the value uniformity of soil, people have been using statistical computation; however, geospatial technology gives easier access to assess the uniformity level of the subgrade. Thus, the selection of geospatial technology is a foundational reason to have efficient measurement of the subgrade density in the road construction [1].

Subgrade is an important factor in the pavement system so that there needs to be Quality Control (QC) and Quality Assurance (QA). In this study, sandcone test was used for the QC and QA. Some of the problems rising in the pavement system are 1) limited sample spots which do not represent the whole construction area; and 2) the possibility of the weak soil undientification which leads to bad long-term performance, higher cost, and shorter life cycle [2].

Geostatistical method is used to acquire information on the measurement data of a certain spatial location so that the data distribution trends and the uniformity level of the subgrade density are presented [3]. The value measurement of the subgrade density was done based on the limited number of samples. The sampling carried out in this study several spots in between every 200 meter according to SNI 2828-2011, it has been found that statistically, the condition was not ideal for the density. Thus, a more representative sampling technique is needed because the more representative the sample of a populcation is, the more the chance of generaliability rises.

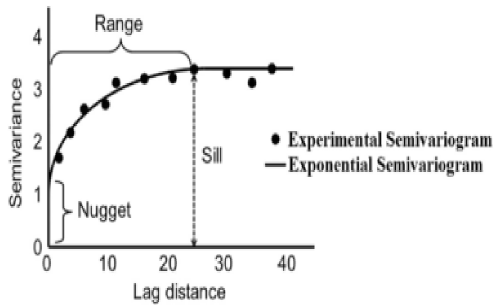
The use of the soil density value on soil compaction becomes a quite serious issue when it is used to describe the uniformity of subgrade compaction [4]. Whereas, it is known that in a certain area, the value of the subgrade compaction is determined spatial inuniformity. The term "geostatistics" is used to analyze space-based data using such statistical data as mean, deviation standard, and correlational distance among samples [5]. The development of geostatistics-based technology has been conuducted in several studies. One of which has been done in Oklahome, the US, on the use of Intelligent Compation Analyzer (ICA) device to evaluate the subgrade module when investigating the compaction process [6]. Geostatistical approach used in Intelligent Compaction aims to reach uniformity of the compaction of the pavement layer in an attempt to improve the quality of construction, pavement performance, and construction cost [7].

Geostatistical analysis using semivariogram model is able to describe the characteristics and measure the inuniformity of the soil embankment compaction. This is an important element in compaction construction [8]. Geostatistics is also able to visualize the value distribution of the subgrade density as the result of soil compaction. This study is expected to be able to determine the distance sampling patterns of the subgrade density so that the uniformity of the soil compaction can be evaluated. The soil density testing can use sand cones according to the national standard of SNI 03-2828-1992 (compaction testing method using a sand cone as a tool). Soil compaction results in the improvement of soil density, bulk density, volume of water, carrying capacity in the total porosity decrease, air compressing of the soil, water infiltration line, and the conductivity of saturated hyrolics [9].

As science and technology develops, geostatistics is used more widely, particularly in relation to data influenced by spatial inuniformity. Two set of data with equal mean, deviation standard, and other elements possibly have different spatial representation [3]. In this context, geostatistics focuses on spatial data seti with semivariogram as a tool to describe spatial relation.

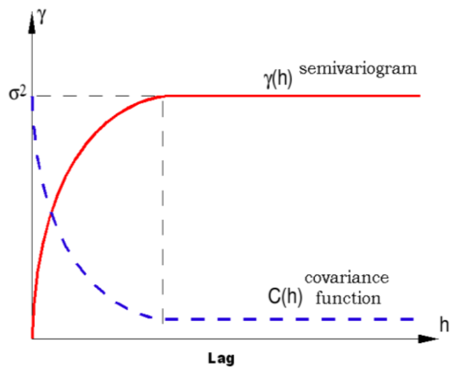
Semivariogram is defined as one and a half of the average squared difference between a certain value and distance. If this value is calculated several times for difference distance, the experimental semivariogram plot y (h) is calculated as follows [10]:

$$\gamma(h) = \frac{1}{2n\ (h)} \sum_{i=1}^{n(h)} |z(x_i + h) - z(x_i)|^2 \quad (1)$$



Sourcer: Hu et al. [10]

Figure 1. Typical Semivariogram Sample



Source: Laksana [11]

Figure 2. Plot of Covariance Function with Semivariogram

The purpose of the study is to mao the value of subgrade density on the development of Cisumdawu highway (KM 10+700 – 12+000).

RESEARCH METHOD

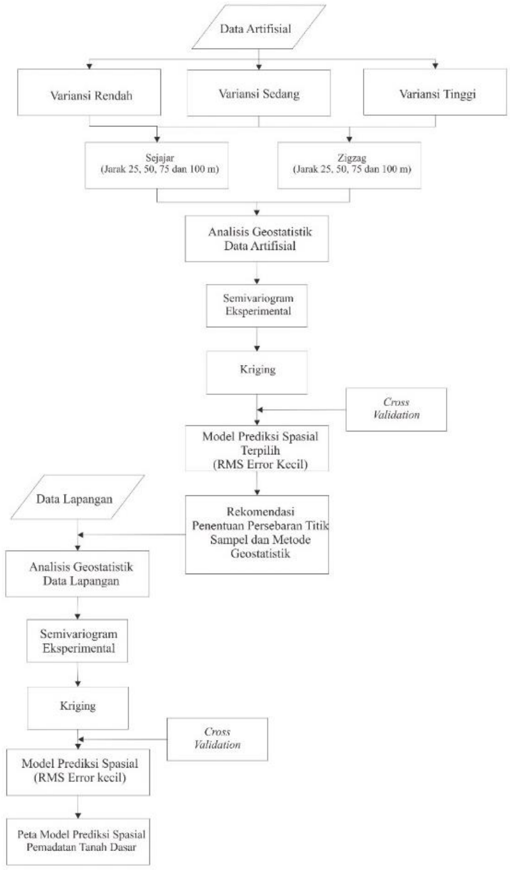


Figure 3. Diagram of the development of subgrade density level uniformity model

The model development consits of several phases. The first phase involves analysis to determine the appropriate model based on the data tendency. The model developed should not only depend on the characteristics of data, but also other factors. In addition to data pre-processing, there needs to be spatial correlation analysis as well. Some methods such as kriging requires the data analysis process using semivariogram and covariance functions.

RESULTS AND DISCUSSION

Artificial data are used to acquire strategic recommendation on data analysis.

Table 1. Results of the Soil Density Measurement using Sandcone

No	Klasifikasi Sebaran Data	Hasil Perhitungan Statistik Data Kepadatan (gr/cm2)				
		Min	Max	Mean	Std. Dev	Tingkat Keseragaman %
1	Rendah					
	Sejajar:					
	- 25 meter	1,18	1,191	1,184	0,00256	99,78
	- 50 meter	1,181	1,191	1,1841	0,0028076	99,76
	- 75 meter	1,181	1,19	1,184	0,0023679	99,80
	- 100 meter	1,181	1,191	1,1841	0,0029182	99,75
	Zigzag:					
	- 25 meter	1,18	1,19	1,1837	0,0025677	99,78
	- 50 meter	1,181	1,191	1,1842	0,0029814	99,75
	- 75 meter	1,181	1,191	1,1837	0,0024541	99,79
	- 100 meter	1,181	1,191	1,1837	0,003199	99,73
2	Sedang					
	Sejajar:					
	- 25 meter	1,18	1,275	1,218	0,03848	96,84
	- 50 meter	1,18	1,275	1,2277	0,040117	96,73
	- 75 meter	1,18	1,275	1,2098	0,037127	96,93
	- 100 meter	1,181	1,275	1,2493	0,034509	97,24
	Zigzag:					
	- 25 meter	1,18	1,275	1,2181	0,038578	96,83
	- 50 meter	1,18	1,275	1,2276	0,040691	96,69
	- 75 meter	1,18	1,275	1,2101	0,038044	96,86
	- 100 meter	1,181	1,271	1,2488	0,035039	97,19
3	Tinggi					
	Sejajar:					
	- 25 meter	1,161	1,341	1,2646	0,07953	93,71
	- 50 meter	1,161	1,338	1,2594	0,079701	93,67
	- 75 meter	1,163	1,34	1,276	0,076981	93,97
	- 100 meter	1,167	1,338	1,2665	0,07977	93,70
	Zigzag:					
	- 25 meter	1,161	1,341	1,2651	0,080177	93,66
	- 50 meter	1,168	1,335	1,2583	0,079463	93,68
	- 75 meter	1,163	1,34	1,2772	0,07862	93,84
	- 100 meter	1,167	1,335	1,2663	0,081087	93,60

Table 2. Errors on the predictive results on the distance and type of value distribution of subgrade density

No	Klasifikasi Sebaran Data	Nilai Kesalahan					
		Jumlah Sampel	Mean Error	RMS Error	Mean Standar Error	RMS Standar	Rata-rata Kesalahan Standar
1	Variansi Rendah ($0.011<\gamma<0.086$)						
	Sejajar:						
	- 25 meter	128	-2,15E-06	0,000149	-0,0066	1,0310	0,000144
	- 50 meter	63	7,478E-07	0,00023	0,00135	0,8848	0,000276
	- 75 meter	44	0,0000022	0,000247	0,00593	1,047	0,000235
	- 100 meter	32	-0,000013	0,000256	-0,02044	0,9556	0,000263
	Zigzag:						
	- 25 meter	66	3,6804E-06	0,000305	0,00715	0,91581	0,00036
	- 50 meter	31	0,00029	0,00056	0,038	1,033	0,00054
	- 75 meter	22	2,9405E-06	0,000132	0,0077	0,8976	0,00019
	- 100 meter	16	0,000016	0,00024	0,023	0,6060	0,00041
2	Variansi Sedang ($0.086<\gamma<0.161$)						
	Sejajar:						
	- 25 meter	72	-0,0000421	0,0052	-0,00098	0,71433	0,0071
	- 50 meter	36	-0,0002461	0,0043	-0,04916	1,60090	0,0027
	- 75 meter	24	0,0001098	0,0041	0,02135	1,01074	0,0040
	- 100 meter	20	-0,0000407	0,0046	-0,00168	1,25620	0,0037
	Zigzag:						
	- 25 meter	36	-0,0019707	0,0141	-0,04032	0,49101	0,0256
	- 50 meter	18	-0,0031616	0,0139	-0,05873	0,48453	0,0278
	- 75 meter	12	-0,0001923	0,0042	-0,01691	0,70349	0,0061
	- 100 meter	10	0,0004435	0,0032	0,03693	0,39805	0,0079
3	Variansi Tinggi ($\gamma\geq0.086$)						
	Sejajar:						
	- 25 meter	68	0,0001550	0,0087	0,01093	1,11750	0,0080
	- 50 meter	36	-0,0000437	0,0061	-0,00616	0,75694	0,0081
	- 75 meter	24	0,0004242	0,0061	0,04128	1,19845	0,0052
	- 100 meter	20	0,0001671	0,0048	0,01687	0,97084	0,0049
	Zigzag:						
	- 25 meter	34	0,0009774	0,0695	0,00522	0,88072	0,0782
	- 50 meter	18	-0,0008758	0,0112	-0,01750	0,60560	0,0208
	- 75 meter	12	-0,0002039	0,0083	-0,00607	0,56446	0,0183
	- 100 meter	10	0,0001985	0,0083	0,01830	0,45580	0,0195

The predictive model made from the different distribution type gives the average of error in the process of cross validation.

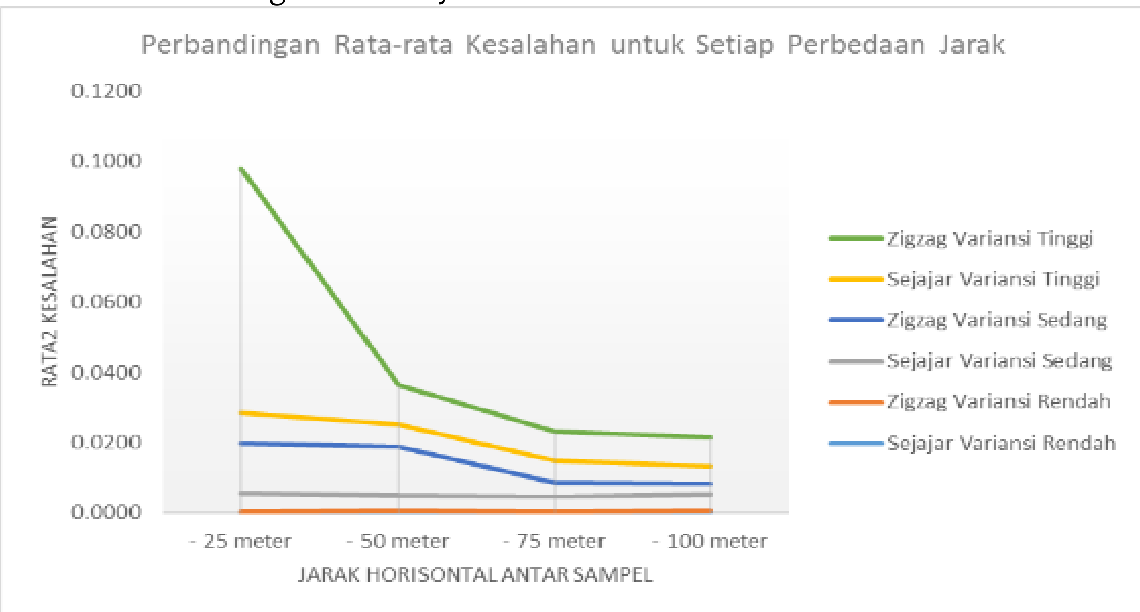
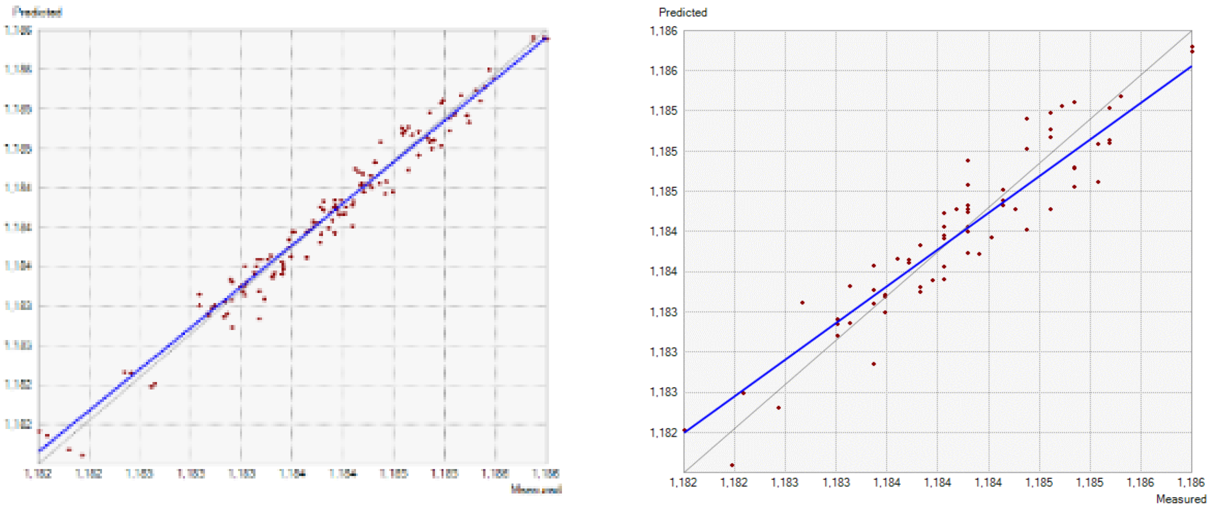


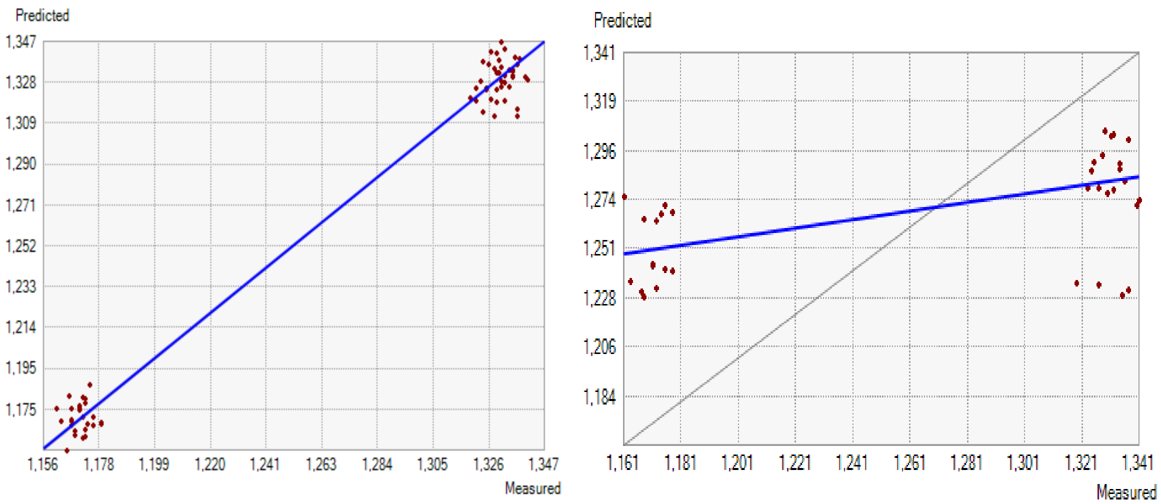
Figure 4. Comparison of the average of standard errors on every distance difference



(a) (b)

Figure 5. Comparison of cross validation results on low variance (a) parallel distribution type; and (b) zigzag type

Figure 5 shows the results of cross validation comparison of the soil density with low variance that the parallel type with 25 meter sample space gives the value of predictive line coinciding with the predictive equation line and results of the measuremen.



(a) (b)

Figure 6. Results of cross validation on high variance (a) parallel type; and (b) zigzag type

The distribution of the subgrade density value with a parallel type an high variance gives the results of cross validation which have more uniformity than those in zigzag type in frour different distances. The sampling selection in 25 meter with zigzag pattern shows inconsistency between the predictive results and the real results. Using a geostatistical method as the predictive model, a Gaussian semivariogram model was created. The range value on the same lag is obtained from several trial models of semivariogram (stable, sphrerical, exponential, and Gaussian).

Table 3. Results of geostatistical model on the value of subgrade density and relative compaction (RC)

No	Results	Zone 1	Zone 2
1	Number of samples	128	80
2	*Mean* data (gr/cm3)	11,845	1,332
3	Deviation standard	0,003	0,005
	Semivariogram		
1	*Range* (meter)	135,667	319,8
2	*Partial Sill*	1,63E-02	9,72E-02
3	*Nugget*	5,26e-006	2.06E-01
	Error Prediction		
1	*RMS*	0,0025	0,004
2	*RMS Standardized*	0,995	0,994

Table 3 infers that the maximum distance of the sampling tehcnique lies on the zones with various values. The number of samples are in line with the samples needed. The value of soil density in zone 1 is lower than that in zone 2. The semivariogram model proves that the highest range is in zone 2 (336 meters), whilethe maximum distance in zone 1 is 135 meters. The predictive moel in zone 1 has 99.5% of the matching value and zone 2 is 99.4%. It has also been found that zone 1 has smaller error value compared with that of zone 2.

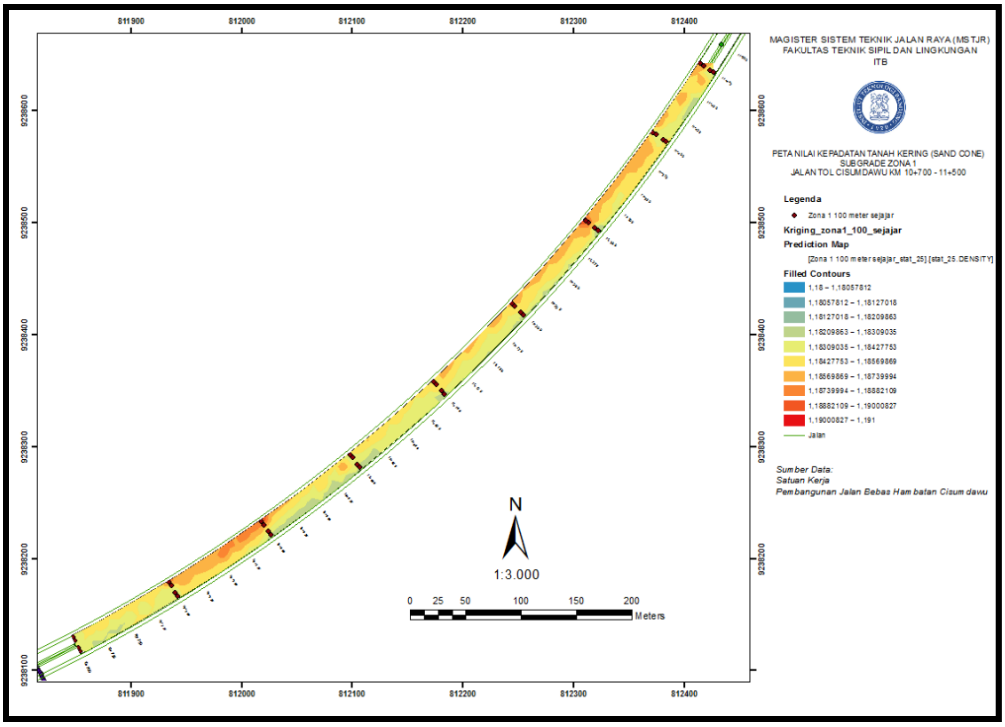


Figure 7. The map of data prediction in zone 1 with parallel type and 100 meter distance

The map shows the value distribution of the subgrade density in zone 1 (KM 10+700 – 11+500). The high value of the densidy lies on the left lane at KM 10=800 until KM 10=900. Zone 2 shows significance decrease started from KM 11+700 to KM 12+000.

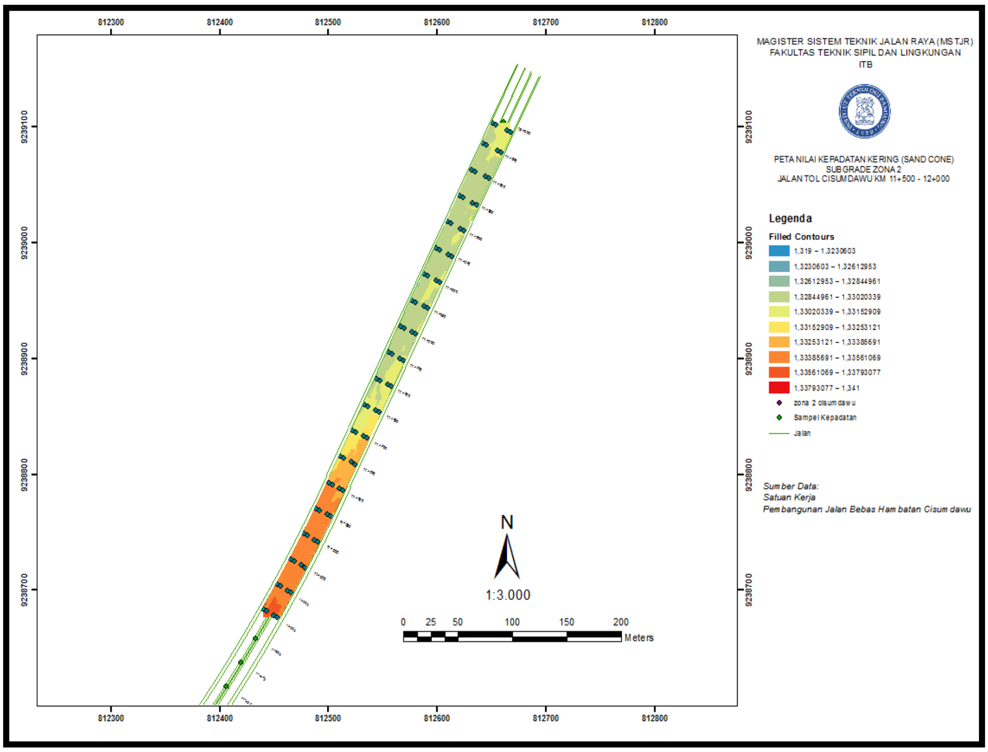


Figure 8. Map of the data prediction model zone 2 with parallel type and 25 meter distance

CONCLUSION

The mapping of the subgrade density value is influenced by data normally distrbuted, distance among samples and the distribution patterns. The selection of semivariogram model gives the deviation standard value on zone 1 as much as 0.0025 and on zone two as much as 0.004 at the level of signifiance at 95%.

RECOMMENDATION

Further studies are expected to use CBR data in determining the carrying capacity of the subgrade. The distance is also needed to be increased to 300 meterse.

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