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Modelling spatio-temporal energy consumption from nighttime radiance satellite dataset

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Abstract: National electricity consumption increases in line with continuous population growth and other socio-economic factors. The national electric power capacity goal develops largely for industrial manufacture and new settlement. The electrification- ratio on the target; is based on the accessibility of electricity services. The spatial distribution of electricity services coverage over the Indonesian territory is insufficient, particularly over the remote area that is out of electric services. Modeling by spatial (location) and temporal (year) to estimate electricity or energy consumption is necessary to develop using a low-light nighttime satellite dataset, therefore spatial boundaries can be accomplished. The modeling procedure starts by preparing the data frame of the independent variable input (amount of radiance) and the dependent variable output (the consumption of electricity or energy). The modelling method uses the curve-fitting approach where the indicator results by evaluating the R-square and RMSE values. The output model function is used to convert radiances into electrical power consumption units with a certain degree of accuracy. The selection of the input-output variable was achieved after variable analysis with the highest R-square outcome. Results indicate that the model functions in a polynomial form and correlations between variables are not simple. The selection of various model functions did not change the degree of correlation. The accumulative of energy radiances as independent variable input provides the optimum correlation result. The energy consumption from street lighting, in general, offers appropriate information that can be seen from satellites. The model function can be applied to a narrower spatial scale by input variable constraints.

Keywords: curve fitting, energy consumption, modelling, NTL nighttime, radiances

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Introduction

Energy and electricity demand grows continuously in line with the world or national population growth, foreign tourist arrivals, and other socio-economic factors. According to the national statistical agency [1], [2], Indonesia has a national population growth of about 1.27%. The national electric power capacity of 35,000 MW mainly has emphasized the manufacturing industry supply and development of the new settlement. The national electrification ratio had claims of 95% in 2017 based on the accessibility of people to get electricity services, not from the distribution of spatial distribution of electricity service coverage to the territory of Indonesia. Therefore, remote areas that require electricity services are not covered by this electrification ratio. Bali's tourism industry has a growth rate of about 23.14% and electricity demand continues to increase by about 8.49% per year [1]. Bali tourism is concentrated in the southern part of Bali Island, at Denpasar City and Badung Regency. This condition brings the disparity of electricity distribution that results in constraints in developing new tourism areas, generally located in remote areas.

Remote sensing satellites (RS) satellites are widely used for wide-area and even global coverage issues. RS has the capability of temporal, multi-spectral, and multi-polarization, and many types of sensors can be carried. Specifically, SRS low-light nighttime imagery carries a Photo Multiplier Tube (PMT) a passive panchromatic sensor of low-light imaging that is operated on a 0.47-0.95 μm spectral channel which is useful for observing low light at night on the surface of the earth [3], [4]. Nighttime light can be used as an indicator of human activity that can be measured from satellites and is suitable for mapping various settlement problems [5]. Applied in the socio-economic field [6]. Modelling of spatial distribution and human population growth [7], overall electricity and energy consumption [8], economic growth rate [9], gas emissions from anthropogenic [10], and estimation of various other parameters [11].

The spatio-temporal dynamics of electricity consumption on a global scale have been reported in [12] using The Defence Meteorological Program (DMSP) Operational Line-Scan System (OLS) data, calibrated radiances of nighttime light (NTL) and global electricity consumption from World- bank. The results show that using calibrated radiances modified invariant region (MIR method) gives better results in estimating electricity consumption [13]. However, the input model does not include other socio-economic factors. Investigators [14] analyzed the spatio-temporal dynamics of electric power consumption on an urban and sub-urban scale in China by including NTL DMSP OLS data, vegetation index, socio-economic factors such as population and GDP from NASA's socioeconomic data and application center, and electricity consumption in China. However, the supporting dataset is not as input for modelling to estimate electricity consumption, but just for calibrating the NTL pixel. Researchers [15] use NTL DMSP OLS data in Indonesia by assessing the electrification progress of the NTL brightness level and showing the imbalance between the percentage of electrification in Java-Bali and other regions. However, it does not perform calibration processing and consumption of electric power modelling [16], [17].

Previously the method of predicting the growth rate of electricity consumption was only based on customer growth, GDP, and other socio-economic factors, and the electrification ratio was only based on the accessibility of the public to get electricity services. This paper will model spatially (based on location) and temporally (based on time/year trends) national electricity consumption in general, low-light SRS data at night. The results of the model will be able to be used to estimate trends in electricity consumption in a specific region (spatial). Besides, it specifically examines the electrification of ratios in Bali Province related to the development of new tourist destinations that require electricity networks. With this study, developing electricity infrastructure can be straightforward. Because model results can be used to estimate energy demand rapidly from satellite data.

Methodology

The outline of the modelling procedure is shown in Figure 1. The modelling step consists of twelve procedural blocks. The RS NTL dataset uses two operational satellites with NASA's NTL mission, i.e., DMSP OLS year 1992 until 2013 (22 years) and the Visible Infrared Imaging Radiometer Suite (VIIRS) year 2012 present [18]. The dataset is available in the global mosaic form (6 tile-scenes). The mosaic procedure results are subset into Indonesian territory (6oN-11oS, 95oE- 141oE) [4]. The modelling uses an annual scale of a dataset, the aggregation procedure is required for datasets that are not on an annual scale. The DMSP OLS dataset radiances require calibration procedural to eliminate saturation and inter-annual discrepancy from inter-change satellite missions [13]. The calibration procedure uses the modified invariant region (MIR) method [12]. The MIR method requires an NTL radiances composite dataset calibrated with regions known to have NTL level stability. Investigators in [12] use Japan as a calibration region. This paper uses their published calibration constants for the calibration procedure.

Figure 1 shows block process number 3 is MIR NTL calibration. MIR is a power regression function as seen in Equation (1), where NTLcorr is corrected NTL with a=5.400 and b=0.462 are parameters that had been obtained in [12].

$$NTL_{corr} = \left(\frac{NTL}{a}\right)^{\frac{1}{b}} \tag{1}$$

Block process number 4 is an aggregation of corrected NTL bases on each regional province of Indonesia per year. Every pixel on the NTL dataset had been tagged with their province-regency ID and year. Therefore, aggregation of corrected NTL solves as Equation (2).

$$NTL_{ID,YEAR} = \sum\nolimits_{ID,YEAR} NTL_{corr} \tag{2}$$

The next procedure uses spatial analysis of the Indonesian province spatial data for spatial statistics or zonal statistics of each province in Indonesia from the calibrated radiances dataset [19]. The zonal statistical results measure 34 (rows) of provinces, in 29 years, and 6 statistical quantities of calibrated radiances (columns). This dataset becomes the independent variable (x) in the modelling i.e., the value of minimum (xmin), maximum (xmax), range (xrange), xmean (mean), standard-deviation (xstd) and accumulative (xsum) of radiances NTL.

The zonal statistics are shown as block process number 6 in Figure 1. For short, zonal statistics are described as follows, $NTL_{minimum}$ is minimum value of NTL, $NTL_{maximum}$ is the maximum of NTL, NTL_{range} is NTL maximum minus NTL minimum, NTL_{sum} is the summation of NTL concerning their province ID and year. While NTL_{mean} is the averaging of NTL and NTLstd is the standard deviation of NTL shown in Equation (3) and Equation (4).

$$the\ NTL_{mean} = \frac{\sum_1^n NTL_{corr}}{n} \tag{3}$$

$$NTL_{std} = \sqrt{\frac{1}{n}\sum\nolimits_1^n (NTL_{corr} - NTL_{mean})^2} \tag{4}$$

The dependent variable (y) results in processing electricity and energy statistical data which became available from the year 2006 [1], [2]. Meanwhile, the NTL DMSP OLS data available from the year 1992 [4], [13]. Consequently, the modelling uses only the dataset from 2006, in 13 years. This dataset consists of 34 (rows) of provinces, in 13 years, and 7 types of customers (GWh) or 6 types of energy (kilolitres) (columns) i.e., power electricity of all costumers' sector (ypel), household (yrt), industrial (yin), commercial (yko), government (ygd), social (yso) and street-lighting (yjl). Modelling uses only 80 percent of these datasets for training models and the rest for testing models. The development of the model uses a fitting curve training process [20]. Several experiments were performed to obtain the suitable functions and parameters of the model. The model function will be in the form of a polynomial, power, or sum of sine [21].

The purpose of experiments gain the highest correlation coefficient between the independent variable (x) and the dependent variable (y). There are 6 statistical quantities of calibrated radiances as an independent variable (x) and 7 types of customers or 6 types of energy as a dependent variable (y). The model candidate was then tested to validate the model using the test dataset. The root means square error (RMSE) is used as an indicator of validation. The validated model as a national scale model was then applied to a smaller spatial scale i.e., Bali province. This implementation procedure analyses any deficiency of the model.

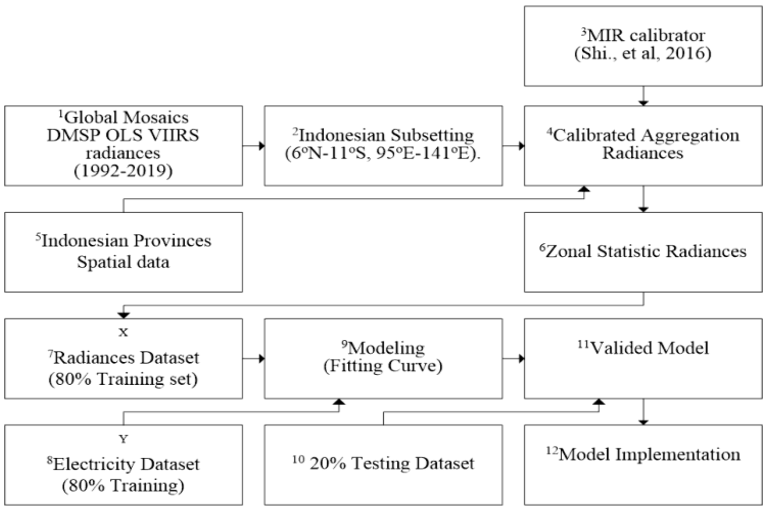

Figure1. The modelling procedural

Results and Discussions

Profiling of dataset

The profiling of the dataset is useful to identify the characteristics of each index. Figure 2 shows the accumulated energy radiances of NTL at a pixel (sum). The sum of NTL increases gradually until the year 2013. However, the sum of NTL seen has two distinct profiles. This is due to the dataset of NTL consisting of two types of NASA's NTL satellite mission. Starting from the year of 2012 the satellite NTL mission changes from the DMSP OLS to the VIIRS program mission. Unfortunately, there is no valid inter-satellite calibration for both missions [22]. The accumulated energy radiances of NTL dominate from Java Island where the West Java Province is known as the main industrial concentration. Figure 3 shows the electric power consumption in the unit of GWh. The trend of electric power consumption increases gradually corresponds with accumulated energy radiances of NTL. Figure 4 shows the energy (coal) consumption in unit Ton. The energy consumption also corresponds with both of the indices above. If looks at the mean of the NTL dataset for several provinces is described as follows. DKI has the highest mean NTL value (2.0 – 2.5e+02 $nWcm^{-2}\mu m^{-1}sr^{-1}$) and other provinces have an average of mean NTL below 0.5e+02 $nWcm^{-2}\mu m^{-1}sr^{-1}$.

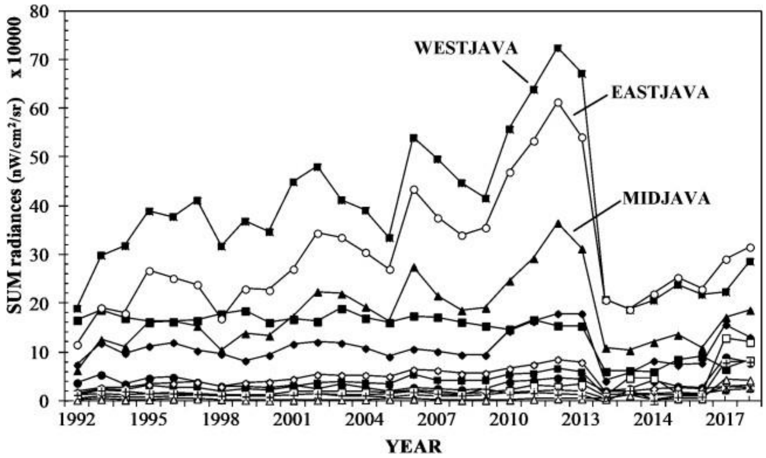

Figure 2. Profile of accumulative radiances dataset (sum)

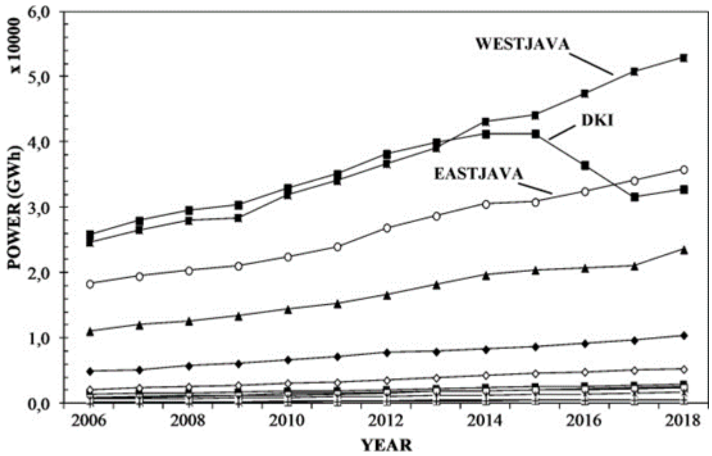

Figure 3. Profile of electric power consumption dataset (GWh)

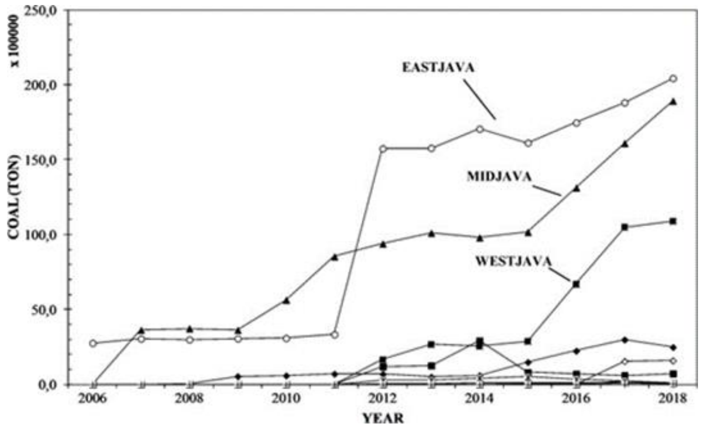

Figure 4. Profile of energy (coal) consumption dataset (Ton)

Curve-fitting experiments

The first, curve-fitting experiment sets the independent variable x as xmean radiances of NTL and the dependent variable y as the consumption of electrical power for all types of customers. After several curve-fittings experiments obtained the result as in Table 1. Overall, the R-Square is around 0.25 (low) and the selection of curve-fitting function does not provide a significant change in correlation results. The next, curve-fitting experiment sets the independent variable x is xsum radiances of NTL and the dependent variable y is ypel (the consumption of electrical power based on all customers). The results are as shown in Table 2. The R-Square is around 0.50 (adequate) and again the selection of curve-fitting function does not provide a significant change in correlation results.

Table 1. Summary of modelling experiment results for variable ypel against xmean

Curve Fitting	SSE	R Square	DFE	Adj R Square	RMSE	Coeff
Polynomial deg.1	2.63e+10	0.23	432	0.23	7.80e+03	2
Polynomial deg.2	2.62e+10	0.23	431	0.23	7.80e+03	3
Power nterms 1	2.49e+10	0.27	432	0.27	7.59e+03	2
Power nterms 2	2.47e+10	0.28	431	0.27	7.58e+03	3
Sum of Sine nterms 1	2.63e+10	0.23	431	0.23	7.81e+03	3

Table 2. Summary of modelling experiment results for variable ypel against xsum

Curve Fitting	SSE	R Square	DFE	Adj R Square	RMSE	Coeff
Polynomial deg.1	2.08e+10	0.48	440	0.48	6.87e+03	2
Polynomial deg.2	1.99e+10	0.51	439	0.50	6.73e+03	3
Power nterms 1	2.03e+10	0.50	440	0.49	6.80e+03	2
Power nterms 2	2.02e+10	0.50	439	0.50	6.78e+03	3
Sum of Sine nterms 1	1.99e+10	0.51	439	0.50	6.73e+03	3

Variables analysis

The two experimental results above (Table 1 and Table 2) show the relationship (correlation) between the NTL radiances with electricity consumption is not simple. The xsum radiances of NTL as an independent variable provide a better correlation approach. Furthermore, variable analysis is performed to determine the modelling parameter. The first analyzed performance with the dependent variable ypel (electric power consumption for all consumers GWh) is fixed and the independent variables x are varying for all statistical indexes of the radiance NTL dataset (nWcm-2µm-1sr-1). The model function uses polynomial degree 2 which provides the highest correlation (according to the highest R square value in Table 2). Results show in Table 3, xsum provides the highest R square.

Table 3. R-square results of the variable analysis with fixed ypel

ypel	xmin	xmax	xrange	xmean	xstd	xsum
R Square	0.03	0.07	0.07	0.34	0.16	0.51

The next analyzed fixed of independent variable xsum (according to the highest R square value in Table 3 above) with various of dependent variable y (GWh) for all types of electricity consumers and model function stick to polynomial degree 2 giving the R square results as Table 4 follows. The highest R square gained from yjl (the highway lighting consumer type).

Table 4. R-square results of the variable analysis with fixed xsum

xsum	ypel	yrt	yin	yko	ygd	yso	yjl
R Square	0.51	0.52	0.54	0.20	0.16	0.38	0.55

Modelling development

Model development determines the model function and its parameters. From variable analysis results, the model will develop using a polynomial degree-2 function with xsum as an independent variable and yjl as a dependent variable. The model has a national-scale scope and the curve-fitting plot result is shown as follows in Figure 5. In the figure, black points are scattering of xsum against yjl and the line is the fit curve of the model. The curve-fitting result gives the equation of the power consumption model (EPGWh) in Equation (5).

$$EP_{GWh} = p1 * NTL^2 + p2 * NTL + p3 \tag{5}$$

Where constants as follows: $p1 = -21.28$; $p2 = 154.8$; $p3 = 113.2$

Equation (1) requires normalizing of input NTL with the mean value of 7.42e+04 and the standard deviation value of 1.093e+05. Before entering Equation (1) above, NTL must be normalized by Equation (6) below.

$$nNTL = (NTL - 7.4e + 04)/1.093e + 05 \tag{6}$$

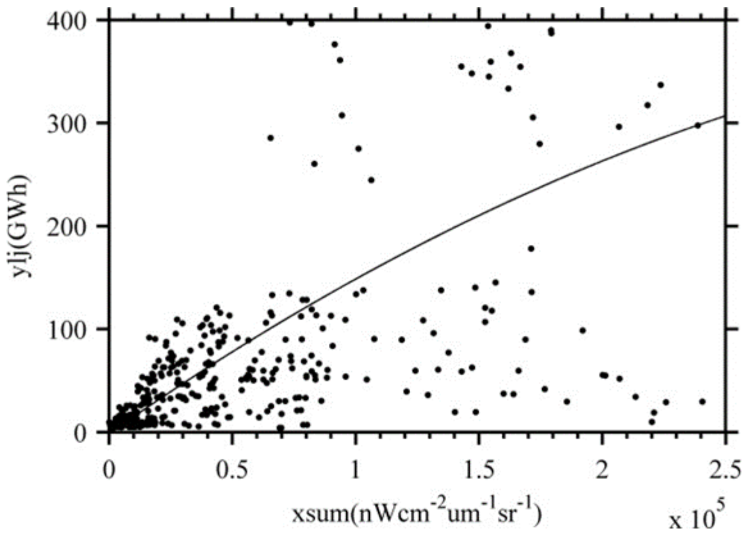

Figure 5. Plot of curve-fitting model result

Model validation

Furthermore, the model function results were validated using RMSE computation. RMSE is computed from differences (error) of EPGWh results with statistical data (BPS) of electricity consumption per province as in Equation (7).

$$RMSE = sqrt(mean(EP_{GWh} - BPS)^2) \tag{7}$$

As a result for the national-scale case, the RMSE has about 89.63 GWh. This value is lower than the mean value of the input dataset to the model. For more clearly comparison of the validation process, again it is shown in Figure 6. In the figure, the lines are the electrical power consumption of the original dataset and the black point is the scatter of output model results. As seen in Figure 6, the original dataset of electrical power consumption (straight line) quite coincides with the model output results (dots). The modelling achieved RMSE 11.56%, this result comparable with the investigator [7], who revealed RMSE 15% in a related study.

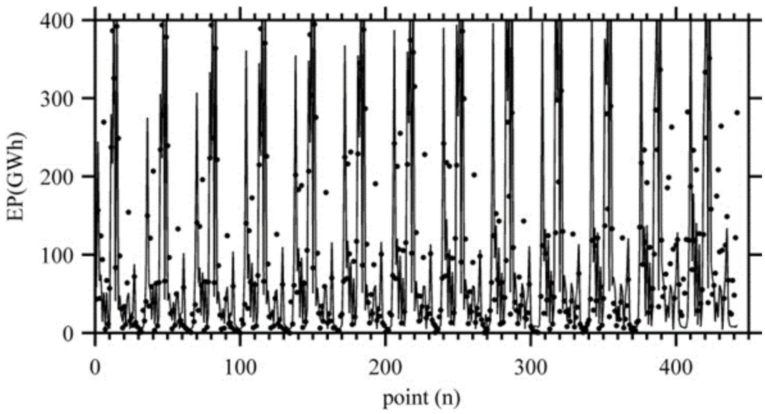

Figure 6. The plot of the model validation result

Model implementation and constraints

The modelling of energy or electrical power consumption from radiances of satellite datasets has huge potential in the application. In this paper, the model that was developed will be implemented into a narrower spatial-scale dataset and discuss the model constraint. As the most tourism industry, Bali province is greatly growing in electrical energy demand. Therefore, a yearly significant change in NTL can be easy to observe from the satellite. The model will be tested to obtain the electrical power consumption of all regencies of Bali province from radiances of satellites as an input of dataset periods from year 1992 to 2019. Results are shown in Figure 7. In the figure, the line on the graph indicates the electrical power consumption for each region of Bali province. As expected, the main cities regencies of Bali province i.e., Denpasar, Badung, and Gianyar show the highest energy consumption. Other regencies that have lower accumulative radiances about 1000 $nWcm^{-2}um^{-1}sr^{-1}$ cannot estimate output results by the model. This is due to the model developed using the national scale of the dataset that has a high mean accumulative of radiance as an independent variable.

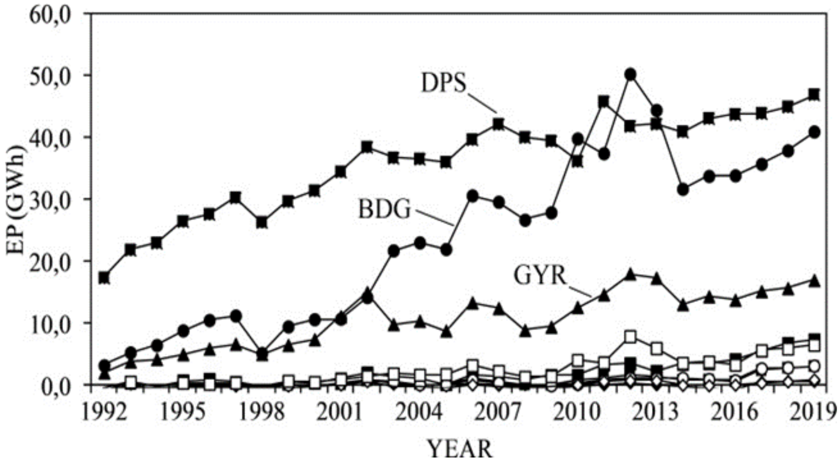

Figure 7. Model implementation

Forecasting

The electrical power load forecasting purposes to plan the optimal power generation. In forecasting, the study requires the observation or measurement data, state data or estimate from the model (this manuscript result), and optimally from both those data (the Kalman's based filter) [23]. The forecasting method can be used in the Auto-Regressive Integrated Moving Average (ARIMA) model [24].

Conclusion

Estimation of energy consumption from nighttime radiances of satellite dataset aims to rapidly obtain results within a wider area even globally. Modelling can be used to convert the nighttime radiances of satellites into energy consumption units with a certain degree of accuracy. The modelling procedure starts by preparing the dataset of the independent variable input (amount of radiance) and the dependent variable output (the consumption of electricity or energy). The relationship equation between variables is approached from a curve-fitting experiment. The variable analysis was used to select an approved variable with a large R-square outcome and validated with RMSE. Naturally, the model is in a polynomial form, and correlations between variables are not simple. The selection of various model functions did not change the degree of correlation. The accumulative of energy radiances as independent variable input provides the optimum of correlation result. The energy consumption from street lighting, in general, offers appropriate information that can be seen from satellites. The model function can be applied to a narrower spatial scale by considering input variable constraints. This study presents a novel method to estimate energy consumption rapidly with great accuracy. The model archives an RMS error of about 11.56%. The estimated energy consumption of Bali province from this model implementation makes the development of electricity infrastructure straightforward in the future.

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References

[1] BPS Indonesia, "Statistik Listrik Indonesia: Electric Statistics Indonesia 2018," Jakarta: BPS Indonesia, 2018. [Online]. Available: https://www.bps.go.id/publication.html?Publikasi%5BtahunJudul%5D=2018&Publikasi%5BkataKunci%5D=statistik+listrik&Publikasi%5BcekJudul%5D=0&Publikasi%5BcekJudul%5D=1&yt0=Tampilkan

[2] BPS Indonesia, "Statistik Indonesia: Statistical Yearbook of Indonesia 2022," Jakarta: BPS Indonesia, 2022. [Online]. Available: https://www.bps.go.id/publication/2020/04/29/e9011b3155d45d70823c141f/statistik-indonesia-2020.html

[3] H. Letu, M. Hara, G. Tana, and F. Nishio, "A saturated light correction method for DMSP/OLS nighttime satellite imagery," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 2, pp. 389–396, 2012, doi: 10.1109/TGRS.2011.2178031.

[4] I. K. Swardika, P. A. W. Santiary, I. B. I. Purnama, and I. W. Suasnawa, "Development of Green Zone Energy Mapping for Community-based Low Carbon Emissions," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 10, no. 6, pp. 2472–2477, 2020, doi: 10.18517/ijaseit.10.6.12642.

[5] O. Venter, E. W. Sanderson, A. Magrach, J. R. Allan, J. Beher, K. R. Jones, H. P. Possingham, W. F. Laurance, P. Wood, B. M. Fekete, M. A. Levy, and J. E. M. Watson, "Global terrestrial Human Footprint maps for 1993 and 2009," *Sci. Data*, vol. 3, p. 160067, 2016, doi: 10.1038/sdata.2016.67.

[6] J. Proville, D. Zavala-Araiza, and G. Wagner, "Night-time lights: A global, long term look at links to socio-economic trends," *PLoS One*, vol. 12, no. 3, p. e0174610, 2017, doi: 10.1371/journal.pone.0174610.

[7] P. Kumar, H. Sajjad, P. K. Joshi, C. D. Elvidge, S. Rehman, B. S. Chaudhary, B. R. Tripathy, J. Singh, and G. Pipal, "Modeling the luminous intensity of Beijing, China using DMSP-OLS night-time lights series data for estimating population density," *Phys. Chem. Earth*, vol. 109, pp. 31–39, 2019, doi: 10.1016/j.pce.2018.06.002.

[8] B. R. Tripathy, H. Sajjad, C. D. Elvidge, Y. Ting, P. C. Pandey, M. Rani, and P. Kumar, "Modeling of Electric Demand for Sustainable Energy and Management in India Using Spatio-Temporal DMSP-OLS Night-Time Data," *Environ. Manage.*, vol. 61, no. 4, pp. 615–623, 2018, doi: 10.1007/s00267-017-0978-1.

[9] K. Qi, Y. Hu, C. Cheng, and B. Chen, "Transferability of economy estimation based on DMSP/OLS night-time light," *Remote Sens.*, vol. 9, no. 8, p. 786, 2017, doi: 10.3390/rs9080786.

[10] B. Yu, S. Deng, G. Liu, C. Yang, Z. Chen, C. J. Hill, and J. Wu, "Nighttime Light Images Reveal Spatial-Temporal Dynamics of Global Anthropogenic Resources Accumulation Above Ground," *Environ. Sci. Technol.*, vol. 52, no. 20, pp. 11520–11527, 2018, doi: 10.1021/acs.est.8b02838.

[11] B. N. Kusuma and D. B. Santoso, "Improvement of the automatic gamma correction method in cloud image detection," *Matrix J. Manaj. Teknol. dan Inform.*, vol. 12, no. 3, pp. 137–146, Nov. 2022, doi: 10.31940/MATRIX.V12I3.137-146.

[12] K. Shi, Y. Chen, B. Yu, T. Xu, C. Yang, L. Li, C. Huang, Z. Chen, R. Liu, and J. Wu, "Detecting spatiotemporal dynamics of global electric power consumption using DMSP-OLS nighttime stable light data," *Appl. Energy*, vol. 184, pp. 450–463, 2016, doi: 10.1016/j.apenergy.2016.10.032.

[13] I. K. Swardika, P. A. W. Santiary, and I. N. E. Indrayana, "Radiance Threshold of Nighttime Satellite Data for Green Zone Energy Mapping," *ICEEIE 2019 - International Conference on Electrical, Electronics and Information Engineering: Emerging Innovative Technology for Sustainable Future*, 2019. https://ieeexplore.ieee.org/abstract/document/8981451 (accessed Jun. 15, 2020).

[14] Y. Xie and Q. Weng, "Updating urban extents with nighttime light imagery by using an object-based thresholding method," *Remote Sens. Environ.*, vol. 187, pp. 1–13, 2016, doi: 10.1016/j.rse.2016.10.002.

[15] F. Ramdani and P. Setiani, "Multiscale assessment of the progress of electrification in Indonesia based on brightness level derived from nighttime satellite imagery," *Environ.*

Monit. Assess., vol. 189, no. 6, p. 249, 2017, doi: 10.1007/s10661-017-5949-8.
[16] C. D. Elvidge, M. Zhizhin, K. Baugh, F. C. Hsu, and T. Ghosh, "Extending Nighttime Combustion Source Detection Limits with Short Wavelength VIIRS Data," *Remote Sens.*, vol. 11, no. 4, p. 395, 2019, doi: 10.3390/rs11040395.
[17] D. Yang, W. Luan, L. Qiao, and M. Pratama, "Modeling and spatio-temporal analysis of city-level carbon emissions based on nighttime light satellite imagery," *Appl. Energy*, vol. 268, p. 114696, 2020, doi: 10.1016/j.apenergy.2020.114696.
[18] H. Chen, X. Xiong, D. O. Link, C. Sun, and K. Chiang, "NOAA-20 Visible Infrared Imaging Radiometer Suite day–night band on-orbit calibration and performance," *Journal of Applied Remote Sensing*, 2020. https://www.spiedigitallibrary.org/journals/Journal-of-Applied-Remote-Sensing/volume-14/issue-3/034516/NOAA-20-Visible-Infrared-Imaging-Radiometer-Suite-daynight-band-on/10.1117/1.JRS.14.034516.short?SSO=1 (accessed Oct. 07, 2020).
[19] I. Ketut Swardika, P. Alit, W. Santiary, J. T. Elektro, and P. N. Bali, "Analisis Potensi Angin Sebagai Pembangkit Tenaga Listrik Di Indonesia Dengan Data Meteorologi Satellite Remote Sensing," *Matrix J. Manaj. Teknol. dan Inform.*, vol. 8, no. 3, pp. 52–58, 2018, doi: 10.31940/MATRIX.V8I3.1059.
[20] R. Hammad, V. C. Hardita, and A. Z. Amrullah, "Topic modeling and sentiment analysis about Mandalika on social media using the latent Dirichlet allocation method," *Matrix J. Manaj. Teknol. dan Inform.*, vol. 12, no. 3, pp. 109–116, 2022, doi: 10.31940/MATRIX.V12I3.109-116.
[21] K. Karsid and R. Aziz, "Identifikasi Model Parametrik Sistem Suhu Dan Kelembaban Udara Greenhouse Secara Eksperimental," *Matrix J. Manaj. Teknol. dan Inform.*, vol. 9, no. 2, pp. 61–67, 2019, doi: 10.31940/MATRIX.V9I2.1442.
[22] M. M. Bennett and L. C. Smith, "Advances in using multitemporal night-time lights satellite imagery to detect, estimate, and monitor socioeconomic dynamics," *Remote Sens. Environ.*, vol. 192, pp. 176–197, 2017, doi: 10.1016/j.rse.2017.01.005.
[23] V. Vikias, C. Manasis, A. Ktena, and N. Assimakis, "Forecasting for Temperature Dependent Power Generation Using Kalman Filtering," in *2019 IEEE 60th Annual International Scientific Conference on Power and Electrical Engineering of Riga Technical University, RTUCON 2019 - Proceedings*, 2019, pp. 1–6. doi: 10.1109/RTUCON48111.2019.8982328.
[24] S. Noureen, S. Atique, V. Roy, and S. Bayne, "Analysis and application of seasonal ARIMA model in Energy Demand Forecasting: A case study of small scale agricultural load," in *Midwest Symposium on Circuits and Systems*, 2019, pp. 521–524. doi: 10.1109/MWSCAS.2019.8885349.