# Estimation Relationship Between Electricity Consumption And Urban Area From Night Satellite Imagery: A Case Study For Istanbul

E. Yücer<sup>1</sup>, İ. Kahraman<sup>2,</sup> İ. R. Karaş<sup>3</sup>

<sup>1</sup> Karabük University, Karabük / Turkey, <u>emreyucer@ karabuk.edu.tr</u>
 <sup>2</sup> Karabük University, Karabük / Turkey, <u>idriskahraman@karabuk.edu.tr</u>
 <sup>3</sup> Karabük University, Karabük / Turkey, <u>ismail.karas@karabuk.edu.tr</u>

*Abstract* - Satellite imagery of night-time lights provided by the us air force defense meteorological satellite program (dmsp), using the operational linescan system (ols), has been used to estimate the spatial distribution of electricity consumption throughout istanbul. There are very high correlation between state electricity consumption and night-time lights. it can be also extract urban area from night time satellite image. Population and urban area have high correlation with night lights, and also change in population and urban area will be estimated from images between 2002-2013.

*Keywords:* Night Satellite Imagery, Classification, Correlation

### I.INTRODUCTION

Urbanization in the world is increasing rapidly and according to data of United Nations Population Organization, it is estimated that by 2050 the world population will be 12 billion and 80% of this population will live in cities. The rapid increase in population is mainly due to the large metropolitan areas such as Istanbul, Ankara, Izmir, Kocaeli, Bursa etc. such as industrialization and job opportunities are concentrated towards the provinces. After allowing immigrants the electricity consumption intensifies on these cities.

The wave of migration towards metropolitan cities causes the physical structure of the city to change as well as the population. Unplanned and distorted construction with rapid population growth causes many environmental problems, from the deterioration of the socio-economic structure of the city to the misuse of natural resources. Energy resources are decreasing, demand and cost of energy are increasing. This affects the cost of the product. In addition, it uses climate resources more efficiently and positively with global warming and drought. As resources used in electricity production are limited and their prices are increasing, new alternatives for temperature control in the greenhouse system are being investigated. Therefore, cities with variable and dynamic structure should be monitored and followed up regularly. Letu and others, presented a methodology for estimating electric power consumption from saturated nighttime DMSP/OLS imagery using a stable light correction. They performed an area correction and developed a correction method of saturation light by a cubic regression equation. Correlation rises after the correction of saturation light. Electric power consumption and the CO2 emission have depended on statistical data. Their study shows that the electric power consumption can be estimated with high precision from the stable light [1].

Levin and Duke used night imagery in Israel and West Sharia to examine economic and demographic differences and compared these results with population data (Arab and Jewish) [10]. Identifying the dynamics of urban expansion [11], studies in areas such as revealing changes in urban areas [12]. In recent studies, many scientists have used low-resolution MODIS or DMSP-OLS images to quickly identify expansion in rapidly growing cities [2,13, 14].

### II.DATA SOURCE

The basic data source used in the determination of urban areas is satellite images. In parallel with the developments in satellite technology, the quality and variety of images have increased. DMSP-OLS (Defense Meteorological Satellite Program- Operational Linescan System) at night. It is a data set created by Air Force Meteorological Satellite Program and has been widely used in recent years. The temporal series of images is available from 1992 to 2013 and is available to obtain from http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html.

Each pixel at night images has a resolution of 30x30 arcseconds (or 0.86 km2 in equator) and the images cover the longitude between +180 and -180 of the Earth and the area between -65 and +75 latitudes. Night images were created as a composite presentation of two satellite images taken during cloudless nights. The data consists of three different groups. "F1? YYYY\_v4b\_stable\_lights.avg\_vis.tif" data set was used in our study. The reason for the use of the data in question is that it includes lights, cities and towns with permanent

illumination including gas flare. Short-lived events such as fires are not included in the image data set. In addition, the background noise detection is performed in the image and these values have been changed to zero and the image has been cleared of these values. The images are 8 bits in geoTIF format and 43201x16801 in size. The cropped images of Istanbul by years shown in Figure 1.



Figure 1. The nighttime imagery of Istanbul city

The population and the electricity consumption data we used in our study were provided from TSE(Turkey Statistical Institute).

## III.METHODOLOGY

### A. Extraction of the Urban Areas

In the study, cell based image analysis Otsu method was used to determine urban areas. The Otsu method is a threshold detection method that allows the detection of the optimal threshold value that can be used when a gray level image is reduced to two groups. The Otsu method is named from Nobuyuki Otsu, who developed this method. When using this method, it is assumed that the image consists of two color classes, the background and the foreground. Then, for all threshold values, the intra-class variance value of these two color classes is calculated. The threshold value that makes this value the smallest is the optimum threshold value. While the variance value in the class is the minimum value, the variance value among the classes is at the maximum value. Calculating the variance between classes requires less processing, but the calculation of variance between classes for background and foreground pixel classes results in faster results. The method works on gray level images and only looks at how many times the colors are on the image. Therefore, the color histogram of the image is calculated first and all operations are performed on the histogram sequence [7]. After the Otsu method, urban

areas of Istanbul by years (Figure 2.) extracted from nighttime satellite image.

After obtaining urban areas of Istanbul city, the pixels are counted as urban area and rural area. The results of the otsu threshold method 2-class images gathered.

Year	Total Consumption (MWh)	Number of Pixels	
2013	33,925,455	2885	
2012	33,084,858	2972	
2011	32,672,285	2643	
2010	30,525,034	2816	
2009	29,147,130	2385	
2008	30,008,801	2398	
2007	28,501,616	2465	

Table 1. Electricity consumption and number of pixels

# *B.* Correlation Calculation Between Electricity Consumption and Urban Area

The relationship between free and dependent variables, the level and degree of this relationship is called the method of correlation analysis. In the correlation analysis, if there is only one independent variable, this type of analysis is called simple correlation analysis, and if there are multiple independent



Figure 2. Urban areas of Istanbul by years

variables, this is called multiple correlation. The most commonly used correlation analysis in scientific research [15].

It is very difficult to make the interpretation of the correlation coefficient for the intermediate values except for the exact values. When evaluating coefficients for intermediate values, the number of sample observations (n) is very important. Even in the case of observations based on too many observations, a correlation coefficient of up to 0.25 can be considered meaningful. However, in a small number of 10-15 observations, the correlation coefficient is expected to be above 0.71. According to the value of the correlation coefficient (r), the following comments can be made about the degree of correlation. Pearson correlation coefficients are the most commonly used correlation coefficients used to examine whether there is a relationship between numerical (quantitative) variables in terms of force and direction.

Table 2. Qualification for Pearson r values [8]

0,00 - 0,19	No relationship or unimportantly low
0,20 - 0,39	Weak (low) relationship
0,40 - 0,69	Intermediate relationship
0,70 - 0,89	Strong (high) relationship
0,90 - 1,00	Very strong relationship

Pearson correlation coefficient r; x: Independent variable, y: Equation (1) is used to indicate the dependent variable.

$$r = \frac{\sum x_l y_l - \frac{\sum x_l \sum y_l}{n}}{\sqrt{\left(\sum x_l^2 - \frac{(\sum x_l)^2}{n}\right)} \sqrt{\left(\sum y_l^2 - \frac{(\sum y_l)^2}{n}\right)}}$$
(1)

In this study electricity consumption and urban area correlation are calculated. The electricity consumption values by years were gathered from TUIK. There is a high correlation between night lights data and electric power consumption between 2007 and 2013 years. The correlation was calculated by 0.806.

 Table 1. Correlation of electricity consumption and urban area for Istanbul

Image	Year	Energy Consumption (MWh)	Number of Pixels	Correlation
Ist_2013.jpg	2013	33,925,455	2885	
Ist_2012.jpg	2012	33,084,858	2972	
Ist_2011.jpg	2011	32,672,285	2643	
Ist_2010.jpg	2010	30,525,034	2816	0.806
Ist_2009.jpg	2009	29,147,130	2385	
Ist_2008.jpg	2008	30,008,801	2398	
Ist_2007.jpg	2007	28,501,616	2465	

International Conference on Advanced Technologies, Computer Engineering and Science (ICATCES 2019), Apr 26-28, 2019 Alanya, Turkey

The explanatory coefficient ( $\mathbb{R}^2$ ) gives the explanatory rates of the basic variables. If there is a linear relationship between the two variables, the square of the correlation coefficient is equal to the coefficient of explanation.  $\mathbb{R}^2$  ranges from 0 to 1. The approach of  $\mathbb{R}^2$  to 1 indicates that most of the change in the dependent variable is explained by the independent variable (Alpar, 2014). According to our correlation result 0.806, the explanatory coefficient is 0.6496. According to the coefficient result, 64% of the variation or variation on the variable X (energy consumption) may be explained by the variation or variation on the Y variable (urban area).

#### **IV.CONCLUSION**

Urban area is a parameter that changes every year. The fact that the electricity consumption can be estimated using light activity value and usage of 7-year data for this estimation have created effective results in this study. The R value is 0.806 and  $R^2$  is 0.6496. The result shows that there is strong relationship between urban area and electricity consumption.

#### V.REFERENCES

[1] Letu, Husi & Hara, Masanao & Yagi, Hiroshi & Tana, Gegen & Nishio, Fumihiko. (2009). *Estimating the energy consumption with nighttime city light from the DMSP/OLS imagery*, 2009 Joint Urban Remote Sensing Event. 1 - 7. 10.1109/URS.2009.5137699.

[2] Yücer, Emre & Erener, Arzu. (2018). *GIS Based Urban Area Spatiotemporal Change Evaluation Using Landsat and Night Time Temporal Satellite Data*, Journal of the Indian Society of Remote Sensing. 46. 1-11. 10.1007/s12524-017-0687-5.

[3] Tilottama Ghosh, Sharolyn J. Anderson, Christopher D. Elvidge, and Paul C. Sutton, *Using nighttime satellite imagery as a proxy measure of human well-being*, Sustainability, 5(12):4988–5019, 2013. ISSN 2071-1050. doi: 10.3390/su5124988.

[4] Shi, Kaifang & Yu, Bailang & Huang, Yixiu & Hu, Yingjie & Yin, Bing & Chen, Zuoqi & Chen, Liujia & Wu, Jianping. (2014). Evaluating the Ability of NPP-VIIRS Nighttime Light Data to Estimate the Gross Domestic Product and the Electric Power Consumption of China at Multiple Scales: A Comparison with DMSP-OLS Data, Remote Sensing. 6. 10.3390/rs6021705.

[5] Elvidge, C.D., Erwin, E.H., Baugh, K.E., Ziskin, D., Tuttle, B.T., Ghosh, T., et al., 2009. *Overview of DMSP night-time lights and future possibilities*, Urban remote sensing event, pp. 1–5.

[6] Imhoff, M.L., Lawrence, W.T., Stutzer, D.C., Elvidge, C.D., 1997. *A technique for using composite DMSP/OLS 'city lights' satellite data to map urban area*, Remote Sensing of Environment, 61(3), pp. 361–370.

[7] H. Atasoy, (2016), *Otsu Eşik Belirleme Metodu*. [Online]. Available: http://www.atasoyweb.net/Otsu-Esik-Belirleme-Metodu

[8] Alpar, R. (2014), Spor Sağlık ve Eğitim Bilimlerinden Örneklerle Uygulamalı İstatistik ve Geçerlik-Güvenirlik, Ankara: Detay Yayıncılık. [9] Turan, Muhammed & Yücer, E & Şehirli, Eftal & Karaş, İsmail. (2017). *Estimation Of Population Number Via Light Activities On Night-Time Satellite Images.* ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. XLII-4/W6. 103-105. 10.5194/isprs-archives-XLII-4-W6-103-2017.

[10] Levin, N., and Duke, Y., 2012. *High spatial resolution night-time light images for demographic and socio-economic studies*, Remote Sensing of Environment, 119, pp. 1–10.

[11] Liu, Z., He, C., Zhang, Q., Huang, Q., Yang, Y., 2012. Extracting the dynamics of urban expansion in China using DMSP-OLS nighttime light data from 1992 to 2008, Landscape and Urban Planning, 106(1), pp. 62–72.

[12] Wei, Y., Liu, H., Song, W., Yu, B., Xiu, C., 2014. Normalization of time series DMSP-OLS nighttime light images for urban growth analysis with Pseudo Invariant Features, Landscape and Urban Planning, 128, pp. 1-13.

[13] Huang, X., Schneider, A., Friedl, M.A., 2016. *Mapping sub-pixel urban expansion in China using MODIS and DMSP/OLS nighttime lights*. Remote Sensing of Environment, 175, pp. 92-108.

[14] Small, C., Elvidge, C.D., 2013. *Night on Earth: Mapping decadal changes of anthropogenic night light in Asia,* International Journal of Applied Earth Observation and Geoinformation, 22, pp. 40-52.

[15] Türkbal, A., Bilimsel Araştırma Metodları Ve Uygulamalı İstatistik, Atatürk Üniversitesi Basım Evi, 1981