

Population Estimation Using Geographic Information System and Remote Sensing for Unorganized Areas

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Abstract: Population estimation using remotely sensed data had been largely discussed in the literature relative to human geography. However, the previously established models can be applied to organized areas (mainly urban areas), but they are not suitable for unorganized areas that already suffer from a lack of population data. So, this study aims to establish a statistical model for population estimation based on remote sensing data and suitable for unorganized areas. To do so, the morphological characteristics have been studied and bivariate analysis was carried out to determine factors having a strong relationship with population data as a first step. Second, factors with the strongest correlations have been chosen to establish the required model. As a result, an equation has been generated, which relates the population data to building volume, the density of roads, number of nodes, actual urban areas, and urban trend.

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1. INTRODUCTION

Population estimation using remotely sensed data is a relevant data source for geographers and urban planners as it allows a huge range of applications. The roots of population estimation in urban geography are the simple gravitational population density model, which can also be called "social physics" (Stewart & Warntz, 1958). In this context, Clark (1951) is the first to associate the population estimation with a mathematical equation (Liu, 2003). This equation was valid for many cities of the United States (Weiss, 1961) and outside the U.S. (Newling, 1966). After that, several equations have been proposed to estimate populations such as the Gaussian and the parabolic forms (Sutton, 1997), the inverse power functions, and the negative exponential functions (Parr, 1985). Those equations were efficient in describing population distribution, but they can't be used for population estimation. For that, aerial interpolation might be used to transform data from one spatial unit (source zone) to another (target zone) and it may be done with or without ancillary information (Lam, 1983).

Aerial interpolation without ancillary information is divided into two sets of methods: Point-based methods, which consist of representing each zone by a control point, then using those points to estimate grid point values. The accuracy of those methods depends on the chosen method of interpolation and their major disadvantage is their inability to conserve total value within each source zone. The area-based methods can be done through several methods, but the simplest one is an overlay operation between the target zone and the source zone, where the proportion becomes a weight for the linear function of source zones. This approach assumes homogeneity within each source zone, and this consists of its major limitation. Aerial interpolation with ancillary information consists of assessing population interpolation by relating it to other information such as land use and transportation networks. The most well-known method is the dasymetric method, developed by Wright (1936), and aims at using the locality's knowledge to identify areas within

zones with different population densities in order to adjust the estimation procedure (Fisher & Langford, 1995).

Moreover, the development of GIS technologies facilitates the application of this method by using the overlay process in GIS and the integration of different types of ancillary spatial data such as the classified land use land uses, as shown by Monmonier & Schnell (1984). In the 1950s, Another approach has been used to estimate population, which consists a combination between the remotely sensed data and the statistical modeling, considering that population distribution in urban areas is affected by morphological factors (such as distance to the central business district (CBD), distance to roads, etc.) and those factors can be extracted from remotely sensed data (Sutton, 1997; Batty & Longley, 1994; Parr, 1985).

However, this approach can be used to estimate population count rather than population density. Statistical modeling for population estimation was initiated as an alternative to population census characterized by several problems such as the lack of data caused by the low frequency of census (Kraus et al., 1974) as well as to check the reliability of census enumeration (Clayton & JE, 1980) and the effect of socio-economic characteristics (Forster, 1983). Generally, there are five categories of methods according to the relation between population and urban areas (Lo & Welch, 1977; Lee, 1989), land use (Weber, 1994; Kraus et al., 1974), dwelling units (Green, 1956; Porter, 1956; Kraus et al., 1974; Sun, 1971; Lo & Chan, 1980), image pixel characteristics (Hsu, 1973; Lo, 1986; Iisaka & Hegedus, 1982; Webster, 1996) and other physical or socioeconomic characteristics (Dobson et al., 2000; Liu & Clarke, 2002; Green, 1957; Green & Monier, 1959). In the literature, several statistical models have been constructed to estimate population from remotely sensed data such as Kaimaris & Patias (2016) who used an empirical equation to determine the people living in a building, Karume et al. (2017) who adopted a dasymetric mapping approach to derive land use data using two GeoEye images and Dong et al. (2010) who evaluated a small area population estimation using LiDAR, Landsat TM and parcel data.

The previously presented methods might be accurate in structured urban areas. However, those methods are not compatible with unorganized areas where finding a pattern seems to be difficult. For that, it is essential to find a method to be accurate and useful for unorganized areas. In this context, Lebanon, as the majority of third world countries, witnessed a rapid and uncontrolled urban sprawl as a result of the corruption and the limited planning regulations (Council for Development and Reconstruction, 2005). As a result, the establishment of plans to handle this situation faces huge challenges since it is difficult to obtain the required data related to constructed areas and its population data. For that, this situation imposes the elaboration of precise methods to provide researchers and specialists in urban planning with the necessary information about the built-up and population characteristics. Consequently, the aim of this study is to construct a model for population estimation in unorganized areas using only remotely sensed data.

2. DATA AND METHODS

2.1. Case Study

The Lebanese Republic, occupying an area of 10452 square kilometers, is located in western Asia on the eastern shore of the Mediterranean Sea between latitudes 33° and 35° N and longitudes 35° and 37° E. It borders the Sea in the west, Syria in the north and east, and Occupied Palestine in the south. In order to extract the necessary data for this study, a sample of 30 villages (e.g., unorganized areas) have been chosen. Those municipalities are arbitrarily chosen and geographically well distributed throughout the country (Figure 1).

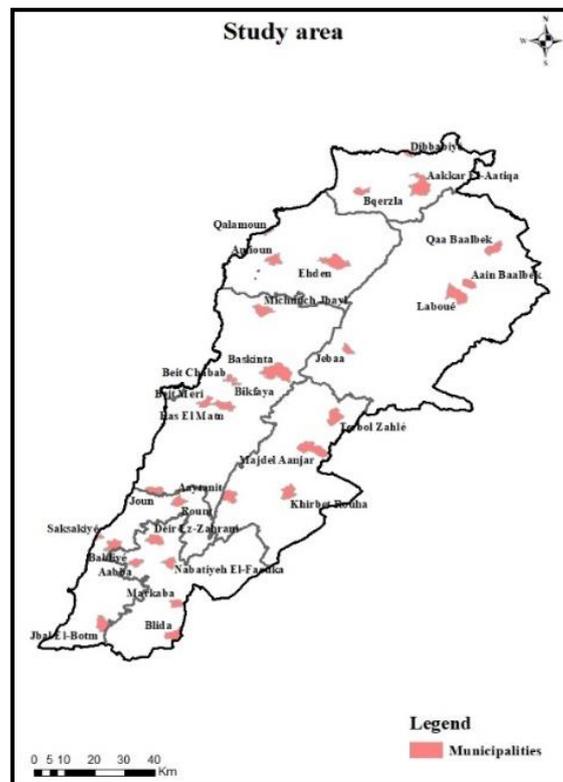


Figure 1. Distribution of the selected municipalities on the Lebanese map

2.2. Methodology and Data

2.2.1. Process

The used methodology was divided into 3 phases: Data collection, bivariate analysis, and multivariate analysis. During the first phase, the population data for each municipality has been determined as a product of the residential units and the mean residents per unit. Moreover, each one of the chosen factors has been studied independently. The second phase consists of evaluating the relationship between each factor and the population data using simple regression. The factors which show a strong relationship with population data were chosen to construct the statistical model. During the third phase, a multiple regression was done to generate an equation relating the population data to each one of the factors.

2.2.2. Data Collection

1. Building volume

The determination of buildings' volumes for each municipality required the determination of the number of buildings, the average area, and the mean height of buildings. To do so, the RGB image has been transformed into HSI image using ERDAS Imagine software and the band I have been transformed into shapefile using ArcGIS software. The convex hull tool in ArcGIS has been used to determine the polygons representing buildings. Based on statistical data, residential buildings have been extracted, and the total area of buildings has been determined. In order to determine the height of buildings, the RGB image has been transformed into LAB format and using Otsu's method. The image has been divided into several categories according to brightness value. The shadows have been specified on the image and the height of buildings has been determined using the relation between the azimuth of the sun, the dimension of shadow, and the height of the building. In the end, the volume of buildings has been determined using the following equation (Allaw et al., 2019) (Eq 1). The results have been summarized in Table 1.

$$\text{Built - up volume} = \text{Mean area} * \text{number of buildings} * \text{mean height} \text{ (Eq. 1)}$$

Table 1. The number, area, and volume of buildings

Municipality	Total number of building	Mean area (m ²)	Buildings area (m ²)	Building Volume (m ³)
Aabba	1080	144	155520	544320
Aain Baalbek	1003	171	171513	600295.5
Aakkar El-Aatiqa	909	265	240885	963540
Aaytanit	54	203	10962	43848
Amioun	656	280	183680	642880
Babliy�	540	185	99900	349650
Baskinta	824	204	168096	588336
Beit Chabab	813	178	144714	578856
Beit Meri	1080	288	311040	1244160
Bikfaya	440	298	131120	458920
Blida	617	240	148080	518280
Bqerzla	233	197	45901	137703
Deir Ez-Zahrani	942	241	227022	908088
Dibbabi�	187	140	26180	78540
Ehden	904	310	280240	1120960
Jbal El-Botm	417	199	82983	248949
Jebaa	46	203	9338	28014
Joun	489	198	96822	338877
Khirbet Rouha	602	251	151102	528857
Labou�	1438	165	237270	949080
Majdel Aanjar	1266	263	332958	1331832
Markaba	433	219	94827	331894.5
Michmich Jbayl	264	208	54912	192192
Nabatieh El-Faouka	1104	210	231840	927360
Qaa Baalbek	844	175	147700	516950
Qalamoun	568	225	127800	511200
Ras El Matn	351	198	69498	277992
Roum	251	226	56726	170178
Saksaki�	1042	161	167762	587167
Terbol Zahl�	533	261	139113	486895.5

2. Road network characteristics

- a. Length of roads: The length of primary roads, secondary roads, and the total length of roads have been determined using the data available at <https://extract.bbike.org>. However, many roads were not available in this data, so the digitalization of roads on satellite images has been used to cover the missing data.
- b. The density of roads: The density of roads' network has been calculated, using ArcGIS, by dividing the total length of the roads by the built-up area of each municipality (it is expressed in kilometer per kilometer square).
- c. The number of nodes: The number of nodes has been determined using the following method: The intersect tool has been used to determine intersection points between roads. However, this will generate many points on the same location, so, using the dissolve tool (according to points' coordinates), those points can be replaced by a unique node. Then, the number of nodes for each municipality has been calculated.

The results have been summarized in the following [Table 2](#).

Table 2. road network elements for each municipality

Municipalities	Length of primary roads (km)	Length of secondary roads (km)	Total length of roads (km)	Density of roads (km/km ²)	Number of nodes
Aabba	4511.99	47339.03	51851.02	7.00	331
Aain Baalbek	2489.34	62923.81	65413.15	7.45	380
Aakkar El-Aatiqa	5177.72	128869.59	134047.30	6.00	402
Aaytanit	3306.35	32420.58	35726.93	2.59	101
Amioun	4789.66	76987.78	81777.44	7.18	329
Babliyé	11630.99	44018.25	55649.24	5.80	205
Baskinta	27028.84	64205.41	91234.25	4.67	422
Beit Chabab	1589.58	37470.39	39059.97	7.80	175
Beit Meri	4252.83	70301.84	74554.67	8.74	267
Bikfaya	1337.00	45177.91	46514.92	6.10	258
Blida	5223.25	78362.46	83585.71	6.29	316
Bqerzla	4955.98	39493.44	44449.42	5.44	145
Deir Ez-Zahrani	10363.79	77518.40	87882.20	7.27	497
Dibbabiyé	2137.68	13830.91	15968.59	4.12	52
Ehden	7299.78	114370.58	121670.37	7.21	528
Jbal El-Botm	3371.57	63785.64	67157.21	4.64	223
Jebaa	443.42	7239.93	7683.35	1.16	20
Joun	6523.03	56044.80	62567.83	5.24	235
Khirbet Rouha	2332.14	66320.06	68652.20	5.60	236
Laboué	3773.60	98874.65	102648.25	6.24	550
Majdel Aanjar	18935.54	121078.75	140014.29	5.53	509
Markaba	9582.24	46024.56	55606.80	6.88	355
Michmich Jbayl	5432.31	56538.86	61971.17	4.52	178
Nabatiyeh El-Faouka	8874.45	75827.76	84702.21	8.20	430
Qaa Baalbek	5648.52	54640.73	60289.25	6.30	400
Qalamoun	4112.17	36042.06	40154.23	6.20	234
Ras El Matn	5934.13	63132.26	69066.38	5.46	259
Roum	3232.61	29939.44	33172.06	2.78	104
Saksakiyé	1830.96	46812.80	48643.77	7.10	408
Terbol Zahlé	4182.47	72842.06	77024.53	5.50	266

3. Spatial dynamics

- a. Urban trend: The evolution of urban areas is usually correlated with population growth. For that, the digitalization of built-up areas has been done using Google Earth. For each municipality, the built-up areas have been determined for the period (2005-2018). The urban trend is the amount of urban areas evolution over the chosen period.
- b. Distance to the capital and distance to the governorate's center: Administratively, Lebanon is divided into 8 governorates (mohafazas) and the capital city is Beirut. For each municipality, the distance to the Lebanese capital and the distance to the governorate's center has been determined using Google maps.

Table 3. Spatial dynamics factors for each municipality

Municipalities	Urban areas "2018" (m^2)	Urban trend "2005-2018" (m^2)	Distance to the capital (Km)	Distance to the governorate's center (Km)
Aabba	152489	3456	12	84
Aain Baalbek	183269.1	3764.456	24	120
Aakkar El-Aatiqa	155425	3547	49.4	132
Aaytanit	62458.89	1760.097	45	80
Amioun	211860.1	2936.779	24.9	73
Babliyé	117399.4	3211.295	1.9	64
Baskinta	150503.9	3397.768	30.3	43
Beit Chabab	212645	3945	23	23
Beit Meri	164432.7	3945	18	18
Bikfaya	152347	3154	24	24
Blida	105024.6	3674.234	40.3	117
Bqerzla	105630.3	2145	25.6	108
Deir Ez-Zahrani	182758.1	4047.427	8.7	69
Dibbabiyé	57275.97	1471.368	46	129
Ehden	244288.3	4621	38	100
Jbal El-Botm	103840.9	2546	17	99
Jebaa	95231	2654	22	79
Joun	102992	2361.767	14	49
Khirbet Rouha	120548	3465.15	36	84
Laboué	188433.2	4132	29	116
Majdel Aanjar	145654	4586	19.7	65
Markaba	154036	3147.25	29	103
Michmich Jbayl	71239.48	2582.913	21	59
Nabatiyeh El-Faouka	194941.2	4256	1.9	76
Qaa Baalbek	214486.8	3125	50	137
Qalamoun	160865.7	3356	8.5	74
Ras El Matn	163830.2	2387.586	30	30
Roum	77409.68	2339.347	23	63
Saksakiyé	173248	4628.2	20	64
Terbol Zahlé	109769.7	3971.101	11.6	67

3. RESULTS AND DISCUSSION

3.1. Simple regression

The relation between each one of the dependent variables and the population has been evaluated using linear regression (Figure 2-11). The results have been summarized as follows:

Relationship between building volume and population

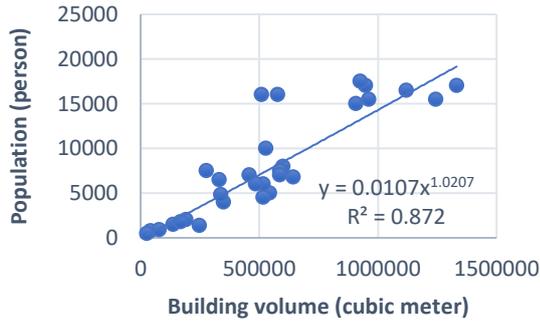


Figure 2. The relationship between building volumes and population data

The relation between population data and the total length of roads

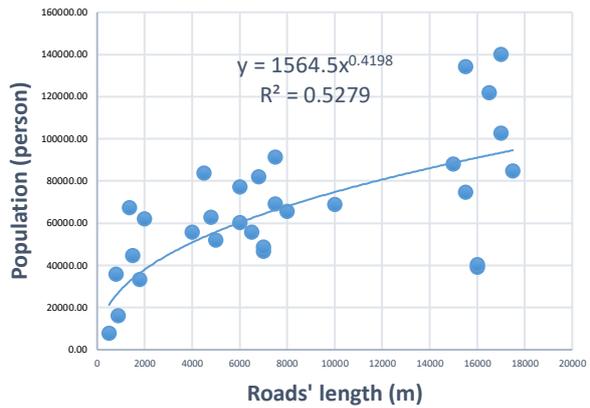


Figure 3. The relationship between the total length of roads and population data

The relationship between population data and the nombre of nodes

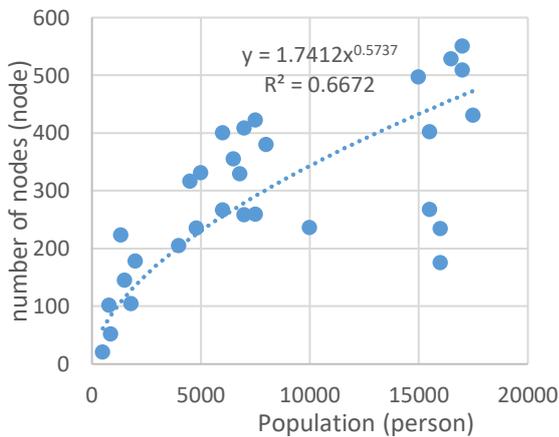


Figure 4. The relationship between the number of nodes and population data

The relationship between population data and the nombre of nodes

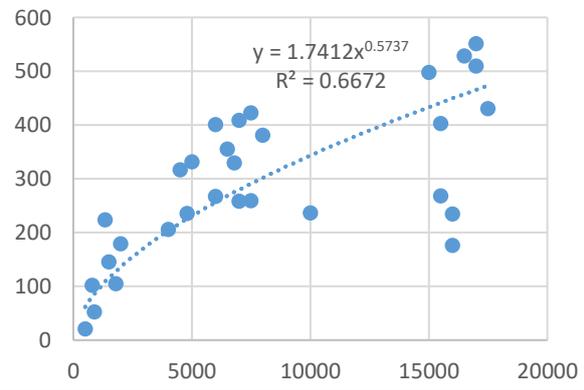


Figure 5. The relationship between the number of nodes and population data

The relationship between population data and the density of roads

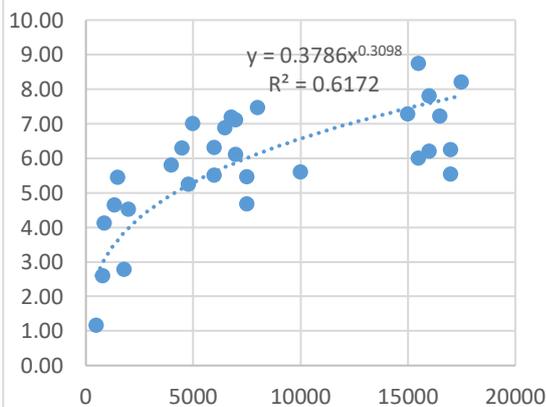


Figure 6. The relationship between the density of roads and population data

The relationship between population data and the length of secondary roads

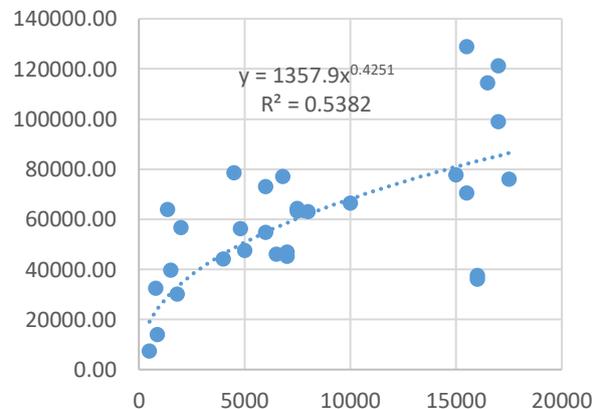


Figure 7. The relationship between the length of secondary roads and population data

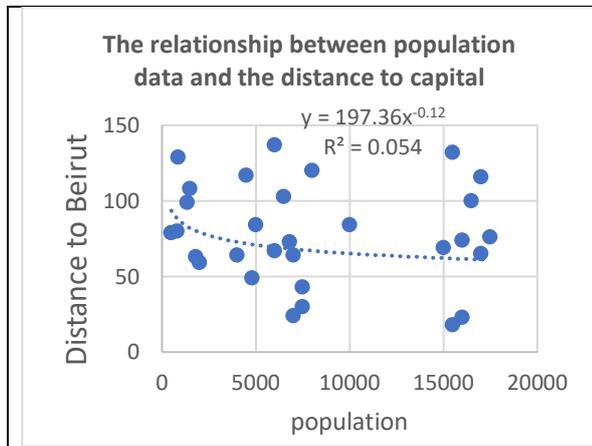


Figure 8. Simple regression between population and distance to the capital

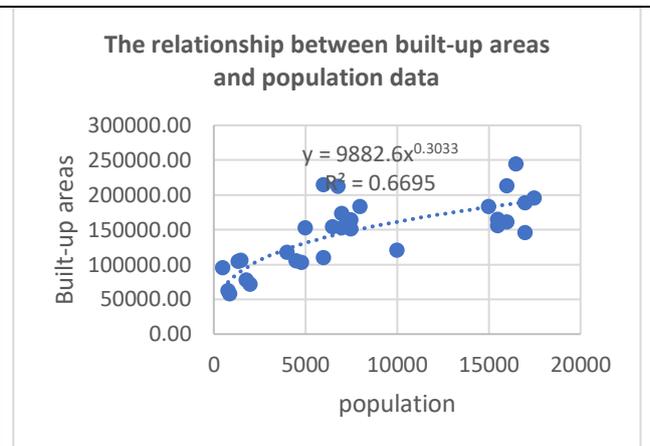


Figure 9. Simple regression between population and built-up areas

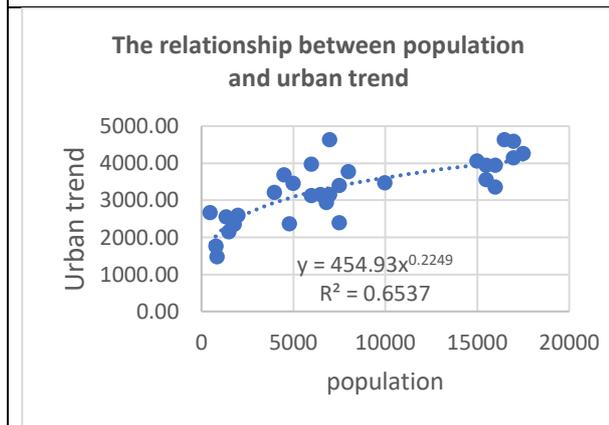


Figure 10. Simple regression between population and urban trend

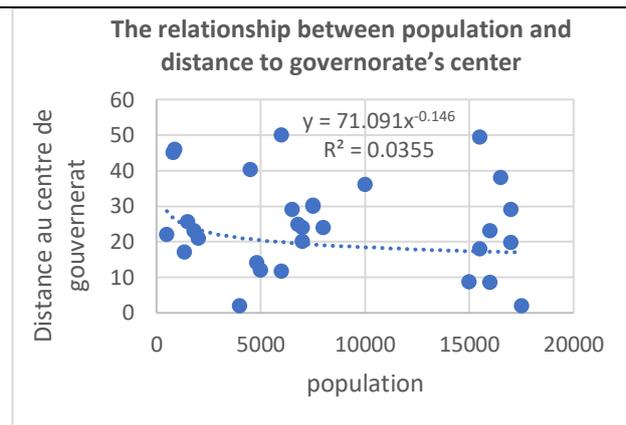


Figure 11. Simple regression between population and urban trend

Those graphs affirm that the factors with the highest correlation with population are: Building volume, the density of roads, number of nodes, actual urban areas, and urban trend.

3.2. Model: Multiple Regression

Multiple regression is an extension of simple linear regression. The general purpose of multiple regression is to learn more about the relationship between several independent or predictor variables and a dependent variable. Multiple regression estimates the β 's in the equation

$$y_j = \beta_0 + \beta_1 * x_{1j} + \beta_2 * x_{2j} + \dots + \beta_p * x_{pj} + \varepsilon_j$$

The X 's are the independent variables (IV's). Y is the dependent variable. The subscript j represents the population (row) number. The β 's are the unknown regression coefficients. The ε_j is the error (residual) of observation j and p is the number of predictor variables. The sample multiple regression equation is

$$\hat{y}_j = \beta_0 + \beta_1 * x_{1j} + \beta_2 * x_{2j} + \dots + \beta_p * x_{pj}$$

The basic regression model is

$$Y = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \dots + \beta_p * X_p + \varepsilon$$

For the measure of the goodness-of-fit of the regression model to the data. We use the coefficient of determination R^2 , which is defined as the sum of squares due to the regression divided by the adjusted

total sum of squares of Y. R^2 varies between zero (no linear relationship) and one (perfect linear relationship). The formula for R^2 is

$$R^2 = \frac{SS_{Model}}{SS_{Total}} = \frac{\sum_{j=1}^p (\hat{y}_j - \bar{y})^2}{\sum_{j=1}^p (y_j - \bar{y})^2}$$

For our application, a multiple regression has been done to establish the equation relating the chosen factors to population data, which results in a strong relationship ($R^2 = 0.82$) between the independent and dependent variables. Figure 12 shows the results of the predicted population by multiple regression against real populations. The obtained equation is as follows:

$$Y = 0.0154 * X_1 - 289.6425 * X_2 - 9.2800 * X_3 + 0.0365 X_4 - 0.2678 X_5$$

Where

$Y = Population$

$X_1 = Building\ volume$

$X_2 = Roads'\ density$

$X_3 = Number\ of\ nodes$

$X_4 = Urban\ areas$

$X_5 = Urban\ trend$

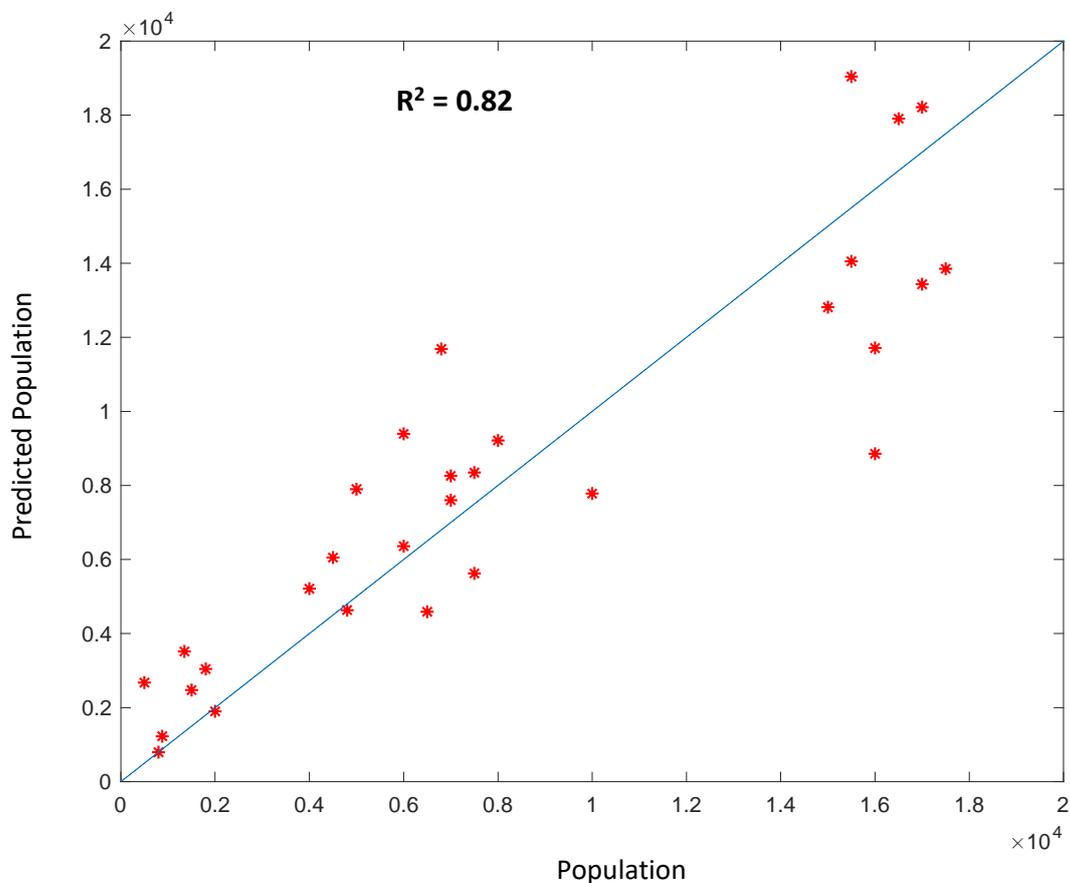


Figure 12. Results (Population & predicted population) by multiple regression model the evaluation by the determination coefficient R^2

3.3. Results' validation

In order to validate the obtained results, a sample of five villages was chosen by chance. For each village, we have evaluated the elements composing our model: Building volume, roads' density, number of nodes, urban areas, and urban trend. Then, we applied the obtained equation to estimate the population of each village. Then, we calculated the residuals, which are the differences between the real values and the estimated ones. The calculated residuals have been used to calculate the root mean squared error using the following equation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (Y' - Y)^2}{N}}$$

Where

N = Sample size

Table 4. Results' validation

ID	True population	Building volume	Roads' density	Number of nodes	urban areas	urban trend	Estimated population	residual
1	8062	502650.0	5.854350	271.00	149872.00	2783.000	7787.596949	-274.403100
2	12239	867186.0	5.400000	361.80	139882.50	3192.300	11780.515860	-458.484100
3	8810	563680.3	6.816000	391.68	166318.10	4443.072	8905.323345	95.323345
4	12205	561490.3	7.566000	169.75	206265.70	3826.650	12084.684660	-120.315300
5	3350	308378.1	4.764938	213.85	93722.68	2149.208	3374.950238	24.950238

The value of RMSE shows that this model has an estimation error of 249, which means that the estimated population will be greater or less than the real value by 249 people might be considered as acceptable since it constitutes only 2.5 % of the difference for a village of 10,000 inhabitants. Moreover, this error may be explained by other factors affecting the population.

Research conducted by [Kaimaris & Patias \(2016\)](#), [Karume et al. \(2017\)](#), and [Dong et al. \(2010\)](#) show the results of population estimation using GIS and remote sensing. However, these researches can only be carried out in structured urban areas. This study accurately shows the results of population estimates in Lebanon, a country with rapid and uncontrolled urban expansion.

4. CONCLUSION

Population estimation is a largely studied topic and an important application of human geography. Several approaches have been discussed and applied to estimate population density or population count. In this study, the remotely sensed data treated using GIS combined with statistical modeling are relevant for population estimation through the construction of a robust and accurate model for population estimation in unorganized areas. As a result, an equation relating the count of the population to building volume, the density of roads, number of nodes, actual urban areas, and the urban trend has been generated.

5. REFERENCES

- Allaw, K., Gerard, J. A., Chehayeb, M., & Saliba, N. B. (2019). Detection of Residential Buildings to Estimate Population in Lebanon using GeoEye Images. *International Journal*, 8(1), 3047–3056. [[Crossref](#)]
- Batty, M., & Longley, P. A. (1994). *Fractal cities: a geometry of form and function*. Academic press.
- Clark, C. (1951). Urban population densities. *Journal of the Royal Statistical Society. Series A (General)*, 114(4), 490–496.
- Clayton, C. & JE, E.. (1980). *Image analysis as a check on census enumeration accuracy*.
- Council for Development and Reconstruction. (2005). *National physical master plan of the Lebanese*

- territory. Retrieved from <http://www.cdr.gov.lb/study/sdatl/English/NPMPLT.PDF>.
- Dobson, J. E., Bright, E. A., Coleman, P. R., Durfee, R. C., & Worley, B. A. (2000). LandScan: a global population database for estimating populations at risk. *Photogrammetric Engineering and Remote Sensing*, 66(7), 849–857.
- Dong, P., Ramesh, S., & Nepali, A. (2010). Evaluation of small-area population estimation using LiDAR, Landsat TM and parcel data. *International Journal of Remote Sensing*, 31(21), 5571–5586. [[Crossref](#)]
- Fisher, P. F., & Langford, M. (1995). Modelling the errors in areal interpolation between zonal systems by Monte Carlo simulation. *Environment and Planning A*, 27(2), 211–224. [[Crossref](#)]
- Forster, B. (1983). Some urban measurements from Landsat data. *Photogrammetric Engineering and Remote Sensing*, 49, 1693–1707.
- Green, N. E. (1956). Aerial photographic analysis of residential neighborhoods: An evaluation of data accuracy. *Social Forces*, 142–147. [[Crossref](#)]
- Green, N. E. (1957). *Aerial photographic interpretation and the social structure of the city*. American Society of Photogrammetry.
- Green, N. E., & Monier, R. B. (1959). Aerial photographic interpretation of the human ecology of the city. *Photogrammetric Engineering*, 25(5), 770–773.
- Hsu, S.-Y. (1973). Population estimation from ERTS imagery- Methodology and evaluation. *American Society of Photogrammetry, Annual Meeting, 39 Th, Washington, D. C.*, 583–591.
- Iisaka, J., & Hegedus, E. (1982). Population estimation from Landsat imagery. *Remote Sensing of Environment*, 12(4), 259–272. [[Crossref](#)]
- Kaimaris, D., & Patias, P. (2016). Population estimation in an urban area with remote sensing and geographical information systems. *International Journal of Advanced Remote Sensing and GIS*, 5(6), 1795–1812. [[Crossref](#)]
- Karume, K., Schmidt, C., Kundert, K., Bagula, M. E., Safina, B. F., Schomacker, R., ... others. (2017). Use of remote sensing for population number determination. *The Open Access Journal of Science and Technology*, 5. [[Crossref](#)]
- Kraus, S. P., Senger, L. W., & Ryerson, J. M. (1974). Estimating population from photographically determined residential land use types. *Remote Sensing of Environment*, 3(1), 35–42. [[Crossref](#)]
- Lam, N. S.-N. (1983). Spatial interpolation methods: a review. *The American Cartographer*, 10(2), 129–150. [[Crossref](#)]
- Lee, Y. (1989). An allometric analysis of the US urban system: 1960--80. *Environment and Planning A*, 21(4), 463–476. [[Crossref](#)]
- Liu, X. (2003). *Estimation of the spatial distribution of urban population using high spatial resolution satellite imagery*.
- Liu, X., & Clarke, K. C. (2002). Estimation of residential population using high resolution satellite imagery. *Proceedings of the 3rd Symposium on Remote Sensing of Urban Areas*, 11–13.
- Lo, C. P. (1986). *Applied remote sensing*.
- Lo, C. P., & Chan, H. F. (1980). Rural population estimation from aerial photographs. *Photogrammetric Engineering and Remote Sensing*, 46(3), 337–345.
- Lo, C. P., & Welch, R. (1977). Chinese urban population estimates. *Annals of the Association of American Geographers*, 67(2), 246–253. [[Crossref](#)]
- Monmonier, M. S., & Schnell, G. A. (1984). Land use and land cover data and the mapping of population density. *International Yearbook of Cartography*, 24, 115–121.
- Newling, B. E. (1966). Urban growth and spatial structure: mathematical models and empirical evidence. *Geographical Review*, 213–225. [[Crossref](#)]
- Parr, J. B. (1985). A population-density approach to regional spatial structure. *Urban Studies*, 22(4), 289–303. [[Crossref](#)]
- Porter, P. W. (1956). *Population distribution and land use in Liberia*. London School of Economics and Political Science (University of London).
- Stewart, J. Q., & Warntz, W. (1958). Physics of population distribution. *Journal of Regional Science*, 1(1), 99–121.
- Sun, Y. (1971). Population estimation. *Presented at the Annual Convention of the CC*, 4(11,424), 615.
- Sutton, P. (1997). Modeling population density with night-time satellite imagery and GIS. *Computers, Environment and Urban Systems*, 21(3–4), 227–244. [[Crossref](#)]

- Weber, C. (1994). Per-zone classification of urban land cover for urban population estimation. *In Environmental Remote Sensing from Regional to Global Scales*, 142–148.
- Webster, C. J. (1996). Population and dwelling unit estimates from space. *Third World Planning Review*, 18(2), 155. [[Crossref](#)]
- Weiss, H. K. (1961). The distribution of urban population and an application to a servicing problem. *Operations Research*, 9(6), 860–874. [[Crossref](#)]
- Wright, J. K. (1936). A method of mapping densities of population: With Cape Cod as an example. *Geographical Review*, 26(1), 103–110. [[Crossref](#)]