Virginia Urban Dynamics Study Using DMSP/OLS Nighttime Imagery

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ABSTRACT

Urban dynamics at regional scales has been increasingly important for economics, policies, and land use planning, and monitoring regional scale urban dynamics has become an urgent need in recent years. This study illustrated the use of time series nighttime light (NTL) data from the United States Air Force Defense Meteorological Satellites Program/Operational Linescan System (DMSP/OLS) to delineate urban boundaries and tracked three key urban changes: land cover change, population growth and GDP growth within Virginia. NTL data from different years were inter-calibrated to be comparable by using linear regression model and Pseudo Invariant Features (PIFs) method. Urban patches were delineated by applying thresholding techniques based on digital number (DN) values extracted from DMSP/OLS imagery. Compounded Night Light Index (CNLI) values were calculated to help estimate GDP, and these processes were applied in a time series from 2000 to 2010. Spatial patterns of DN change and the variation of CNLI indicate that human activities were increasing during the 10 years in Virginia. Accuracy of the results was confirmed using ancillary data sources from the U.S. Census and NLCD imagery.

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GENERAL AUDIENCE ABSTRACT

Urban areas concentrate built environment, population, and economic activities, therefore, generating urban sprawl is a simultaneous result of land-use change, economic growth, population growth and so on. Remote sensing has been used to map urban sprawl within individual cities for a long time, while there has been less research focused on regional scale urban dynamics. However, the regional scale urban dynamics for economics, formulating policies, and land use planning has been increasingly important, and monitoring regional scale urban dynamics has become an urgent need in recent years.

Here, we illustrated the use of multi-temporal United States Air Force Satellites data to help monitor urban sprawls by delineating urban patches and we measured a variety of urban changes, such as urban population growth and land cover change within Virginia based on the delineation. For doing so, digital number values, which measures the brightness of satellite imagery, were extracted and other relative index values were calculated based on digital number values, and these processes were applied in a time series from 2000 to 2010. Spatial patterns of digital number values change and the variation of another light index values indicate that human activities were increasing during the 10 years in Virginia.

Table of Contents

Introduction

      According to the US Census Bureau, urban area is defined as core groups of census block and surrounding block groups with a population density > 193/km^2. Currently, there are 1371 urban areas with a population > 10000 in the US (US Census Bureau). Urban areas are crucial because they concentrate the built environment, population, and economic activities. The United Nations estimates that the 2010 3.4 billion global urban population will double by 2050. Economically, the urban economy has steadily squeezed agricultural economy, and nowadays contributes to over 96% of the global GDP (U.N., 2010).

      Worldwide, urban land-use causes species extinction, pollution and the reduction of agricultural lands in many developing countries (Seto, 2011). Research has shown that urban sprawl elevates urban temperature and greatly affects the local climates through the interface between urban atmosphere and regional atmosphere. The changing local atmospheres bring changes in regional precipitation patterns and finally influence local agriculture and biological environments. An assessment of the State of New Jersey estimated that $1180 million more for roads and sewers would be cost and 90 thousand acres of farmland would be destroyed due to urban sprawl, and sprawl would also produce 4,560 tons more water pollutants (Center for Urban Policy Research, 1992). For measuring urban dynamics and evaluating its environmental influence, delineating urban areas, based on spatial metrics, accurately and quickly play a fundamental role.

      Eight spatial metrics were identified by Galster et al. (2001) for measuring urban sprawl are "density, continuity, concentration, clustering, centrality, nuclearity, mixed uses, and proximity". Ji et al. (2006) tried to monitor urban sprawl using several landscape metrics related to land change and land consumption based on construction. However, the interpretation of these metric combinations results is confusing since metrics are large in number and metrics contradict with each others. Ritters et al. (1995) did examinations for the correlations of 55 different spatial metrics and announced only 5 factors are independent. Milesi et al. (2003) monitored land cover changes with single metrics of net primary productivity (NPP) in Southeastern US, which has the highest rates of land productivity in the US. They estimated NPP using MODIS data, and found the correlation between the reduction of NPP and urban land sprawl; however, estimating NPP is very complex, which does not meet our expectation of quick monitoring. Sutton (2003) used two thresholds based on land consumption per capita to delineate urban extent in the mid-west US, and the author proved there is strong correlation between the single spatial metrics of land consumption per capita and urban sprawl. He proved that it doesn't have to be a combination of several metrics for measuring sprawl. Here, we are going to use a single metrics Digital Number (DN) value extracted from DMSP/OLS nighttime imagery for our measurements. Compared with daytime, nighttime imagery has unique advantages in that it avoids classification problems in separating developed urban area with its surrounding land cover by measuring emitted rather than reflected radiation, which (Sutton, 2003), and DN value is always among the most direct and convenient data to be acquired.

      The goal of this thesis is using time series DMSP/OLS nighttime data to delineate urban areas using thresholding techniques in Virginia. Based on the delineation, three key components of urban sprawl were tracked simultaneously during 2000 to 2010 as our results: urban population, urban land cover, and economic activities.

Study Area

The study area is focused on the urban patches within Virginia. Fig. 1 shows the map of the US with Virginia's county boundaries. Virginia is located at the eastern coast of the US between the Atlantic Ocean and the Appalachian Mountains. It occupies an area of 42774.2 mi^2 and bounded by 36°32′ to 39°28′North latitudes and 75°15′ to 83°41′West longitudes.
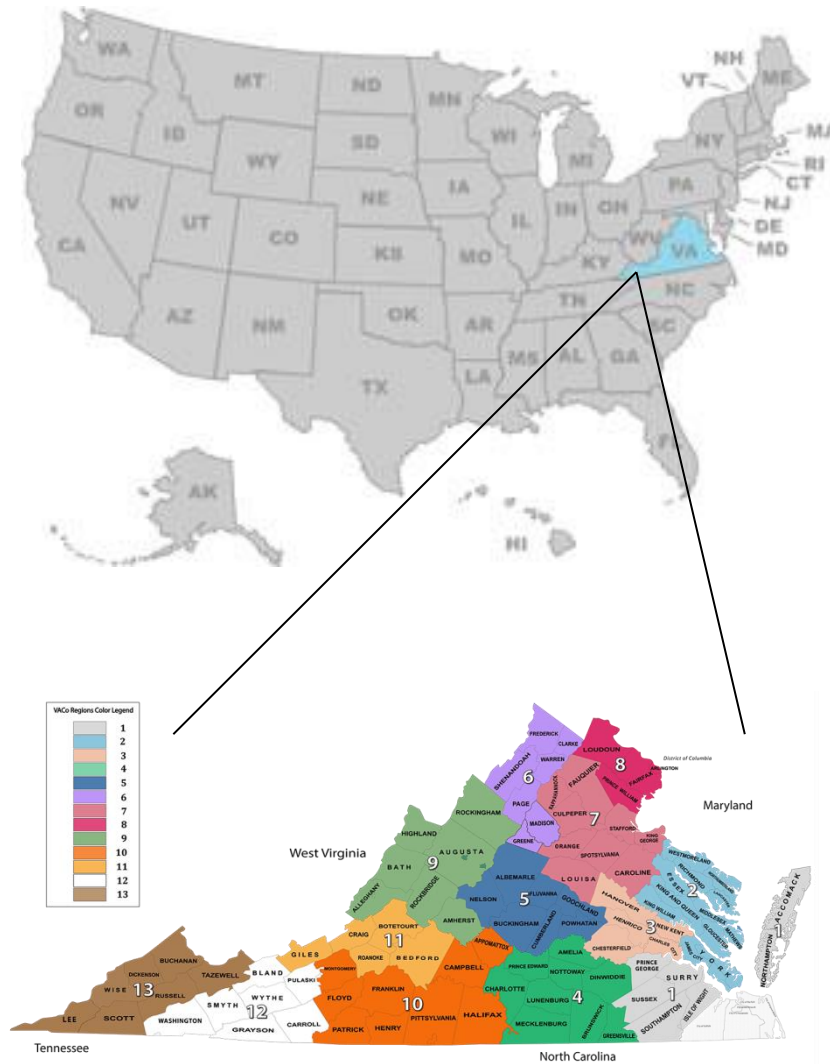

Figure 1 Geographical location of Virginia, USA

Compared with nearby states such as Maryland, and West Virginia, Virginia has a relatively high population growth rate (Fig. 2.). The population growth averages out at around 15% at every Census from 1960 onwards, making Virginia one of the fastest growing states in the US. Analysts estimated that Virginia is going to add over 800 thousand new residents every decade, and will reach 10.5 million by 2040 (Virginia State Data Center), which brings concerns about urban sprawl.
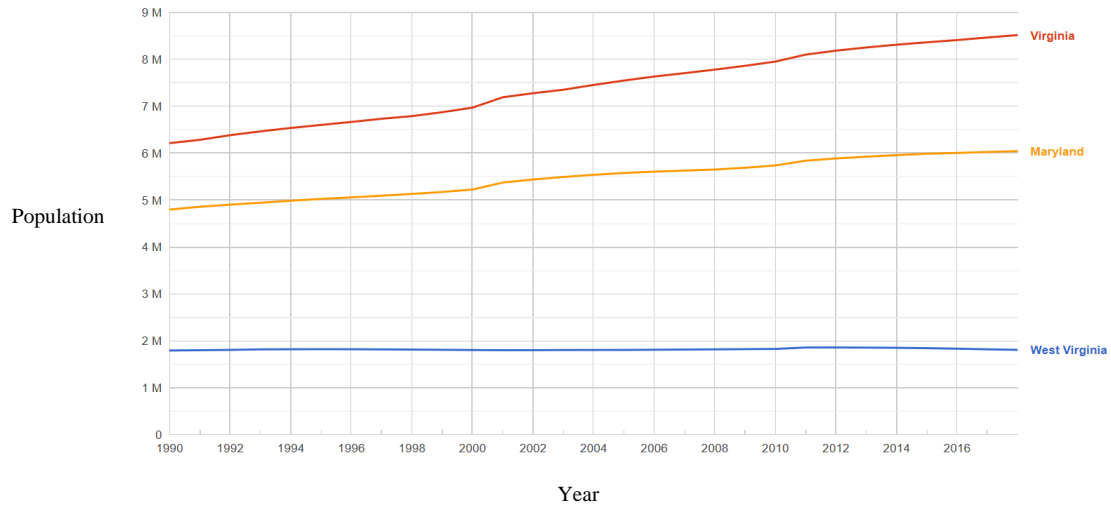
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Figure 2 Population growth of Virginia and its nearby states

Data Sources and Background

The Operational Linescan System (OLS) belongs to the Defense Meteorological Satellite Program (DMSP), and it was designed to observe clouds illuminated by moonlight (Elvidge et al., 1997). Later on, due to the lowlight imaging capability of DMSP/OLS, it started to be used for detecting nocturnal artificial lighting (Zhang et al., 2011). OLS scans the earth surface as wide as 3000 km in one pass, and it has near global coverage spanning from -65 to 75 degrees latitude (National Geophysical Data Center). The system can achieve global coverage every 24 h with a 0.56 km resolution (Elvidge et al., 1999).

Since 2000, several versions of the most commonly used data have been published by the National Geophysical Data Center (NGDC) (Liu et al., 2012). Version1 includes year 1992, 1993, and 2000 data, while Version 2 includes 1992 to 2003; however, the download of these products are not available anymore. NGDC published the Version 4 DMSP-OLS nighttime light dataset in January 2010, and the Version 4 dataset are composites made of all available fine resolution data for each year from 1992 to 2013. For ensuring the selected data into the composites had a smooth resolution, a number of criteria were used:

(1) "Excluding sunlit data and glare according the solar elevation angle.
(2) Excluding moonlit data according to the lunar illuminance calculation.
(3) Excluding clouds impact according to clouds identification using OLS thermal band data.
(4) Excluding aurora lighting features in the northern hemisphere by visual inspection." (National Geophysical Data Center)

The Version 4 dataset contains three types of data: "Cloud Free Coverage, Average Visible, and Nighttime Stable Light (NSL) data." Among the three types of data, lights from cities, towns, and other persistent lighting sites are included in NSL data (Elvidge et al., 2009), which makes fine resolution rapid assessments of global urban expansion possible (Zhang et al., 2011). Therefore, this thesis picked 2000-2010 NSL data for our research. OLS is able to detect nocturnal radiances from 1.54×10^{-9} to 3.17×10^{-7} W·m^{-2}·sr^{-1}·nm^{-1} (Cinzano et al., 2000). Data values are reported in DN, which ranges from 0 (no light) to 63 (max reported light).

After the declassification of DMSP-OLS from military-use only, the potential of nighttime OLS data as a human activity indicator was first noted by Croft in the 1970s. Since then, more and more scientists had explored the relationships and proved the high correlations between nighttime OLS data and key social-economical variables, such as urban population (Amaral et al., 2006), economic activity (Chen et al., 2011), gross domestic product (GDP) (Sutton et al., 2007), and energy consumption (Doll et al., 2010).

Henderson et al. (2003) suggested that the brightness differences between developed urban patches and its surrounding areas make it simple to delineate urban areas using thresholding techniques on the DMSP nighttime imagery. Imhoff et al. (1997) mapped the urban areas of Chicago, Sacramento and Miami metropolitan areas using thresholding techniques according to the nighttime light data. Henderson et al. (2003) used OLS data to delineate urban boundaries for Beijing, Lhasa and San Francisco by acquiring auxiliary information from Landsat TM imagery. He et al. (2006) determined thresholds for Chinese cities on OLS imagery in virtue of the census data from Chinese Academy of Sciences as ancillary information, but incompleteness of the census data impacted the accuracy of the results. No studies to date have

similarly documented urban dynamics in Virginia using DN values, and this thesis is going to fill in the blank.

Besides OLS data from NGDC in this thesis, we used NLCD 2001 Land Cover (CONUS) imagery from Multi-Resolution Land Characteristics (MRLC) Consortium, which is based on a modified Anderson Level II classification system, at a 30m resolution with a 16-class legend (Multi-Resolution Land Characteristics Consortium) as ancillary data. We also acquired population density maps from 2000 and 2010 from NASA's Socioeconomic Data and Applications Center (SEDAC) at a 1km resolution, and population, land cover, and economical activities data from the US Census.

Methodology

a. Data Inter-annual Calibration

The NSL data I used was acquired by different satellites: data for 2000 through 2003 was acquired from satellite F15, 2004-2009 was from satellite F16, and 2010 was from F18. Henderson et al. (2003) claimed the different gain settings, and the atmospheric condition changes make DMSP/OLS data collected in different years not comparable directly. Even the data acquired from the same satellite in different years vary a lot. Liu et al. (2012) revealed these problems in their initial data analysis. For example, in 1999, the average DN value obtained by satellite F12 is 9.82, whereas satellite F14 is 7.27. The average DN value of satellite F12 in 1994 decreased from 10.51 to 8.62 in 1995 (Fig. 3.).
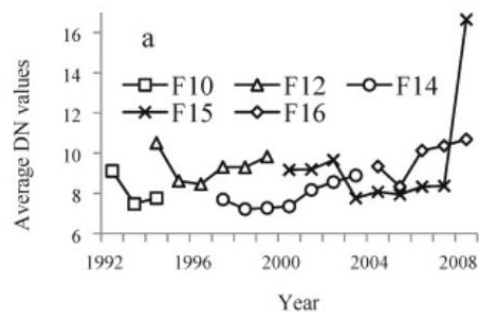

Figure 3 Average DN values from NSL data 1992-2008. Different lines represent different satellites, and we can see the data vary significantly every year even from the same satellite. (Liu et al., 2012)

Some scientists have made efforts to address the time series DMSP nighttime imagery comparability issue.

Elvidge et al. (2009) claimed the inter-calibration fits a 2nd order regression model ($DN_{adjusted} = C_0 + C_1 \times DN + C_2 \times DN^2$), and did experiments for Sicily, Italy and Algeria where the changes in lighting over time are small. The results are positive, but this model only focused on gain settings, sensor degradation such instrumental errors, and it ignored the changes in atmospheric conditions since the author assumed that the recorded nighttime light intensity won't be impacted much by atmospheric changes. The results could be pretty accurate if all the imagery were taken in similar atmospheric conditions accidently, however, ignoring atmospheric conditions could cause big inaccuracies in results.

Liu et al. (2012) made another attempt for DMSP/OLS data inter-calibration, for measuring urban expansion in China, they chose Jixi city of Northeastern China as the calibration area since the city has a relatively stable development over time. They used satellite F16 in 2007 as a reference dataset, and finally concluded a function between year 2007 data and data for other years by comparing DN value of each year with the reference year and using a lot of ancillary data, like land use/land cover data, to help calculate the coefficients. Although this approach included not only instrumental errors but also atmospheric changes, identifying a stable city may not always be easy or if a single city can do calibration for a whole economic region is still questionable.

Wei et al. (2014) explored the urban growth of China's Liaoning region using Pseudo Invariant Features (PIFs) to normalize time series DMSP/OLS nighttime light data. According to the concentric zone model first noted by Burgess (1925), urban growth is a process that central business district (CBD) invades its residential neighborhoods and causes them to expand outward all the time. Therefore, CBDs are always the brightest parts at DMSP/OLS imagery and the light intensity decreases all the time from CBD to urban boundary where new growth happens. In Wei's study, the authors picked out PIFs between CBD part and currently expanding part, which is within boundary 1 and boundary 2 in Fig. 4., since the DN values of the brightest CBD pixels are saturated (DN>63) and the currently expanding part has a lot of new construction with varied light intensity (Fig. 4.). A linear regression model was built to uncover the relationships between PIFs' DN values of each year with their corresponding DN values of the reference year. This is definitely a great normalization method since it considers both the instrumental errors and atmospheric changes and has no need to collect so much ancillary information, however, this approach has two major problems. First, it's not easy to locate the same location pixel in time series OLS imagery in practice because there is always a coordinate error in each image, which causes the pixels at the same location to not have the same coordinates. Second, the unsaturated part can become saturated and old buildings may be replaced by new buildings or moved to somewhere else. All of these possibilities can cause variation in DN values.
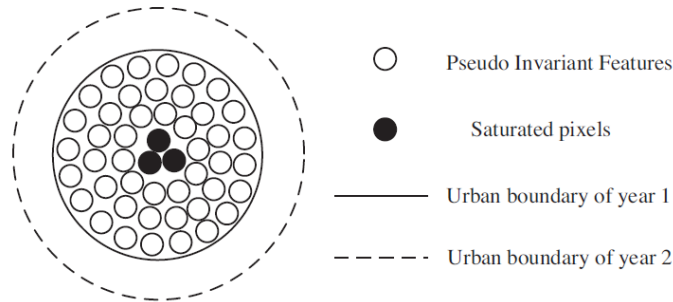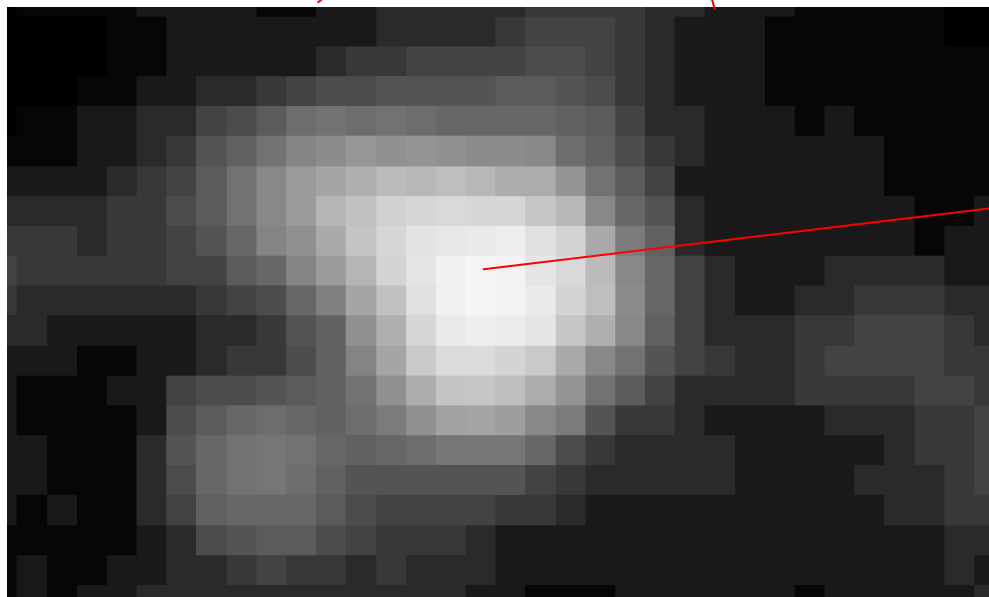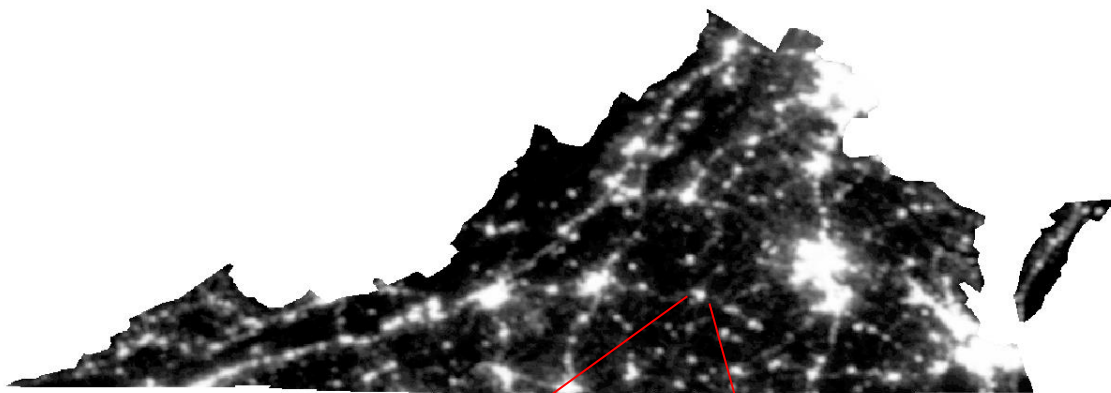

Figure 4 PIFs and simple concentric zone model: Center dark spots represent urban center, and the region between the real line and the dot line is the expansion part. The hollow spots are where Wei's sample collected from. (Wei et al., 2014)

Here, we applied a new approach that can solve the former approach's two problems by collecting DN values of sample pixels from CBD parts of small towns (Fig. 5.).The small towns we chose in Virginia all have population ranges from 5000 to 20000, which can ensure their CBDs are bright enough to be distinguished from surrounding pixels. At the same time their DN values are all below 55, which is much lower than saturation value of 63. By using this approach, we could locate the same pixels in time series nighttime imagery easily even though there are coordinating errors in each image since the CBD pixels are significantly brighter than their surrounding pixels, which can be picked out easily. Since these are already the most prosperous CBD parts of these small towns, the DN values of these pixels are actually 'saturated' for their local small towns. They have much lower chances to be further developed compared with Wei's sample locations. From year 2000 to 2010, we collected DN values of 20 PIFs for each image (220 in total), and we used year 2000 as the reference year. Finally, we established relationships between DN values of each year from 2001-2010 with DN values of year 2000 using linear regression model (Fig. 6., Tab. 1.).
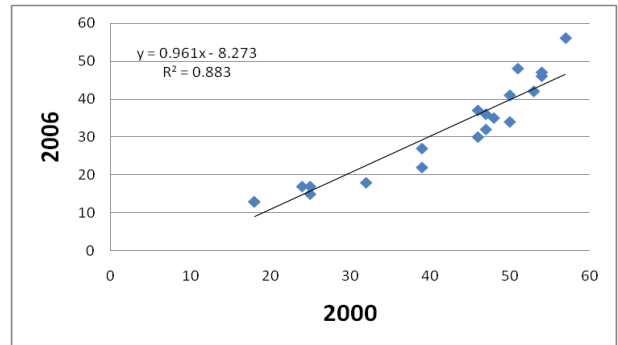
One of our inter-calibration pixels

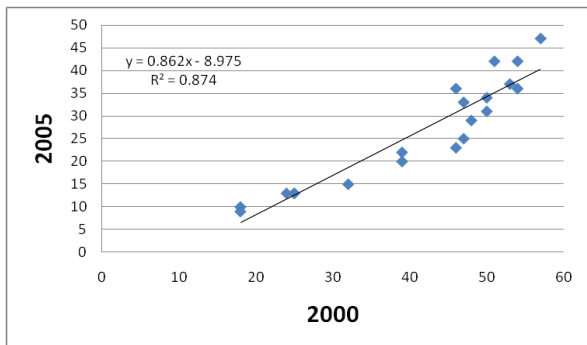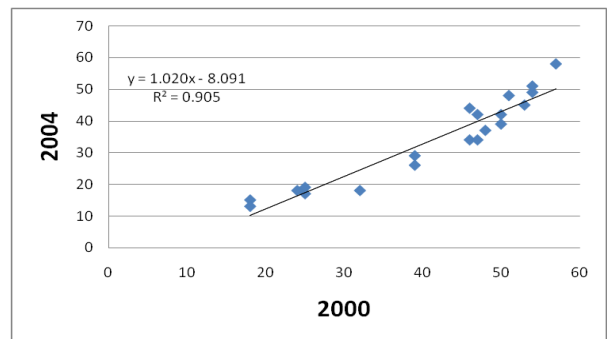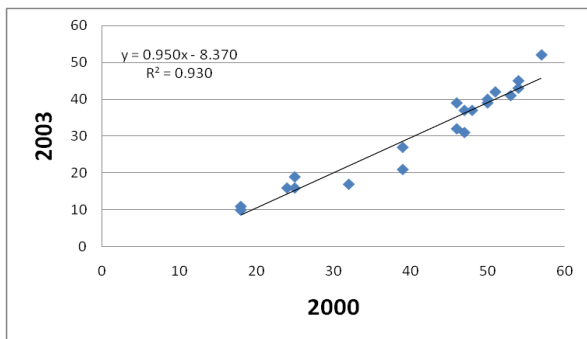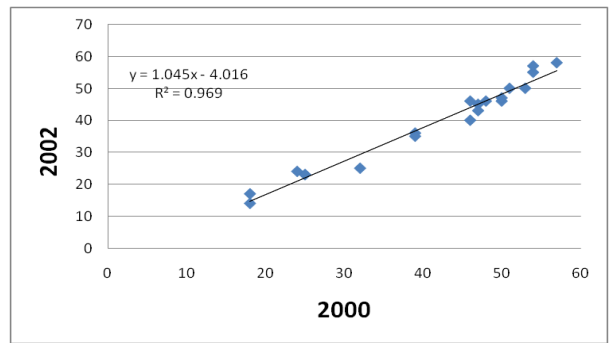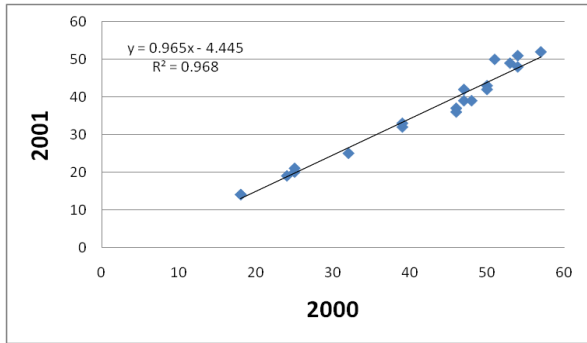Location: Farmville, VA

Figure 5 Sample selection from DMSP/OLS nighttime imagery (year 2000) illustration: Samples collected from CBD parts of towns with population 5000-20000, which are easy to pick out and are under intensity of saturation.

Table 1 DN values collected for inter-annual calibration

Year\Spot	1	2	3	4	5	6	7	8	9	10
2000	46	24	46	47	54	57	25	39	53	18
2001	37	19	36	39	51	52	20	32	49	14
2002	46	24	40	45	55	58	23	36	50	17
2003	39	16	32	31	45	52	19	27	41	11
2004	44	18	34	34	49	58	17	29	45	15
2005	36	13	23	25	36	47	13	22	37	10
2006	37	17	30	32	46	56	15	27	42	13
2007	42	20	37	36	50	60	20	29	48	13
2008	40	18	29	35	44	53	14	27	45	10
2009	38	16	29	35	45	54	16	28	42	11
2010	50	27	48	52	57	59	26	43	56	18

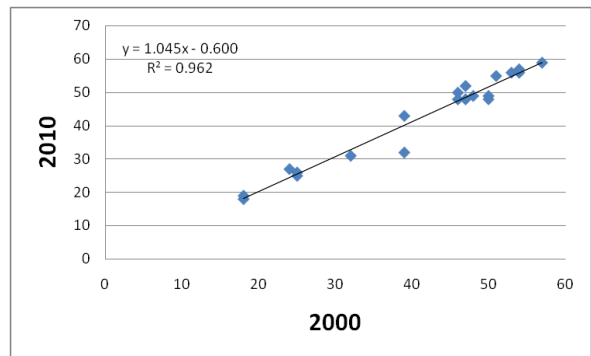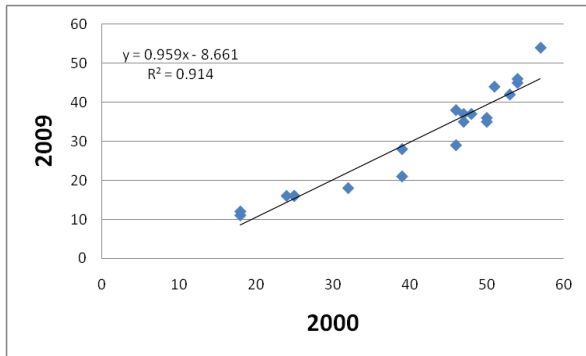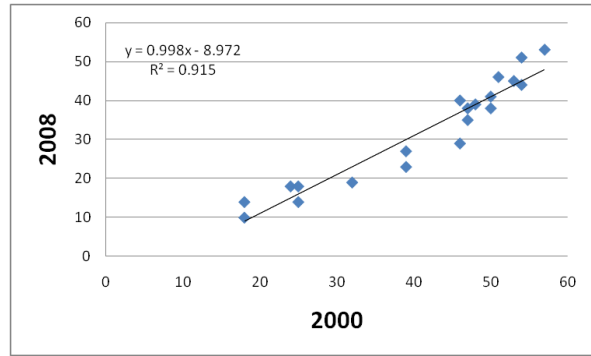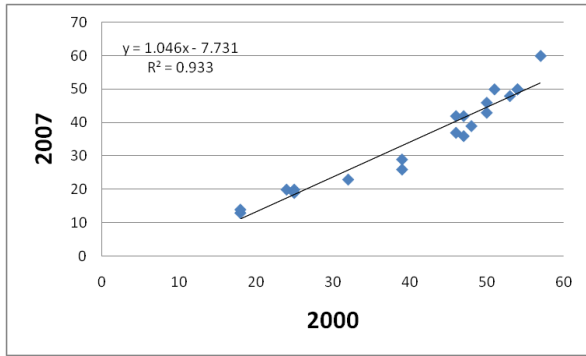| 11	12	13	14	15	16	17	18	19	20
51	25	39	50	54	48	18	47	50	32
50	21	33	43	48	39	14	42	42	25
50	23	35	46	57	46	14	43	47	25
42	16	21	40	43	37	10	37	39	17
48	19	26	42	51	37	13	42	39	18
42	13	20	34	42	29	9	33	31	15
48	17	22	34	47	35	13	36	41	18
50	19	26	46	50	39	14	42	43	23
46	18	23	38	51	39	14	38	41	19
44	16	21	36	46	37	12	37	35	18
55	25	32	49	56	49	19	48	48	31

Figure 6 Inter-calibraton of DN value using linear regression model: We used regression model to calculate the functions between each year data of 2001-2010 and reference year 2000 data, so that data collected from different years can be comparable.

b. Delineating Urban Patches

The thresholding technique is currently the mostly used technique to map urban areas, and it has several different approaches. Imhoff et al. (1997) explored an empirical thresholding to try to map mid-west US urban areas, and they didn't use any ancillary data. The authors increased DN threshold value from 0 to maximum value gradually, and observed the shape variation of urban patches at the same time. At a certain point, the urban patches didn't shrink anymore and started to break up internally. Imhoff et al. believed that the DN value at this point was the thresholding value for separating urban area with its surrounding areas. Compared with the 1990 US Census urban areas, Imhoff's estimated urban areas were only 5% smaller. The results approved the potential of OLS nighttime images for global urban dynamics studies, however, this approach is very empirical in that no any existing theory or research can totally prove its reliability. There are other methods, and the most common ancillary data thresholding etc (Liu et al., 2012).

Thresholding technique along with ancillary data was first developed by Henderson et al. (2003). Since then, it has been widely used due to its relatively high accuracy and reliability. Ancillary data thresholding was adopted to monitor Virginia urban dynamics in this thesis, with the help of unsupervised classification, rapid assessments of urban dynamics has become possible.

Figure 7 Isodata clustering unsupervised classification for year 2000 nighttime imagery

Since we have gotten the relationships between DN values of year 2001-2010 with DN value of reference year 2000, we only need to acquire the thresholding DN value for year 2000. By using Isodata clustering unsupervised classification based on DN value, we generated 15classes on year 2000 OLS input nighttime imagery. (Fig. 7.)

We also extracted the urban distribution of Virginia from NLCD 2001 Land Cover (CONUS) imagery as our ancillary data, which has a 30mhigh resolution that could increase the accuracy of our thresholding. After simple calculations and comparing with ancillary data, we decided to join 2 classes together out of 15 as our urban areas of Virginia urban agglomeration, and most of the pixels of our estimated urban patches have a DN value >= 49. Therefore, we concluded that DN = 49 is the thresholding value for mapping year 2000 nighttime imagery urban areas (Fig. 8.).

According to the functions in the data normalization step, we calculated the DN thresholding value for each year from 2001-2010 (Tab. 2.). Pixels with DN value bigger than or equal to thresholding values are taken as urban pixels.

DN >= 49 urban lit-pixel patches (yellow color)

Extracted NLCD urban distribution (red color)

Figure 8 Ancillary data thresholding technique with the use of unsupervised classification on year 2000 nighttime imagery: By the help of unsupervised classification and ancillary NLCD data, we got the best match quickly.

Table 2 Inter-annual calibrated DN thresholding values for each year from 2001-2010

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
DN thresholding value	49	42.84	47.189	38.18	41.889	33.263	38.816	43.523	39.93	38.33	50.605

Results and Discussion

a. Urban Land Cover Change

By using thresholding technique, we mapped urban areas for each year from 2000-2010, and calculated the total number of urban pixels for each year (Tab. 3.). From 2000 to 2010, Virginia urban pixels increased from 9407 to 10816, expanded around 15%. We compared the 2010 US Census Virginia urban areas with our estimation to support our results, and it was optimistic that our estimated urban area is just 2.5% bigger than the 2010 US Census data.

We also calculated every two-year urban growth rates for 2000-2010 (Fig. 9.). During the two periods 2000-2002, and 2002-2004, Virginia urban growth rates are below 4%. After 2004, till 2006, Virginia experienced a pretty fast urban expansion by above 9%. And 2006-2008, there was a very slow growth rate below 1%. From 2008-2010, the Virginia urban growth increased to around 1.5%.

Table 3 2000-2010 each year total urban pixels

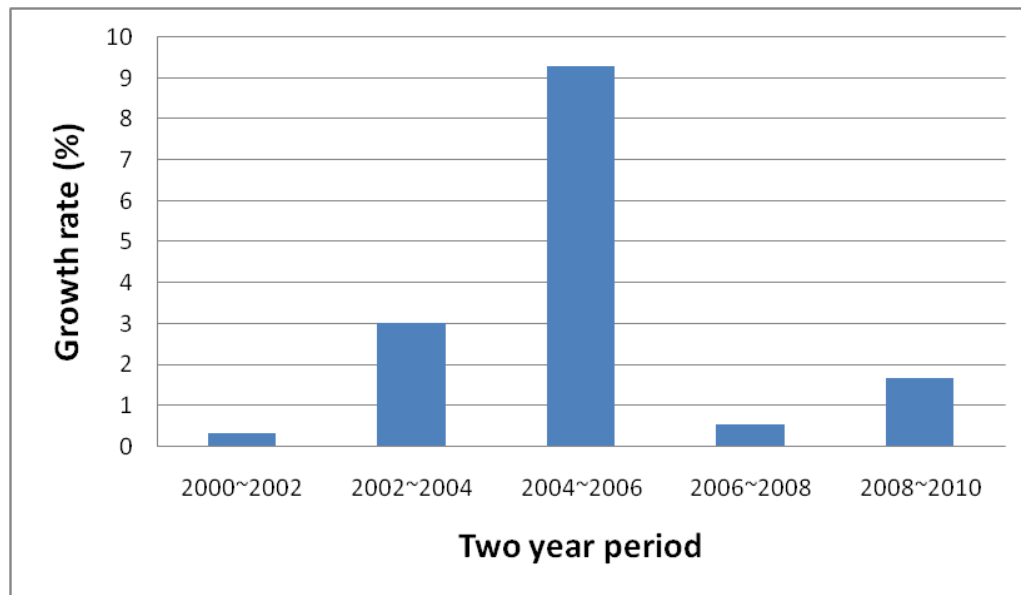| Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
The number of urban lit-pixels	9407	9639	9436	9842	9727	10848	10604	10360	10655	10885	10816

Figure 9 Virginia urban growth rates of every two-year period from 2000-2010

We assume the below 4% rate is a norm for Virginia. Since the US is a highly developed nation, a relatively low growth rate (compared with countries under rapid growth such as China) is not out of our expectation.

14

The 2004-2006 period's abnormally rapid growth and the 2006-2008 period growth rate declining are probably impacted by the huge financial crisis that happened in 2008, and was among the biggest economic disaster with the 1929 Great Depression. The 2008 financial crisis brought down housing prices for 31.8 percent, and unemployment rate reach above 9% according to reports. In 2006, the sign that the economy was in trouble started to occur, and the housing prices began to fall then (Roger, 2012). 2 years right after the disaster, 2008-2010 period was still miserable, yet there was a bit faster growth rate than 2006-2008. 2004-2006 is the period right before financial crisis and the whole nation was in a state of 'financial bubbles,' which can cause more lighting at night no matter because of new construction or more economic activities. Our urban growth graph perfectly fits the scenario, however, this result is still debatable since a zero or negative growth rate doesn't mean all the regions of Virginia were declining, it could mean urban growth in one region was offset by an urban activities contraction in another region of the imagery.

Dietzel et al. (2005) claimed that, according to the theory of urban growth phases, the urban expansion process would always oscillate between diffusion phase and coalescence phase. The authors pointed out that new urban growth always starts with points emerged in the urban periphery, which increased the number of urban patches, and can be taken as diffusion process. Later on, with urban expansion, the big and small urban patches gradually merge together, indicating the process of coalescence (Duncan et al., 1962). Fig. 10 shows the urban expansion from 2000 to 2010. We can clearly see that majority of the growth occurred in the Eastern part of Virginia especially Washington-Arlington-Alexandria metropolitan statistical area (MSA) in the Northeast, and its most expansion belongs to the stage of coalescence.
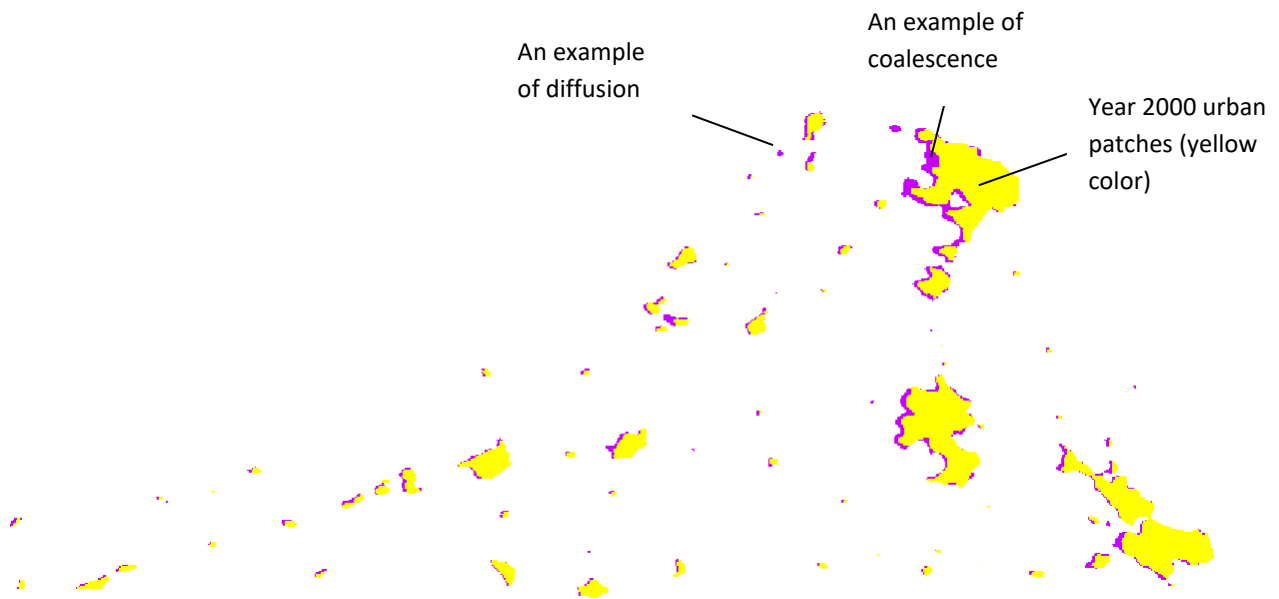

Figure 10 Virginia estimated urban expansion from 2000-2010: The yellow urban patches are our estimated year 2000 urban areas, and purple areas represent areas that have expanded within the ten year time period, which can be classified as diffusion and coalescence

Same as Washington-Arlington-Alexandria MSA, most urban expansion of Virginia Beach-Norfolk-Newport News MSA in the Southeast also can be taken as coalescence. In general, coalescence expansion dominates the urban growth of Virginia. Some smaller sized MSA such as Richmond, Harrisonburg and Winchester, have both diffusion and coalescence expansion, which may indicate they still have a good potential to grow larger and their build-up is not 'totally mature' yet. Finally, these metropolitan areas may finally merge together as we can already see the trend from Fig. 13, and economical radiation effect is supposed to accelerate the process.

b. Population Growth

Based on our acquired urban areas in the last step and fine-resolution population density maps from SEDAC (Fig. 11, Fig. 12), by using Zonal Statistics spatial analysis tool, we estimated the total urban population of year 2000 and year 2010 for Virginia. Because the US Census conducts a population census every ten years, we only have access to population data of year 2000 and 2010. From 2000 to 2010, we estimated that population increased by 15.5% with the actual growth rate is 17.9%. Our estimated populations were compared with actual populations from US Census, and our year 2000 estimated population is 6% smaller than actual population, year 2010 is just 8% smaller (Tab. 4).

Figure 11 Year 2000 urban population density and estimated urban boundaries: The yellow lines delineate urban parts with its surrounding areas, and the degree of gray color represent population density.

Figure 12 Year 2010 urban population density and estimated urban boundaries

As we can see from Fig. 11 and Fig. 12, our thresholding boundaries fit population dense areas very well. 20 years ago, Sutton et al. (1997) explored the quantitative relationship between population density and nighttime light intensity for some cities of the US. They built a regression

model for population density and nighttime light intensity and got a coefficient of determination (R^2) of 0.84, which means the two are indeed highly correlated. However, it has been proved that the densities in urban centers are always underestimated and the densities in suburban areas are always overestimated by the model, and finally the authors suggested not using intensity to estimate population density directly.

Table 4 Estimated populations and the actual populations from the US Census

Year	2000	2010
Estimated urban population of VA	4770675	5512022
Actual urban population of VA	5088100	6002250
Accuracy	94%	92%
Actual total population of VA	6.97M	7.95M

Therefore, we used DN values as the thresholds to delineate urban areas, and then we took advantage of the log-log relationship between urban populations and urban areas for analysis, by which DN values and urban populations were linked indirectly.

According to former studies, many scholars believe that urban land area and its corresponding population has a linear relationship (Sutton et al., 2003; Amaral et al., 2006):

$$Ln(Population) = B_0 + B_1*Ln(Area)$$

Based on this function, we built a linear regression model for our estimated urban patches (population > 50 thousand) and their corresponding populations (calculated by using 'US Census regional total population * urbanized population percentage') for year 2010 (Fig. 13., Tab. 5.).
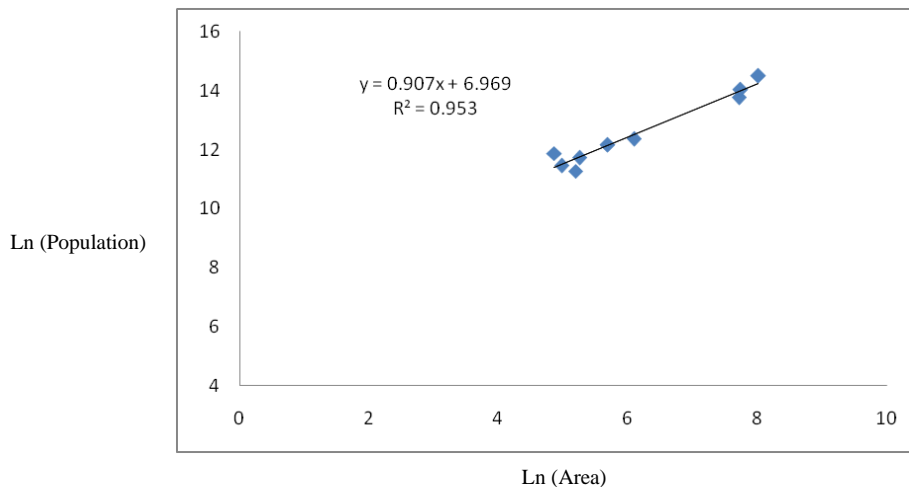

Figure 13 Linear regression model for urban patch areas and their corresponding populations

Table 5 Urban patch areas and their corresponding populations

Region	Pixel Number (area)	Calculated Corresponding Population	Ln (Area)	Ln (Population)
Richmond	2249	949980	7.71824095	13.76419621
Winchester	180	78904	5.19295685	11.2759872
Lynchsburg	296	190739	5.69035945	12.15866128
Harrisonburg	145	94547	4.97673374	11.45685234
Charlottesiville	129	143660	4.8598124	11.87520468
Roanoke	443	233074	6.09356977	12.35911128
Arlinton	3021	1980425	8.01334318	14.49882203
VB	2309	1244343	7.74456981	14.03411824
Bla-Chris-Radford	191	123033	5.25227343	11.72020789

As we can see in Fig. 13, the calculated urban population using US Census data and our estimated urban areas based on DN values together generated a coefficient of determination (R^2) of 0.953, which represents a strong correlation between them. This result is definitely an encouragement for using this approach to link DN value and population density monitor.

We also noted another usage of the trend line in Fig. 13. Some scholars call this trend line a 'sprawl line', which represents average relationship between urban areas and their corresponding population in the study area. Cities above this line are thought to have bigger population pressure than that of a balanced situation, and vice versa. In 2010, all of these big urban regions of Virginia didn't vary so much across the line, which indicates they are now in a kind of balanced situation.

c. Economic Activities

Elvidge et al. (2001) did research on 21 countries with different economies, and found that lit areas delineated by DN values are correlated with GDP data and energy consumption. The linear relation between the lit areas with electrical power consumption produced R^2=0.96 and with GDP resulted in R^2=0.97. Doll et al. (2000) also claimed that the total lit area of a country has high correlation value with other parameters, specifically GDP and total carbon dioxide emission. These former researches proved that DMSP/OLS nighttime imagery can be applied to infer urban sprawl from economic aspect in our study.

Here, we used a spatial metrics called Compounded Night Light Index (CNLI) which is directly calculated based on both DN value and urban area, CNLI is defined as:

$$CNLI = I \times S$$

I is the light index which indicates the average brightness level in a region:

$$I = \frac{1}{N_L \times DN_M} \times \sum_{i=P}^{DN_M} (DN_i \times n_i)$$

"where DN_i is the ith gray level DN value, n_i is the number of ith gray level lit pixels, P is the thresholding DN value to delineate urban boundaries, DN_M is the maximum DN value, and N_L is the number of lit pixels with a DN value between P and DN_M."

S is the rate of lit urban areas versus total area of a region:

$$S = \frac{Area_N}{Area}$$

"where $Area_N$ is the area of lit urban areas and Area is the total area of the region." CNLI was first noted by Zhuo et al. (2003), and it was preprocessed for regional urbanization estimation by Japan National Institute of Environmental Studies, considering the light spatial distribution and intensity based on DN value and thresholding methodology. Former research has confirmed the high correlation between CNLI and indexes derived from socioeconomic census data (Gao et al., 2015). We can clearly see that I is highly correlated with light intensity and S is with light spatial distribution from these formulas, therefore, changes in CNLI are able to reflect the urban economic perspective dynamics with urban expansion simultaneously. Higher CNLI may indicate more built-up environment and higher economic level, and we calculated CNLI value for each year from 2000-2010 (Tab. 6.).

Table 6 CNLI and urban brightness value of each year

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Urban brightness value	558151	541249	549159	534463	556747	570627	578956	600273	594372	603008	634429
CNLI	0.057116	0.055387	0.056196	0.054692	0.056973	0.058393	0.059245	0.061427	0.060823	0.061707	0.064922

We used linear regression again to check on the correlation between our CNLI data and actual GDP of Virginia from 2000-2010, and we got a coefficient of determination (R^2) of 0.705 (Fig. 14.).

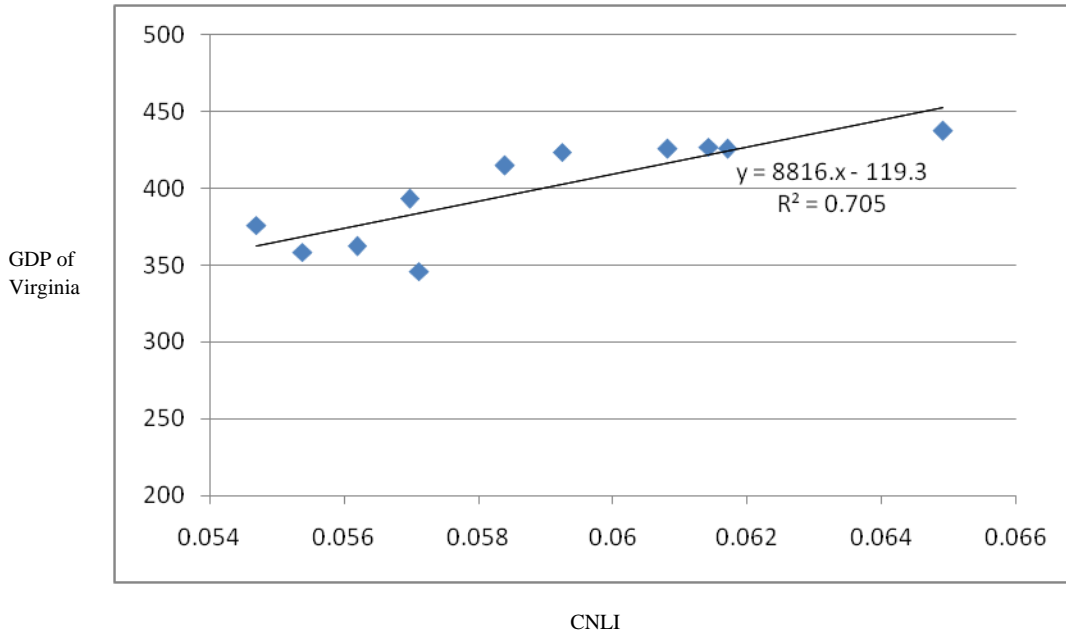$$y = 8816.x - 119.3$$
$$R^2 = 0.705$$

Figure 14 Linear regression of Virginia GDP and CDLI from 2000-2010: Used regression model to check how correlated our CNLI data with actual GDP data, and got the coefficient of determination R2 = 0.7

Besides $R^2 = 0.7$, we also analyzed the trend of both CNLI and GDP and found they didn't match perfectly well. The main reasons that our results in economic part are not as accurate or super correlated as they are in land cover change and population parts are probably due to:

(1) Oversaturation and yearly variation of DN values. The pixels in urban centers are usually oversaturated, but in CNLI formula they were still counted as 63.

(2) Compared with land cover and population, GDP is much more complex, our single CNLI spatial metrics cannot absolutely cover all aspects.

(3) Different regions of Virginia have different types of economy, focusing on a smaller area may get better results.

Summary

The thesis explored the usage of DMSP/OLS nighttime data to monitor urban dynamics within Virginia from 2000 to 2010.Three key components of urban sprawl: land cover, population and economic activities were tracked for the time period 2000-2010 as our results.

For achieving this goal, DN values were extracted from the imagery, and the data of each year was normalized by using PIFs method with our own approach based on concentric zone model. By the help of ancillary high resolution NLCD data and Isodata unsupervised classification tool, we delineated urban patches within Virginia and got our thresholding DN value for each year from 2000-2010; this normalization procedure was essential for the whole research.

Our mapping was only 2.5% smaller than the 2010 US Census Virginia urban areas, and we made graphs to analyze urban growth rate in a two-year interval and the expansion phase of urban areas of Virginia. One of the greatest financial disasters happened in 2008, and our growth rate trend perfectly fit the scenario. We also found the coalescence expansion was dominating, which indicates a relatively mature economy.

We estimated population and population growth by using zonal statistical tool based on DN thresholding method, and we compared our 2000 and 2010 population estimations with the US Census data since they compile a population census every ten years, and our estimations were only 6% and 8% smaller, which proved the credibility. We also used linear regression to analyze the sprawl situation according to 'sprawl line' theory noted by former researchers, and got almost all the major regions within Virginia are in a balanced situation.

In the section of economic activities, we brought a new metrics CNLI considering the light spatial distribution and intensity based on DN thresholding. We tried to find out the correlation between CNLI and annual GDP data of Virginia, and we got a coefficient of determination (R^2) of 0.705 due to the complexity of economy and the oversaturation, variation errors.

There are still some limitations were found during my research, such as transportation corridors and industrial zones, which were considered having higher population density than regular residential zones, can be nearly empty after the 8-12 working hours; The phenomenon of diffuse lighting in rural environment of densely populated regions, like Washington-Arlington-Alexandria MSA, may cause overestimation of urban land cover. Former research suggests an advanced radiance calibration quantitative method could help with these (Elvidge et al., 1999).

DN value urban dynamics study still has great potential, especially in a quantitative approach. With the improvement of satellite resolution, and more and more quantitative methods being developed, DN values will play a more and more important role in the future because of their easily acquired and understood characteristics.

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