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Intercalibration between DMSP/OLS and VIIRS night-time light images to evaluate city light dynamics of Syria’s major human settlement during Syrian Civil War

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\textbf{ABSTRACT}

Monthly composites of night-time light acquired from the Meteorological Satellite Program’s Operational Linescan System (DMSP/OLS) had been used to evaluate socio-economic dynamics and human rights during the Syrian Civil War, which started in March 2011. However, DMSP/OLS monthly composites are not available subsequent to February 2014, and the only available night-time light composites for that period were acquired from the Suomi National Polar-orbiting Partnership satellite’s Visible Infrared Imaging Radiometer Suite (Suomi NPP/VIIRS). This article proposes an intercalibration model to simulate DMSP/OLS composites from the VIIRS day-and-night band (DNB) composites, by using a power function for radiometric degradation and a Gaussian low pass filter for spatial degradation. The DMSP/OLS data and the simulated DMSP/OLS data were combined to estimate the city light dynamics in Syria’s major human settlement between March 2011 and January 2017. Our analysis shows that Syria’s major human settlement lost about 79\% of its city light by January 2017, with Aleppo, Daraa, Deir ez-Zor, and Idlib provinces losing 89\%, 90\%, 96\%, and 99\% of their light, respectively, indicating that these four provinces were most affected by the war. We also found that the city light in Syria and 12 provinces rebounded from early 2016 to January 2017, possibly as a result of the peace negotiation signed in Geneva.

\section{1. Introduction}

The Syrian Civil War, which broke out in March 2011, has been one of the most severe humanitarian disasters since World War II. Human rights groups have estimated that by September 2016, the war had caused about 430,000 deaths and more than 11,000,000 displaced persons (Syrian Observatory For Human Rights 2016). The Syrian Civil War is very complex that there are multiple sides, including the Assad Regime, the Free Syrian Army, Jihad groups (e.g. the Islamic State [IS] and al-Nusra Front), and ethnic minority (e.g. Kurdish forces), with international military intervention from both US-led coalition and Russia. Syria
is extremely dangerous for journalists (BBC 2014) and aid workers (Young and Cunningham 2016); therefore, it is difficult to monitor humanitarian conditions in Syria during the war. Remotely sensed imagery, which can record Earth’s surface information from outer space, has been proved to be an efficient and objective data source for evaluating armed conflicts and human rights (AAAS 2013; Sulik and Edwards 2010). In particular, night-time light images have played an important role in evaluating the Syrian Civil War (Li and Li 2014; Corbane et al. 2016), because these images can directly capture a measure of human activities with large spatial cover and low cost.

Night-time light images record visible light at night and have been widely used in research fields of economics (Chen and Nordhaus 2011; Li, Xu et al. 2013), human geography (Liu et al. 2012; Pandey, Joshi, and Seto 2013; Yu et al. 2014), energy (Elvidge et al. 2009, 2016), light pollution (Jiang et al. 2017), and medical sciences (Bauer et al. 2013). As night-time light is strongly correlated to the economy in both spatial (Elvidge et al. 1997; Li, Xu et al. 2013) and temporal dimensions (Ma et al. 2012), a decline of night-time light can be used to measure the economic effect of the armed conflict and natural disasters (Witmer and O’Loughlin 2011; Li et al. 2015; Li and Li 2014; Kohiyama et al. 2004; Li, Chen, and Chen 2013).

The study by Li et al. (2015) used night-time light monthly composites from Meteorological Satellite Program’s Operational Linescan System (DMSP/OLS) between January 2008 and February 2014 to evaluate the humanitarian crisis in Syria, showing that the spatiotemporal dynamics of human rights conditions in Syria can be retrieved by these images. Following this study, Corbane et al. (2016) evaluated recent dynamics of Syrian Civil War by Suomi National Polar-orbiting Partnership satellite’s Visible Infrared Imaging Radiometer Suite (Suomi NPP/VIIRS).

Unfortunately, the National Geophysical Data Center (NGDC) of the USA stopped producing monthly composites of DMSP/OLS after February 2014. The successor product is the Suomi NPP/VIIRS day-and-night band (DNB) monthly composite, which has been systematically produced for the period started at April 2012. Therefore, each data set only covers a part of the Syrian Civil War, but intercalibration between DMSP/OLS and S-NPP/VIIRS data sets for change detection has not previously published. This article aims to evaluate the Syrian Civil War from March 2011 to January 2017 by combining DMSP/OLS and Suomi NPP/VIIRS DNB monthly composites with an intercalibration model.

2. Study area and data

Syria is located in the Middle East, with Turkey, Jordan, Israel, Iraq, and Lebanon as its neighbouring countries. Syria is made up of 14 provincial regions with Damascus city as its capital. This study makes use of three types of data, administrative borders, night-time light images, and land-cover maps. Syria’s international and provincial border data, shown in Figure 1, were retrieved from the Global Administrative Areas (http://www.gadm.org/). The night-time light images include DMSP/OLS and Suomi NPP/VIIRS DNB monthly composites. In rest of this article, we use ‘DMSP/OLS images’ and ‘VIIRS images’ to represent these two data sets briefly. The DMSP/OLS images with spatial resolution of 0.008333° were ordered from NGDC and have been intercalibrated (Li and Li 2014), and the VIIRS images with spatial resolution of 0.004167° were downloaded from NGDC. Both data sets were retrieved from the panchromatic band, with a wavelength range of 0.5–0.9 μm. The land-cover map of
Syria for 2010 was retrieved from a global land-cover map in 30 m resolution (GLC30) produced by National Geomatics Centre of China (Chen et al. 2015). An urban proportion map in resolution of 0.008333° for 2010 was derived from the GLC30 using spatial aggregation. From these data, an urban mask was derived by defining an urban pixel as one where the urban proportion is no less than 10%. In this study, we only analyse the city light dynamics in this urban mask, by ignoring human settlement of which the urban proportion is less than 10%; thus, only major human settlement in Syria is analysed in this study.

As designed by NGDC, the VIIRS images have two types of data sets, VIIRS Cloud Mask Configuration (VCMCFG) and VIIRS Cloud Mask Stray-light Corrected Configuration (VCMCC). The availability of night-time light images in this study is shown in Table 1.

Table 1. The availability of night-time light images in this study.

<table>
<thead>
<tr>
<th>Year</th>
<th>January</th>
<th>February</th>
<th>March</th>
<th>April</th>
<th>May</th>
<th>June</th>
<th>July</th>
<th>August</th>
<th>September</th>
<th>October</th>
<th>November</th>
<th>December</th>
</tr>
</thead>
<tbody>
<tr>
<td>2011</td>
<td>DMSP</td>
<td>DMSP</td>
<td>DMSP</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>DMSP</td>
<td>DMSP</td>
<td>DMSP</td>
<td>DMSP</td>
</tr>
<tr>
<td>2012</td>
<td>DMSP</td>
<td>DMSP</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>DMSP</td>
<td>DMSP</td>
<td>DMSP</td>
</tr>
<tr>
<td>2013</td>
<td>DMSP</td>
<td>DMSP</td>
<td>–</td>
<td>–</td>
<td>–NPP</td>
<td>NPP</td>
<td>NPP</td>
<td>–</td>
<td>DMSP</td>
<td>DMSP</td>
<td>DMSP</td>
<td>DMSP</td>
</tr>
<tr>
<td>2014</td>
<td>NPP</td>
<td>NPP</td>
<td>NPP</td>
<td>NPP</td>
<td>NPP</td>
<td>NPP</td>
<td>NPP</td>
<td>–</td>
<td>DMSP</td>
<td>DMSP</td>
<td>DMSP</td>
<td>NPP</td>
</tr>
<tr>
<td>2015</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>NPP</td>
<td>NPP</td>
<td>NPP</td>
</tr>
<tr>
<td>2016</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>NPP</td>
<td>NPP</td>
<td>NPP</td>
</tr>
<tr>
<td>2017</td>
<td>–</td>
<td>–</td>
<td>NPP</td>
<td>NPP</td>
<td>NPP</td>
<td>NPP</td>
<td>NPP</td>
<td>–</td>
<td>–</td>
<td>NPP</td>
<td>NPP</td>
<td>NPP</td>
</tr>
</tbody>
</table>

DMSP denotes the DMSP/OLS images, and NPP represents the Suomi NPP/VIIRS images. For each month, there are two grids showing the availability of the two satellite images. ‘–’ Denotes that the image is not available. We have discarded VIIRS images which do not covered the whole Syria, so VIIRS images were not temporally continuous.

Figure 1. The administrative border of Syria and its neighbouring countries.
(VCMSLCFG). In this study, we choose VCMCFG which has much longer temporal coverage than VCMSLCFG. For some summer months, the VCMCFG data are unavailable for a part of Syria, and we have discarded the images for 3 months. After the selection, the availability of the DMSP/OLS and VIIRS images is shown in Table 1, and there are 13 months covered by both of the two types of images.

3. Intercalibration between the two data sets

3.1. Background

DMSP/OLS has provided the main source for remote sensing of night-time light because NGDC has produced annual composites of DMSP/OLS night-time light for 1992–2013. Radiometric intercalibration of DMSP/OLS composites is an important issue since there is no on-board radiometric calibration on DMSP satellites. The radiometric intercalibration is based on the invariant region method, which assumes there are invariant pixels in multi-temporal night-time light images. These invariant pixels are used as training samples to generate an intercalibration function (Elvidge et al. 2009; Wu et al. 2013; Li, Chen, et al. 2013; Zhang, Pandey, and Seto 2016).

The launch of Suomi NPP brought a new era for night-time light remote sensing, as the VIIRS DNB images have higher spatial and radiometric quality than the DMSP/OLS images (Elvidge et al. 2013). The Suomi NPP was launched at the end of 2011, and NGDC has produced VIIRS DNB monthly composites from April 2012 to present. The NGDC had stopped producing DMSP/OLS monthly composites later than February 2014. The Syrian Civil War, which broke out in March 2011, shows no sign of stopping, and therefore, DMSP/OLS and VIIRS images both cover a part of the war. It is therefore necessary to combine DMSP/OLS and VIIRS images to evaluate the night-time light dynamics of the war. However, because of the differences in the data, the two data sets must be intercalibrated to a consistent data set.

The intercalibration between DMSP/OLS and VIIRS images has received limited prior attention. Shao et al. (2014) calibrated single-day DMSP/OLS images with VIIRS images using Dome C in Antarctic as the calibration site. However, their method was not designed for DMSP/OLS and VIIRS composites which are mixture of daily images.

Differences between DMSP/OLS and VIIRS images are potentially derived from the following differences between the two sensors: (1) the spatial resolutions of original DMSP/OLS and VIIRS images are 742 m and 2.7 km respectively, thus VIIRS images provide more spatial detail; (2) spectral response of the two data are different; (3) the point of spread function of the two sensors are different; (4) overpass time at night for the two satellites is different, with DMSP around 9:30 pm and Suomi NPP around 1:30 am; (5) VIIRS DNB has a wider radiance range than DMSP/OLS so that VIIRS has stronger low light detection ability and therefore, unlike DMSP/OLS, does not suffer from frequent saturation; and (6) there is no on-board calibration for DMSP/OLS resulting in products based on uncalibrated digital numbers, while VIIRS has on-board calibration, and thus VIIRS images are radiance products.

These factors make the two data sets very different in both spatial and radiometric properties. Figure 2(a,b) illustrate the DMSP/OLS and VIIRS composites of Syria for November 2014. Figure 2(c) shows the urban extent map of major human settlement
Figure 2. Night-time light images, urban extent map, and related analysis in Syria: (a) DMSP/OLS image of Syria for November 2014, (b) VIIRS image of Syria for November 2014, (c) the urban extent map of Syria for 2010, (d) scatter diagram for the DMSP/OLS and VIIRS images in the urban extent (in fact, the largest values of DMSP/OLS and VIIRS composites are exceeding the bound in the scatter diagram), (e) DMSP/OLS image of Raqqa city for November 2014, and (f) VIIRS image of Raqqa city for November 2014.
with a resolution of 0.008333°. Figure 2(d) shows a scatter diagram for the urban pixels in these two images, where the VIIRS composite in original resolution of 0.004167° is aggregated to the resolution of DMSP/OLS. As we only analyse the city light in this study, we used the above strategy to generate a scatter diagram. Figure 2(d) shows that the DMSP/OLS-VIIRS points for the same month are widely scattered, and their data ranges are very different so that the original DMSP/OLS and VIIRS night-time light images cannot be compared quantitatively. Raqqa city, currently the de facto capital of the IS, was used as an example to show the spatial details of the simulated DMSP/OLS image in Figure 2(e,f). Comparing the DMSP/OLS and VIIRS image, the VIIRS image provides more details than the DMSP/OLS image so that they are quite different. In summary, the VIIRS images are quite different from the DMSP/OLS images in both spatial and radiometric dimension.

3.2. Preprocessing the data sets

The spatial resolution of VIIRS composites is 0.004167°, while that of the DMSP/OLS is 0.008333°. Therefore, the VIIRS composites were aggregated to a spatial resolution of 0.008333°. VIIRS, which can detect moonlit reflected by natural land cover such as vegetation, water, and desert, is able to detect lower level of light than DMSP/OLS. We therefore remove VIIRS low light signal that cannot be detected by DMSP/OLS, by simply subtracting a threshold from the VIIRS image. The threshold is set to 0.3 nW cm⁻² sr⁻¹ based on our experience. For the pixels with negative values in the subtracted image, the values are set to 0.

3.3. Nonlinear relationship of DMSP/OLS and VIIRS images

The intercalibration model is based on the temporal overlap of DMSP/OLS and VIIRS images. Three factors should be considered when building the model: (f₁) the nonlinear relationship between the VIIRS radiance and DMSP/OLS digital number, (f₂) spatial degradation of VIIRS images to match DMSP/OLS images, and (f₃) oversaturation occurring in DMSP/OLS composites but not in VIIRS composites.

To investigate (f₁), we should alleviate the effect of (f₂) since the two factors are mixed. The following steps are designed to explore the relationship: (1) for each DN value of a DMSP/OLS image, all pixels in this value are extracted, and the corresponding pixels in the same locations in the VIIRS image for the same month are also extracted; (2) the mean value of the extracted VIIRS pixels was calculated; and (3) for each DN value in the DMSP/OLS image, a corresponding VIIRS value is calculated so that a curve is generated, with DMSP/OLS value as the independent variable and the VIIRS value as the dependent variable. The curve for November 2012 is drawn in Figure 3. This curve is similar to a ridgeline (Zhang, Pandey, and Seto 2016), which can be used to show the general relationship between two data sets.

Figure 3 shows that the two data sets can potentially be fitted by a power function:

\[ y = ax^b \]  

(1)

where x denotes the DMSP/OLS value, y denotes the VIIRS value, a and b are coefficients. The form of this function still exists when the variables of DMSP/OLS
and VIIRS values are exchanged. We find optimal combinations of the coefficients of the power function to best fit the two data sets for each month by generating a value for coefficient of determination, $R^2$, and the averaged $R^2$ value for all the 13 months is 0.6393. In comparison, the linear regression model without a constant, $y = ax$, is not appropriate for the two data sets (we use MATLAB function for modelling and a negative $R^2$ value comes out, indicating that the model is not appropriate for the data). This analysis suggests that the power function can potentially improve the comparability between the two data sets. Therefore, we use the power function to describe the nonlinear relationship between the VIIRS radiance and DMSP/OLS digital number.

### 3.4. The intercalibration model

Firstly, we define $G$ as a function for matrix transformation as

$$G(X, b) = \begin{pmatrix} x_{11}^b & \cdots & x_{1n}^b \\ \cdots & \cdots & \cdots \\ x_{m1}^b & \cdots & x_{mn}^b \end{pmatrix}$$

(2)

where $b$ denotes the coefficient in this function, and $X$ denotes a matrix as the variable:

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \cdots & \cdots & \cdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}$$

(3)
Therefore, we define $G$ as a power function for a matrix. Considering $(f_1)$ and $(f_2)$, we simulate a DMSP/OLS image $Y$ from VIIRS image $X$: \[ Y = aG(X, b) * M \] (4)

$M$ denotes a normalized matrix which stands for a low pass filter, ‘*’ denotes spatial convolution, $a$ and $b$ are coefficients. Considering $(f_3)$, the simulated DMSP/OLS image should be corrected using the following equation:

\[ y'_{ij} = \begin{cases} 
  y_{ij} & \text{if } y_{ij} \leq c \\
  C & \text{if } y_{ij} > c
\end{cases} \] (5)

where $y_{ij}$ denotes value of pixel in location of $i$th row and $j$th column in image $Y$, $y'_{ij}$ denotes the saturation-corrected pixel value in image $Y'$, and $C$ denotes the threshold for the saturation. Using this equation, the simulated DMSP/OLS image $Y$ is corrected to $Y'$. In this study, we set $c$ to 50 based on our experiences. Equations (3)–(5) are used to simulate a DMSP/OLS image $Y'$ from VIIRS composite $X$. If we can get the coefficients $a$, $b$ and matrix $M$, the model can be determined.

### 3.5. The method to estimate the model coefficients

The DMSP/OLS and VIIRS images for the overlapped months are used to construct training data sets to estimate the coefficients in the intercalibration. First, we derive a non-saturated mask for DMSP/OLS image, where the digital numbers are equal or less than $c$ ($c = 50$ as described early). Second, only urban pixels are selected, because the night-time light in nonurban areas tends to be unstable across different time. We multiply the non-saturated mask with the urban extent map, getting a new mask $K$. Let $\{D^{(1)}, \ldots, D^{(k)}\}$ denote the DMSP/OLS images in $k$ months, and $\{V^{(1)}, \ldots, V^{(k)}\}$ denote the VIIRS images in the same period. Therefore, our purpose is to estimate coefficients $a$, $b$ and matrix $M$ using training data sets $\{D^{(1)}, \ldots, D^{(k)}\}$, $\{V^{(1)}, \ldots, V^{(k)}\}$, and $K$, with the following steps:

1. We choose a Gaussian low pass filter for $M$, as this filter has been widely used for smoothing an image. In this filter, there are two parameters, window size and $\sigma$ (Fisher et al. 2003). We set window size to 13 pixels. Thus, $\sigma$ is the only variable for $M$ so that $M$ can be rewritten as $M_\sigma$.
2. Select an original value for $(\sigma, b)$ randomly.
3. We generate a set of matrices $\{Z^{(i)}_{\sigma, b}, \ldots, Z^{(k)}_{\sigma, b}\}$, where $Z^{(i)}_{\sigma, b} = G(V^{(i)}, b) * M_\sigma$.
4. Based on Equation (4), we use linear regression analysis to estimate coefficient $a$ from $\{Z^{(1)}_{\sigma, b}, \ldots, Z^{(k)}_{\sigma, b}\}$, $\{D^{(1)}_{\sigma, b}, \ldots, D^{(k)}_{\sigma, b}\}$, and mask $K$: (A) For each pixel which falls into mask $K$, we select the pixel value pair from $Z^{(i)}_{\sigma, b}$ and $D^{(i)}_{\sigma, b}$ ($i = 1, \ldots, k$), and then we use all the selected pixel value pairs from $k$ image pairs to construct a training set, which is made up of two vectors $Z_{\sigma, b}$ and $D_{\sigma, b}$; (B) we use a linear regression model $d = az$ to fit the set $Z_{\sigma, b}$ and $D_{\sigma, b}$, and the root-mean-square deviation (RMSE) of this regression is recorded as $\text{RMSE}_{\sigma, b}$. 


(5) For coefficients $(\sigma, b)$, we finally find the optimal solution $(\hat{\sigma}, \hat{b})$ with the lowest RMSE, by repeating step 3–4 and using a fast optimization algorithm. And the coefficient $a$ is estimated as $\hat{a}$ based on $(\hat{\sigma}, \hat{b})$.

### 3.6. Evaluation of the model

The proposed model makes use of a number of DMSP/OLS and VIIRS image pairs to estimate the coefficients in the intercalibration model, and a simulated DMSP/OLS image is generated from a VIIRS image by using the model. There are totally 13 months when the DMSP/OLS and VIIRS images coexist. A cross-validation process is used to evaluate the model:

1. In a scenario, image pairs of DMSP/OLS and VIIRS for 12 months are selected to construct a training set, and the remaining image pair is used as the validation set.
2. For each scenario, we estimate the model coefficients from the training set and generate a simulated DMSP/OLS image from the VIIRS image in the validation set. There are totally 13 scenarios so that there are 13 pairs of DMSP/OLS and simulated DMSP/OLS images.
3. The two indices, Pearson correlation coefficient, denoted as $r$, and RMSE, were calculated in the defined urban area for each pair of images. Image pairs before and after intercalibration are compared by the two indices, shown in Table 2.

The RMSE is defined as

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \hat{x}_i)^2}{n}}$$  

where $x_i$ is the DMSP/OLS image value in the $i$th urban pixel, $\hat{x}_i$ is the simulated DMSP/OLS image value in the $i$th urban pixel, and $n$ is the number of urban pixels. After applying the proposed model, the simulated DMSP/OLS image value is calculated from the VIIRS image value. For the original DMSP/OLS and VIIRS images, the simulated DMSP/OLS image value is equal to the VIIRS image value as there was no transformation on the original VIIRS image.

### Table 2. Comparison between original and intercalibrated data sets by $r$ and RMSE.

<table>
<thead>
<tr>
<th>Month</th>
<th>Original data sets</th>
<th>Intercalibrated data sets</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$r$</td>
<td>RMSE</td>
</tr>
<tr>
<td>September 2012</td>
<td>0.1979</td>
<td>40.5282</td>
</tr>
<tr>
<td>October 2012</td>
<td>0.2687</td>
<td>26.8691</td>
</tr>
<tr>
<td>November 2012</td>
<td>0.6276</td>
<td>12.5101</td>
</tr>
<tr>
<td>December 2012</td>
<td>0.2649</td>
<td>20.8784</td>
</tr>
<tr>
<td>January 2013</td>
<td>0.1279</td>
<td>40.8895</td>
</tr>
<tr>
<td>February 2013</td>
<td>0.4849</td>
<td>11.7144</td>
</tr>
<tr>
<td>March 2013</td>
<td>0.4659</td>
<td>12.1966</td>
</tr>
<tr>
<td>September 2013</td>
<td>0.3312</td>
<td>20.0306</td>
</tr>
<tr>
<td>October 2013</td>
<td>0.5952</td>
<td>9.8622</td>
</tr>
<tr>
<td>November 2013</td>
<td>0.4592</td>
<td>12.4806</td>
</tr>
<tr>
<td>December 2013</td>
<td>0.3877</td>
<td>12.0908</td>
</tr>
<tr>
<td>January 2014</td>
<td>0.3474</td>
<td>13.3966</td>
</tr>
<tr>
<td>February 2014</td>
<td>0.2602</td>
<td>20.3114</td>
</tr>
<tr>
<td>Average</td>
<td>0.3707</td>
<td>19.5199</td>
</tr>
</tbody>
</table>
From Table 2, the $r$ value for the data set in all 13 months has been improved, from 0.3707 to 0.9158 for the average value. In addition, the RMSE for all the months has also been improved from 19.5199 to 4.9967. These findings indicate that the proposed intercalibration model helps to improve the consistency between the DMSP/OLS and VIIRS images.

To show some details of the intercalibration process, we select the scenario in which November 2014 was selected as the validation set and select the rest of the month as the training set. The DMSP/OLS, VIIRS, and simulated DMSP/OLS image for November 2014 were shown in Figures 2(a,b) and 4(a), respectively, and the scatter diagram showing the relationship between the DMSP/OLS and simulated DMSP/OLS images for the urban area is plotted in Figure 4(b). Comparing Figures 2(d) and 4(b), the simulated DMSP/OLS generated from the VIIRS image is well correlated to the DMSP/OLS image, while the correlation between the original VIIRS and DMSP/OLS image is much weaker. In summary, the intercalibration model has improved the comparability between the DMSP/OLS and VIIRS images.

### 3.7. Generating a time series night-time light data set for Syria

We use image pairs in all the overlapped 13 months to estimate the coefficients in the intercalibration model and get a solution of $\hat{a} = 1.7142$, $\hat{b} = 0.4436$, $\hat{c} = 11.7319$. We use the intercalibration model and the estimated coefficients to generate simulated DMSP/OLS images after February 2014. Therefore, a time series night-time light data set between January 2011 and January 2017 is generated and denoised with a temporal median filter in size of 3 for further analysis.

![Figure 4](image-url) **Figure 4.** Comparison between simulated DMSP/OLS and DMSP/OLS images. (a) The simulated DMSP/OLS image for November 2014; (b) scatter diagram for DMSP/OLS and simulated DMSP/OLS images in the urban area for November 2014.
4. City light dynamics of major human settlement during the Syrian Civil War

4.1. Analysis at provincial and national level

Based on the time series night-time light data set, we analyse the city light dynamics in major human settlement for Syria (for convenience, ‘major human settlement’ will be omitted in following content). For each province in Syria, we calculate its total city light (TCL) for each month, which is defined as follows:

\[ t = \sum_{i} x_i u_i \]  

where \( t \) denotes the TCL, \( x_i \) denotes the pixel value for \( i \)th pixel, \( u_i \) denotes the urban/nonurban value (if \( i \)th pixel falls into urban area, \( u_i = 1 \), otherwise, \( u_i = 0 \)). To analyse the relative change of TCL, March 2011, when the Syrian Civil War broke out, is used as the baseline. For a certain area, the relative TCL in a month is calculated as the ratio of the TCL in the month to TCL in March 2011. The relative TCL for the whole Syria and its 14 provinces were calculated and illustrated in Figure 5.

Figure 5 shows a general decline of city light for Syria and all the provinces between March 2011 and January 2017. The city light has lost by 65–99% for all the provinces in Syria. Among these provinces, Aleppo, Daraa, Deir ez-Zor, and Idlib are the most affected provinces, losing 89%, 90%, 96%, and 99% of their city light during the period, respectively. These four provinces were reported to have major battles and massacres during the civil war. It is very striking to see Idlib was reduced to less than 1% of its city light during April 2015 to January 2017 compared to the pre-war level, suggesting that this province suffered even more than Aleppo.

Although the city light generally declined for each province, the city light in most of the provinces, such as Al-Hasakah, Al-Raqqah, Al-Suwayda, Daraa, Hama, and Homs, rebounded in early 2014. The rebound may be explained by peace talks in January 2014 that resulted in a ceasefire in some regions (CBS 2014). However, the rebound in city light also occurred in Al-Raqqah, which has been controlled by the IS since January 2014. It has been reported that the IS is not only a military group but also an effective ruler which attempts to provide social services including food and electricity, so we can infer that the IS repaired the damaged power infrastructure after it occupied Al Raqqah (Caris and Reynolds 2014). Nevertheless, the city light in Al Raqqah has seen a general decline, corroborating the claim that the IS-controlled area is suffering from an electricity shortage (Syrian Observatory For Human Rights 2014). Although there was a sharp rise of city light of Al Raqqah in October 2015, it fell back within several months, most likely due to Russia and US-led airstrike in Raqqah city and its surrounding areas.

To demonstrate how the city light changes from year to year, we extract the relative TCL for every March from 2011 to 2016, and also for January 2017. From Table 3, we can find that Syria has lost about 60% of its city lights in the first two years of the war, and this pattern also exists for seven provinces, Al-Hasakah, Aleppo, Al-Raqqah, Daraa, Deir ez-Zor, Idlib, Quneitra. Combining Figure 5 and Table 3, the city light for Syria as a whole and 12 provinces rebounded from the early 2016 to July 2016. This recovery of city light may be a result of the reduced violence associated with the peace negotiation, signed in Geneva and started in February 2016, between the Syrian government and a number of rebel groups.
Figure 5. Relative total city light of 14 provinces in Syria between January 2011 and January 2017: (a) Al-Hasakah, (b) Aleppo, (c) Al-Raqqa, (d) Al-Suwayda, (e) Damascus, (f) Daraa, (g) Deir ez-Zor, (h) Hama, (i) Homs, (j) Idlib, (k) Latakia, (l) Quneitra, (m) Rif Dimashq, (n) Tartus, and (o) Syria.
4.2. Analysis at city level

Six Syrian cities, Kobani, Aleppo, Homs, Raqqah, Deir ez-Zor, and Hama which suffered from intensive battles, are selected to analyse more spatial details of city light dynamics. For each city, we first find the location of its centre by Google Earth and generate a circle to include the urban extent. Radii of these circles are 3, 20, 8, 8, 8, and 8 km for Kobani, Aleppo, Homs, Raqqah, Deir ez-Zor, and Hama, respectively. In each city, the TCL for each month was calculated and recorded.

The city light dynamics was shown in Figure 6 and Table 4. Among these cities, only Kobani city, located in the Syria–Turkey border, is not the provincial capital, but this city was world-famous for ‘Battle of Kobani.’ The IS launched the ‘Siege of Kobani’ on September 2014, resulting in a severe humanitarian crisis. The Kurdish forces, along with Free Syrian Army and international allies, finally win the battle in April 2015. We can see that the city light was steadily declined during March 2011 to April 2015, showing that the long-lasted Syrian civil war and Battle of Kobani had destroyed the city’s power supply system, but it rebounded after April 2015, showing that the city was under reconstruction after the IS retreated. Although there were some fluctuations of the city light during the reconstruction, the city light reached to 36% of the pre-war level in January 2017.

For the five provincial capitals, the city light in Aleppo city and Deir ez-Zor city was declined continuously, only remaining 6% and 1%, respectively, comparing to the pre-war level, showing that these two cities suffered from seemingly endless conflicts. For cities of Homs, Raqqah, and Hama, the city light have a general decline, losing 69%, 70%, and 73%, respectively. In addition, there were obvious fluctuations of the city light in these cities such as the three rebounds in Homs, suggesting that the temporary peace occurred and stopped for several time in these cities.

4.3. Comparison on variation of the three types of images

Although the VIIRS, DMSP/OLS, and simulated DMSP/OLS images in time series can track the dynamics of city light in Syria, their variation of dynamics may be different.

Table 3. The relative total city light for Syria and its provinces.

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As there are 13 months when the DMSP/OLS and VIIRS images coexist, the images of these months are used for analysis. We use the intercalibration model in Section 3.7 to generate simulated DMSP/OLS images in the 13 months, and then there are three final data sets, DMSP/OLS, VIIRS, and simulated DMSP/OLS. In addition, we are interested in the simulated DMSP/OLS data set without operation by Equation (5) so that we add a simulated DMSP/OLS data set without saturation for analysis. For a certain region and a data set, we used coefficient of variation (CV) to measure its dynamics:

$$v_t = \frac{\sigma_t}{\mu_t}$$  \hspace{1cm} (8)

where $t$ denotes time series TCL of $n$ months, which can be expressed as $\{t_1, \ldots, t_n\}$, $\sigma_t$ denotes the standard deviation of $t$, $\mu_t$ denotes the mean of $t$, and $v_t$ denotes the CV. Therefore, for each region and each data set, a value for CV is derived and shown in Figure 7.

**Figure 6.** Relative total city light of the six cities in Syria between January 2011 and January 2017: (a) Kobani, (b) Aleppo, (c) Homs, (d) Raqqah, (e) Deir ez-Zor, and (f) Hama.

**Table 4.** The relative total city light for six Syrian cities.

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</tbody>
</table>
For 14 provinces, there are 12 provinces where the variation of VIIRS data set is larger than that of the DMSP/OLS data set, and Daraa and Homs are two exceptions. In addition, the CV values of VIIRS and DMSP/OLS for Syria are 0.4221 and 0.2535, respectively, indicating that the VIIIRS data set has much higher dynamics than DMSP/OLS data set. For the simulated DMSP/OLS data set, the CV value is between those of DMSP/OLS and VIIRS data sets, with Daraa, Idlib, and Quneitra as exceptions, and the CV value of this data set for Syria is 0.3407, indicating that the dynamics of simulated DMSP/OLS is larger than DMSP/OLS data set and less than the VIIRS data set. This analysis shows that VIIRS data set has larger variation than the DMSP/OLS data set to track the dynamics of city light, which is likely to be explained by the reason that VIIRS has more information than DMSP/OLS. We also found that the simulated DMSP/OLS images without saturation have very similar CV value to the simulated DMSP/OLS images (saturation-corrected images) for all the provinces, but CV value of the former one for Syria is 0.3433, a little larger than that of the latter one (e.g. 0.3407), suggesting that the cutting high radiance values of VIIRS images will result in reduced dynamic information.

5. Conclusion

Our previous study has proved that the night-time light images from DMSP/OLS can play an important role in evaluating the undergoing Syrian Crisis (Li and Li 2014). VIIRS monthly composites have taken the place of DMSP/OLS composites since early 2014, so it is a great challenge to continuously monitor the Syrian Civil War using night-time light images. DMSP/OLS and VIIRS composites are quite different in both spatial and radiometric dimensions, and how to estimate the city light loss from March 2011 to the present is challenging.

In this study, we made use of a power function and a Gaussian low pass filter to simulate DMSP/OLS images from VIIRS images so that the DMSP/OLS and VIIRS images can be combined to evaluate city light dynamics. However, we have not proved whether or not the power function and Gaussian filter are optimal choices for the intercalibration, and therefore finding an optimal intercalibration model will be an important work in
future studies. In addition, the estimated coefficients in the model depend on the training data sets, and therefore the coefficients will change with the change of training data set. As VIIRS images have higher spatial resolution than DMSP/OLS images, they are more effective to detect small objects that emit light at night. However, in this study, we only analyse the TCL of major human settlement in administrative regions or cities, the size of which is not small, so that the advantage of VIIRS is the higher radiometric sensitivity, which is helpful to track the temporal variation of city light.

This study employed an urban mask map to extract city light from the night-time light images. This is a newly developed strategy that was recently used in the Iraq conflict study (Li et al. 2015) but not yet used in previous Syria conflict study (Li and Li 2014). The urban mask can help to exclude ephemeral night-time light (e.g. wildfire), flaring gas light, reflected moonlight, and blooming light in suburban areas, which are not directly related to electricity supply and human rights, so excluding them is useful for monitoring the human activities in Syria. Due to this strategy, the estimated city light, named city light in major human settlement, between March 2011 and February 2014, differs somewhat from that of the previous study (Li and Li 2014), but the temporal trends are similar. This study is the first attempt to intercalibrate DMSP/OLS between VIIRS composites to analyse the night-time light dynamics and the regression analysis shows that the simulated DMSP/OLS and real DMSP/OLS images were consistent. Furthermore, the overpass times for the two satellites are different, likely contributing some errors in the intercalibration method. Therefore, more efforts should be paid to build a more effective and accurate intercalibration model to evaluate night-time light changes from DMSP/OLS and VIIRS images in future studies. However, it is important to mention that some information is missing when VIIRS composites are used to simulate DMSP/OLS composites.

The Syrian Civil War covers a long period from 2011 to present, so that we should use two data sets to evaluate this conflict. More information on the Syrian Civil War will be retrieved if the proposed intercalibration process is combined with the population data (Corbane et al. 2016), and this will be a valuable work. For future conflict, which will be covered only by VIIRS images, the intercalibration between the two data sets is not necessary. On the other side, the annual DMSP/OLS composites are only available for 1992–2013 and VIIRS images will play a unique role for the years after that period; therefore, intercalibration between the annual DMSP/OLS and VIIRS images is particularly valuable to evaluate regional development and urbanization from 1992 to present.

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