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# Measurement of blooming effect of DMSP-OLS nighttime light data based on NPP-VIIRS data

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## ABSTRACT

Nighttime light (NTL) imagery offers important data for socio-economic research since it depicts human activities at night. Blooming effect is one of the main problems of DMSP-OLS NTL data, but the problem has been largely mitigated in NPP-VIIRS data. Blooming effect smooths light intensity through diffusing the brightness from the bright area to the dark areas. This effect could be quantified by the alteration of spatial heterogeneity in light intensity which can be represented by spatial texture indices. Taking NPP-VIIRS data as the standard, this study calculates relative difference of spatial texture indices between NPP-VIIRS and DMSP-OLS images to measure the blooming effect of DMSP-OLS data at pixel scale in mainland China. Results show that within the real urban area, spatial texture indices of DMSP-OLS pixels are generally smaller than that of NPP-VIIRS, suggesting that blooming effect underestimates spatial heterogeneity and it is more serious towards to urban centres where nighttime light is stronger. DMSP-OLS underestimates 90% spatial heterogeneity when NPP-VIIRS value >10. On the contrary, in the region outside real urban area, spatial texture indices of DMSP-OLS data are greater than that of NPP-VIIRS, suggesting that blooming effect introduces fake spatial heterogeneity outside the real urban area.

**Abbreviations:** NTL: Nighttime light; DMSP: Defense Meteorological Satellite Program; OLS: Operational Linescan System; NPP: National Polar-orbiting Partnership; VIIRS: Visible Infrared Imaging Radiometer Suite; NOAA: The National Oceanic and Atmospheric Administration; NGDC: The National Geophysical Data Center; NCV: Normalized coefficient of variation; DN: Digital number

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## KEYWORDS

Blooming effect; nighttime light (NTL); DMSP-OLS; NPP-VIIRS; spatial heterogeneity

## 1. Introduction

Nighttime light remote sensing satellites, such as the US Defense Meteorological Satellite Program (DMSP) and Suomi National Polar-orbiting Partnership (NPP) satellite, provide a unique and direct information on human activities associated with artificial light at night (Bennett and Smith 2017). Originally used to detect night clouds, DMSP Operational Linescan System (OLS) data was deciphered in 1972 and was applied to depict city light, gas combustion, fishing fleets, and other luminaries (Croft 1978). In 1992, the National Oceanic and Atmospheric Administration (NOAA) National Earth Science Data Center established digital access to DMSP-OLS data which covers 1992–2013 years (Elvidge et al. 1997a). This digital archive greatly promoted the application of NTL data in scientific community. Now, although the DMSP-OLS satellite still collect military data, it has stopped providing digital data services. Its successor, the Visible Infrared Imaging Radiometer Suite (VIIRS) on-board

Suomi NPP provides data available starting from 1 December 2011 (Bennett and Smith 2017).

Nighttime remote sensing images have attracted attention due to the unique ability to display human activities at night (Doll 2008). In the past two decades, many studies have shown that nighttime lights are closely related to urbanization (Henderson et al. 2003; Ma et al. 2012; Pandey, Joshi, and Seto 2013; Zhang and Seto 2013, 2011), population (Elvidge et al. 1997b; Raupach, Rayner, and Paget 2010; Sutton 1997; Sutton et al. 2001; Zhuo et al. 2009), and the national or regional gross domestic product (GDP) (Doll, Muller, and Morley 2006; Ebener et al. 2005; Sutton, Elvidge, and Ghosh 2007; Sutton and Costanza 2002). Due to the successful launch of the Suomi NPP-VIIRS satellite, nighttime light research experienced rapid development. However, DMSP-OLS nighttime light data is still very valuable and important because it is the only data source available in the early years.

The lack of on-board calibration, saturation, and blooming effect are three main problems of DMSP-OLS

data (L. Imhoff et al. 1997; Small et al. 2011; Small, Pozzi, and Elvidge 2005). Because the sensor performance degrades with time (Zhang and Seto 2011) and the annual composite images contain DMSP-OLS data from different dates (Bennett and Smith 2017), we cannot accurately compare nighttime light images over years if there is no on-board calibration. Saturation problem is caused by the low memory range and low dynamic range of DMSP-OLS sensor, thus the sensor cannot measure the accurate light intensity higher than a threshold which leads to many saturated pixels with DN value of 63. Up to date, both of the two problems could be mitigated to some degree by the developed methods (Elvidge et al. 2009; Henderson, Storeygard, and Weil 2012; Letu et al. 2012; Ma et al. 2014).

Blooming effect (or named as over-glow) is caused by light scattering, resulting in bright pixels extending beyond the real bright area. Blooming effect is obvious in DMSP-OLS data, while it is much less in NPP-VIIRS data, thus we take NPP-VIIRS data as reference to measure the effect on DMSP-OLS (Shi et al. 2014; Xie, Weng, and Weng 2014). Comparing effective boundary in the same area of NPP-VIIRS and DMSP-OLS data (see example in Figure 1), blooming effect of DMSP-OLS data could be observed obviously. Ou et al. studied the contrast of the nighttime lights between large cities and their satellite cities along the coastline in US. NPP-VIIRS data shows discontinuous connections between cities, while DMSP-OLS data shows them all as one whole block (Ou et al. 2015). If blooming effect is not corrected before using nighttime light data, land surface parameters such as urban extent may be over measured (Small and Elvidge 2013). However, the blooming effect of DMSP-OLS data is not well studied (Bennett and Smith 2017). Though blooming effect could be corrected by threshold, the determination of the optimal threshold value is challenging (Zhou et al. 2014). The development of advanced technologies for adjusting blooming effect of DMSP-OLS data requires quantitative measurement of the blooming effect. To our best knowledge, such studies were not reported.

To this end, the objective of this study is to measure the blooming effect of DMSP-OLS data at pixel scale

using NPP-VIIRS data as a standard. The blooming effect reduces the light intensity of bright areas and diffuses radiation into the dark areas, which alters the spatial heterogeneity of light intensity in real urban as well as area without illumination. Therefore, blooming effect of DMSP-OLS can be quantified by the changes in spatial heterogeneity characterized by the spatial texture indices, such as variance, mean deviation (MD), normalized coefficient of variation (NCV), and entropy. This study will employ these spatial texture indices to quantify the blooming effect of DMSP-OLS data and analyse its spatial pattern.

## 2. Data and study area

We selected mainland of China as our study area because it has cities with various sizes which is ideal for studying blooming effects of DMSP-OLS data (Figure 2). In this study, DMSP-OLS and NPP-VIIRS data both are collected in 2013 because images collected in the same year can ensure the comparability between two data sets and exclude the interference caused by inter-annual changes.

### 2.1. DMSP-OLS data

There are three DMSP-OLS data sets available: stable light data, de-cloud data and non-filter data. The stable light data contains constant light from cities, towns, and other areas with persistent lighting, and excludes temporary disturbances, i.e. ephemeral events, such as fires. In September 2013, NOAA/NGDC updated the fourth version DMSP-OLS nighttime light time series data and provided 1992–2013 stable light data (Baugh et al. 2010; Elvidge et al. 2009). In this study, DMSP-OLS stable data in 2013 was downloaded from the NOAA/NGDC official website (Figure 2).

### 2.2. NPP-VIIRS data

Unlike DMSP-OLS data, NPP-VIIRS data does not remove lights of fire, gas, volcanoes, and lasers.

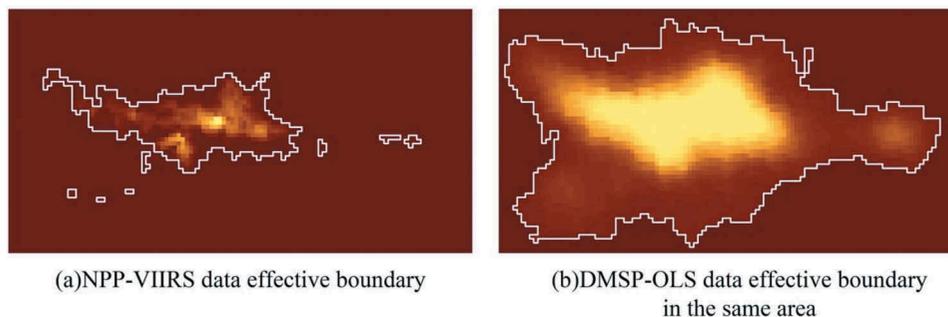
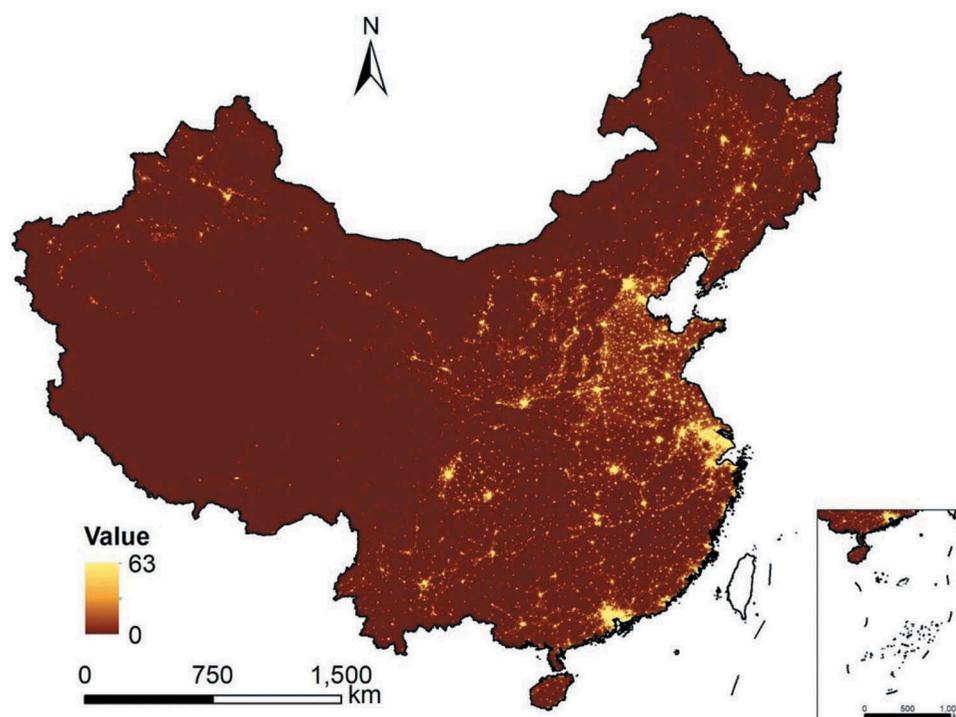


Figure 1. Blooming effect of DMSP-OLS nighttime light data.



**Figure 2.** The 2013 DMSP-OLS nighttime light data in the study area.

Background values are also preserved. At the same time, there is a small number of pixels in NPP-VIIRS data with DN value  $<0$ , which may be background noise and outliers during image synthesis (Jing et al. 2015). However, NPP-VIIRS data has higher spatial and radiometric resolution than DMSP-OLS data (Table 1), is well calibrated and has minimal saturation effect. NPP-VIIRS composite image in January 2013 used in the study was also downloaded from the NOAA/NGDC official website. In this study, NPP-VIIRS data was used as reference data to assess the blooming effect of DMSP-OLS data because current studies compared both data sets for extracting urban extent show that the blooming effect of NPP-VIIRS data is much smaller than DMSP-OLS data (Shi et al. 2014; Xie, Weng, and Weng 2014). It is worth to mention

that the spectral range of these two sensors is slightly different (Table 1). Specifically, NPP-VIIRS is insensitive to blue lights with wavelength shorter than  $0.5 \mu\text{m}$ , so it may underestimate the light intensity for cities which equipped a lot of blue LEDs. Fortunately, white-light LEDs are more often used so that the slight difference in spectral range of two sensors may not affect their comparability too much.

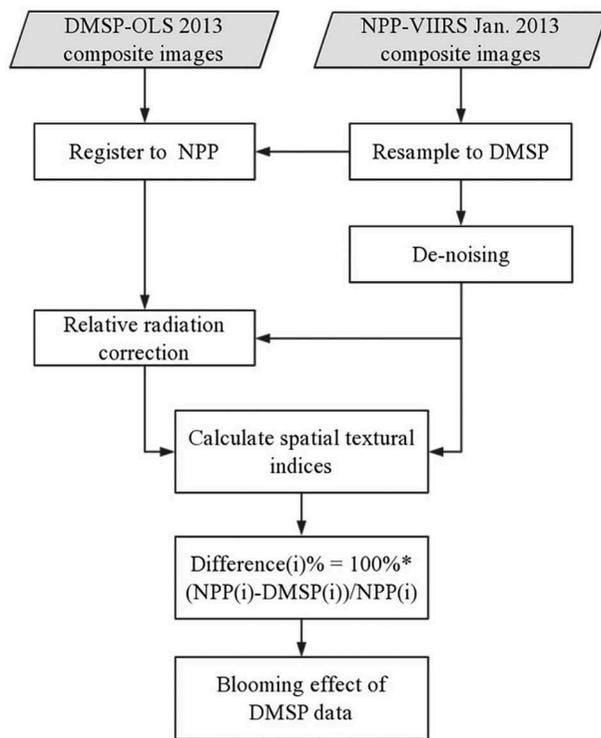
### 3. Methodology

#### 3.1. Data preprocessing

Before the comparison between DMSP-OLS and NPP-VIIRS nighttime images, these two data sets need to be pre-processed following steps in Figure 3.

**Table 1.** Comparison of the major parameters between DMSP-OLS VNIR band and Suomi NPP-VIIRS DNB band.

Satellite (night light band)	DMSP-OLS (VNIR band)	Suomi NPP (VIIRS DNB)
Available data time	1992–2013	April 2012 to date
Wavelength range	$0.4\text{--}1.1 \mu\text{m}$	$0.5\text{--}0.9 \mu\text{m}$
Spatial resolution (composite image)	2.7 km (1 km)	742 m (500 m)
Time resolution	12 h	12 h
Geographical scope	75N/65S/180E/180W	75N/65S/180E/180W
Day/night collection time	8:30–9:30, 20:30–21:30	13:30, 1:30
Radiation resolution	6-bit	12/14-bit
Measuring unit	Relative (0–63 range)	Radiation (nanoWatts/( $\text{cm}^2 \text{sr}$ ))
Brightness upper limit	$3.17 \times 10^{-7} \text{ W cm}^{-2} \text{ sr}^{-1} \mu\text{m}^{-1}$	$0.02 \text{ W cm}^{-2} \text{ sr}^{-1} \mu\text{m}^{-1}$
Brightness lower limit	$1.54 \times 10^{-9} \text{ W cm}^{-2} \text{ sr}^{-1} \mu\text{m}^{-1}$	$3 \times 10^{-9} \text{ W cm}^{-2} \text{ sr}^{-1} \mu\text{m}^{-1}$
Star calibration	No	Yes



**Figure 3.** Flow chart of measuring blooming effect of DMSP-OLS nighttime images.

### 3.1.1. Resampling NPP-VIIRS data

To make NPP-VIIRS data have the same resolution as DMSP-OLS data, it was resampled to 1 km resolution.

### 3.1.2. Registrating DMSP-OLS to NPP-VIIRS data

The two data sets have an offset of 1–4 km in the coordinate system due to the differences in the sensor parameters and the way of image synthesis. Thus, registration needs to be applied to remove the offset. It is difficult to obtain accurate ground control points directly for nighttime lights data. ‘Average-force algorithm’ is used in this paper to select ground control points: 20 small cities or towns without saturated pixel and evenly distributed in mainland China were selected, and then the centroid (i.e. the centre of mass) of these small cities were calculated as the location of ground control points. ‘Average-force algorithm’ is based on the principle that for each city, the average of the light intensity from all locations and directions should be consistent in two data sets. To evaluate the accuracy of the image registration, 15 validation samples were selected in the study area. Result shows that the registration error (RMSE) is within 1 km. Then, both data sets were projected to the UTM-1984-49N projection.

### 3.1.3. De-noising of NPP-VIIRS data

NPP-VIIRS data contains fire, gas, and other disturbances, and there are a few outliers in the western and northeastern regions of Mainland China, which may be caused by flares in oil and gas wells (Shi et al. 2014). In this regard, the de-noising method developed by Shi et al. (2014) was used for de-noising NPP-VIIRS. The specific steps were as follows: Beijing, Shanghai, and Guangzhou were selected as the most developed regions in Mainland China with the highest nighttime lights. The maximum DN value in these three cities was 299,849, and DN values that exceed this value were likely outliers. The outliers were replaced by the maximum value of their nearest eight neighbouring pixels. In addition, there were very small number of pixels with DN < 0 in NPP-VIIRS data, and they are assigned 0 in this study.

### 3.1.4. Relative radiometric correction based on ‘conservation of energy’

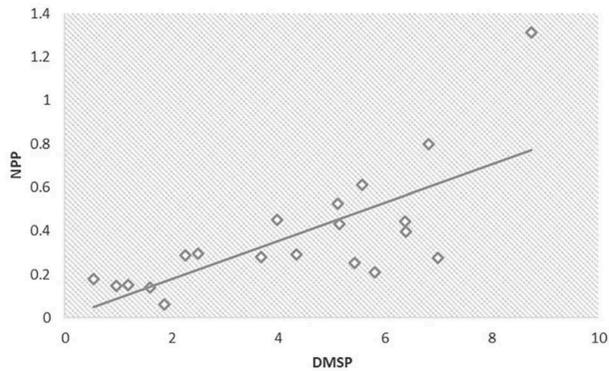
For DMSP-OLS and NPP-VIIRS data, the DN values of the two data sets are not comparable numerically. To enable direct comparison between two data sets, DMSP-OLS data should be calibrated to NPP-VIIRS data. Generally, relative calibration between two images can be implemented by a linear regression model built from pixel samples. Because DMSP-OLS data have large blooming effect, it is difficult to collect pixel samples between DMSP-OLS and NPP-VIIRS images which target the same location. Therefore, this study used an alternative approach to calibrate DMSP-OLS data. This approach builds the linear regression model based on cities rather than individual pixels. The law of ‘conservation of energy’ was served as the theoretical basis of this approach. We assume that total lights of a city collected by DMSP-OLS should be equal to that of NPP-VIIRS. Therefore, for the cities without saturated pixels, the average DN values of DMSP-OLS pixels in each city should be highly correlated to that of NPP-VIIRS data in the same urban extent. In this study, 20 small cities were selected from the study area to build the city-based linear regression model. All these selected cities have clear edges, no interference from other cities, and no saturated pixels in the DMSP-OLS image. Average DN values of DMSP-OLS and NPP-VIIRS data for these 20 small cities were calculated respectively:

$$\text{aver}(i) = \frac{\sum_{ij} x_{ij}}{n} \quad (1)$$

where  $\text{aver}(i)$  is the average DN value in the  $i$ th selected small city,  $x_{ij}$  is DN value of  $j$ th pixel in the  $i$ th city and

$n$  is total number of pixels of the  $i$ th city. Then, a linear regression model was built (Equation (2)) based on these 20 small cities with  $R^2 = 0.530$  ( $P < 0.001$ ) (Figure 4). Then, all DMSP-OLS pixel values were calibrated to NPP-VIIRS data using Equation (2).

$$Y_{\text{NPP}} = f(x_{\text{DMSP}}) = 0.0879x_{\text{DMSP}} + 0.0028 \quad (2)$$



**Figure 4.** Linear regression model between DN values of NPP-VIIRS and DMSP images.

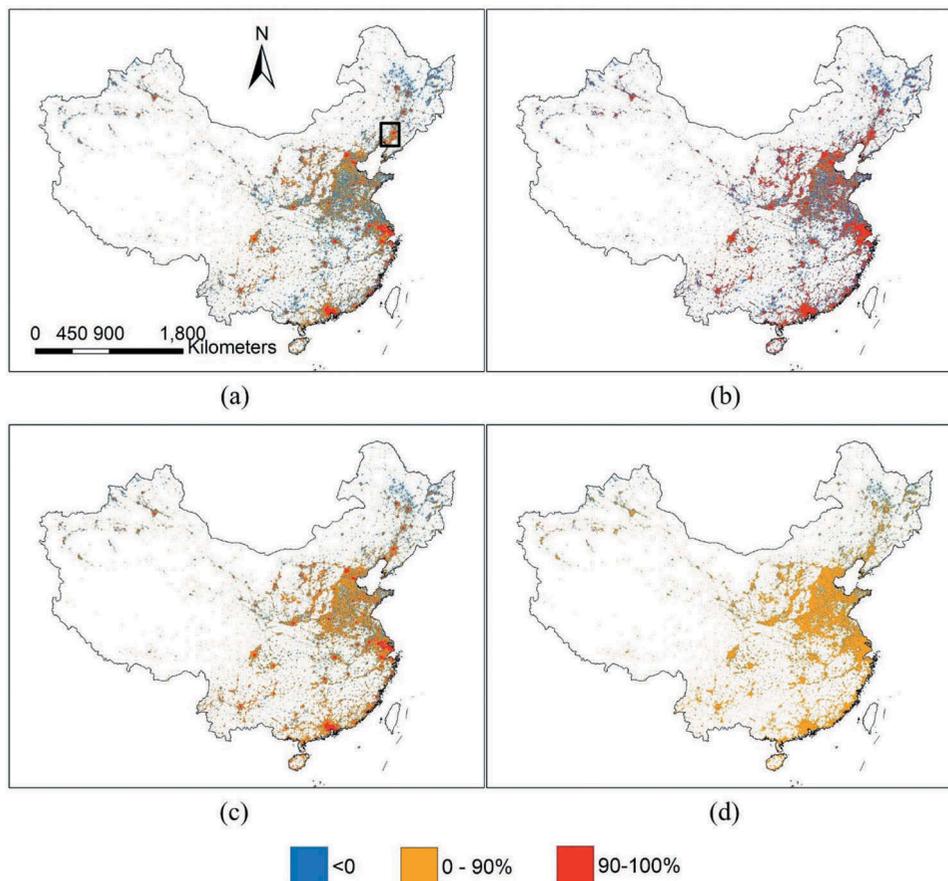
### 3.2. Calculation of spatial texture indices and their differences between two datasets

Blooming effect may alter spatial heterogeneity of the light image. Thus, this study used the relative difference in spatial heterogeneity to characterize blooming effect of DMSP-OLS data. Spatial texture indices have the ability to characterize the degree of spatial heterogeneity. Four spatial texture indices were used in this study: variance, mean deviation (MD), normalized coefficient of variation (NCV), and entropy ( $H$ ). All indices were computed for each pixel using its  $3 \times 3$  window. The stronger the spatial heterogeneity of the data has, the larger the spatial texture index value is.

The variance ( $\sigma^2$ ) was calculated for the calibrated DMSP-OLS and NPP-VIIRS data, respectively, in a  $3 \times 3$  window:

$$\sigma^2(i) = \frac{\sum_{i,j} (x_{ij} - \mu)^2}{n - 1} \quad (3)$$

where  $x_{ij}$  represents the DN value of the  $j$ th pixel in the  $3 \times 3$  window centred at the  $i$ th pixel,  $\mu$  is the mean



**Figure 5.** Spatial distribution of differences of four spatial texture indices between two data sets in the whole study area: (a) MD, (b) variance, (c) NCV and (d) entropy. The area marked by the black box in (a) will be zoomed-in to better show the spatial details (see Figure 7).

value in the window, and  $n$  is the number of all pixels in the window.

The mean deviation (MD) was calculated using Equation (4):

$$MD(i) = \frac{\sum_{i,j} |x_{ij} - \mu|}{n} \quad (4)$$

Normalized coefficient of variation (NCV) was calculated using Equation (5):

$$NCV(i) = \sqrt{\frac{\sigma^2}{\mu}} \quad (5)$$

Entropy ( $H$ ) was calculated using Equation (6):

$$H(i) = \int_{i,j} P_{ij} \ln(P_{ij}), P_{ij} = \frac{x_{ij}}{\sum_{i,j} x_{ij}} \quad (6)$$

After computing the four spatial texture indices for both data sets, their relative difference ( $d$ ) between DMSP-OLS and NPP-VIIRS was calculated (Equations (7–10)) to measure the blooming effect of DMSP-OLS data assuming that blooming effect leads to a reduction in the spatial heterogeneity of the light intensity. If pixels with  $d > 0$ , NPP-VIIRS data has

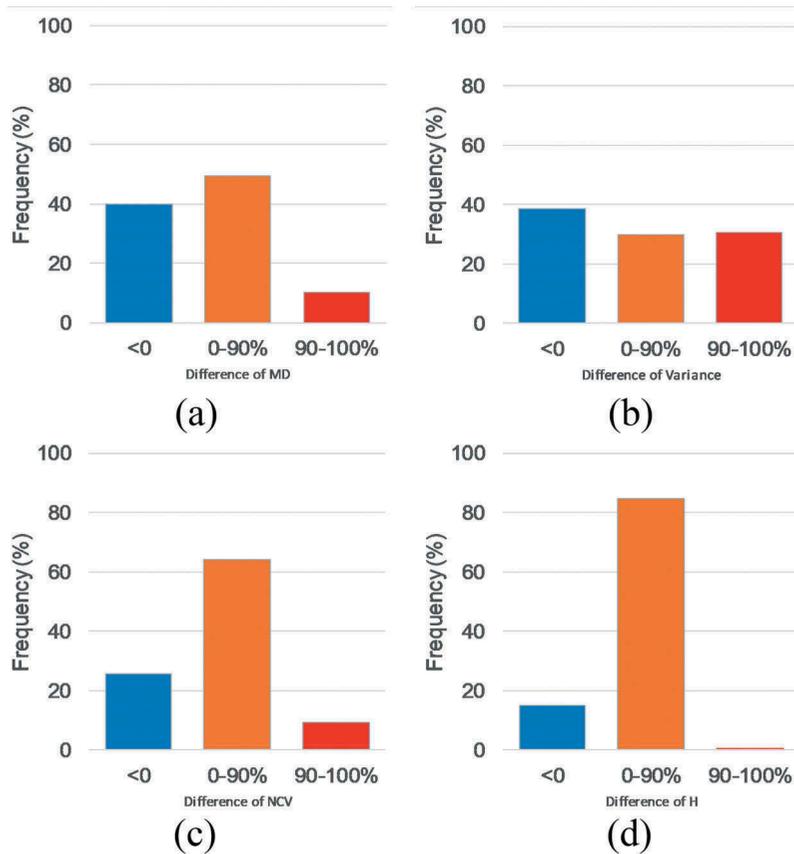
a larger spatial heterogeneity than DMSP-OLS data of in these pixels; if  $d < 0$ , it is the opposite. For example,  $d = 20\%$  means that DMSP-OLS underestimates 20% of spatial heterogeneity for that pixel compared with NPP-VIIRS.

$$d\sigma^2(i) = \frac{\sigma^2_{NPP}(i) - \sigma^2_{DMSP}(i)}{\sigma^2_{NPP}(i)} \quad (7)$$

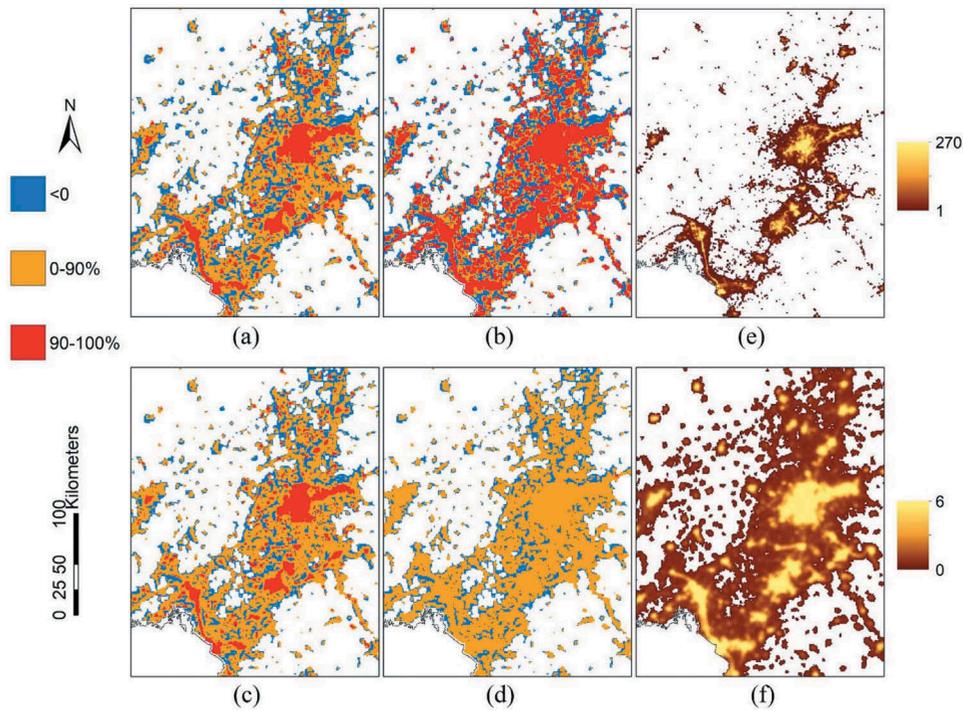
$$dMD(i) = \frac{MD_{NPP}(i) - MD_{DMSP}(i)}{MD_{NPP}(i)} \quad (8)$$

$$dNCV(i) = \frac{NCV_{NPP}(i) - NCV_{DMSP}(i)}{NCV_{NPP}(i)} \quad (9)$$

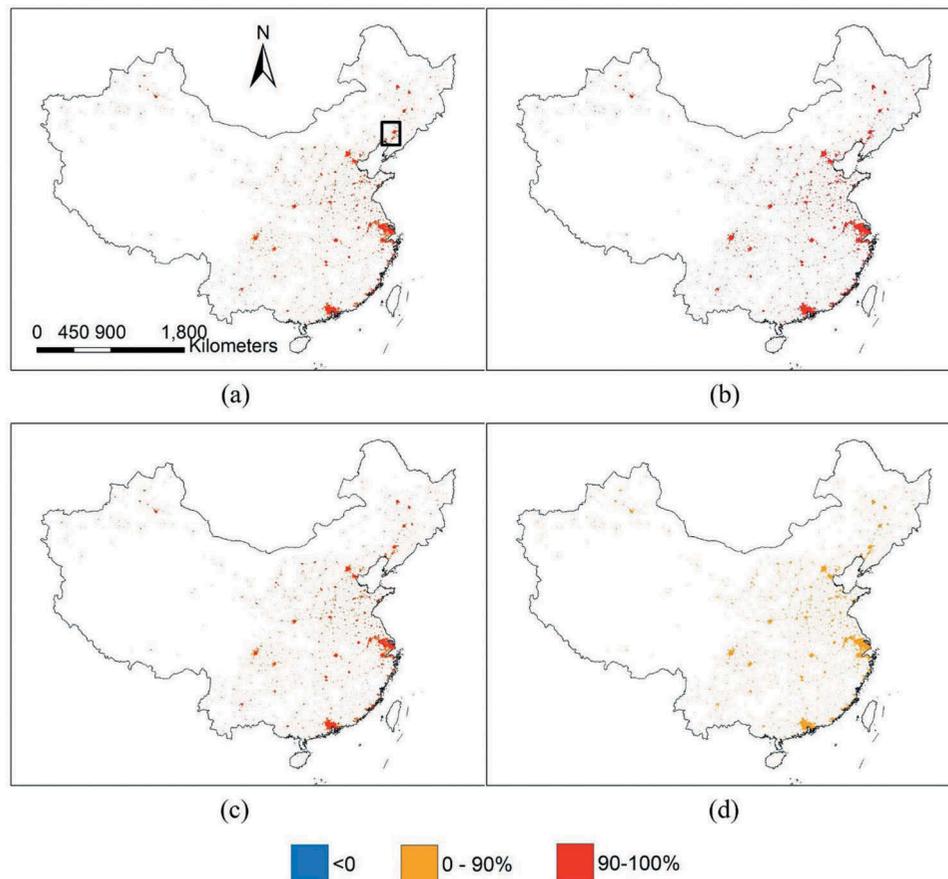
$$dH(i) = \frac{H_{NPP}(i) - H_{DMSP}(i)}{H_{NPP}(i)} \quad (10)$$



**Figure 6.** Frequency histogram of differences of four spatial texture indices between two data sets in the whole study area: (a) MD, (b) variance, (c) NCV and (d) entropy.



**Figure 7.** Spatial distribution of differences of four spatial texture indices and brightness between two data sets in the sub-region highlighted in Figure 5: (a) MD, (b) variance, (c) NCV, (d) entropy, (e) NPP-VIIRS data and (f) DMSP-OLS data.



**Figure 8.** Spatial distribution of differences of the four texture indices between two data sets in the real urban area: (a) MD, (b) variance, (c) NCV and (d) entropy. The area marked by the black box in (a) will be zoomed-in to better show the spatial details (see Figure 10).

## 4. Results and discussion

### 4.1. DMSP blooming effect in the whole study area

Figure 5 shows the spatial distribution of differences in four spatial texture indices between DMSP-OLS and NPP-VIIRS data in the whole study area and their frequency is shown in the histogram figures (Figure 6). Warm colour area represents where DMSP-OLS data has lower spatial heterogeneity than NPP-VIIRS data, and cold blue colour area represents where DMSP-OLS data has higher spatial heterogeneity than NPP-VIIRS data. For MD and variance, a considerable number of pixels have  $d < 0$  (frequency >40%), and rest pixels have  $d > 0$  (frequency >50%). For NCV and Entropy, most pixels have  $d > 0$ . Both warm colour pixels in Figure 5 and warm colour bars in histograms of Figure 6 suggest that in Mainland China, DMSP-OLS data has lower spatial heterogeneity than NPP-VIIRS data in most area. However, there are a considerable number of pixels where the spatial heterogeneity of NPP-VIIRS data is lower than DMSP-OLS data when MD and variance are

used to represent spatial heterogeneity (see the cold blue colour bars in histograms of Figure 6).

In order to better observe the spatial pattern of blooming effect, result in a sub-region highlighted in Figure 5(a) is shown in Figure 7. NPP-VIIRS and DMSP-OLS data in the same area are used for comparison. NPP-VIIRS data (Figure 7(e)) shows the real urban area, while DMSP-OLS data (Figure 7(f)) includes over-estimated urban area due to blooming effect. In Figure 7(a–d), Warm colour pixels are mostly located in the real urban area. On the contrary, cold blue colour pixels are mostly located in over-estimated urban area, where spatial texture indices values of NPP-VIIRS data are close to zero because the pixel values are nearly zero, but DMSP-OLS pixels have values in the over-estimated region because of blooming effect. These results indicate that blooming effect is likely to underestimate spatial heterogeneity within the real urban area, and introduce fake spatial heterogeneity outside the real urban area. In this regard, DMSP-OLS data cannot describe spatial heterogeneity correctly.

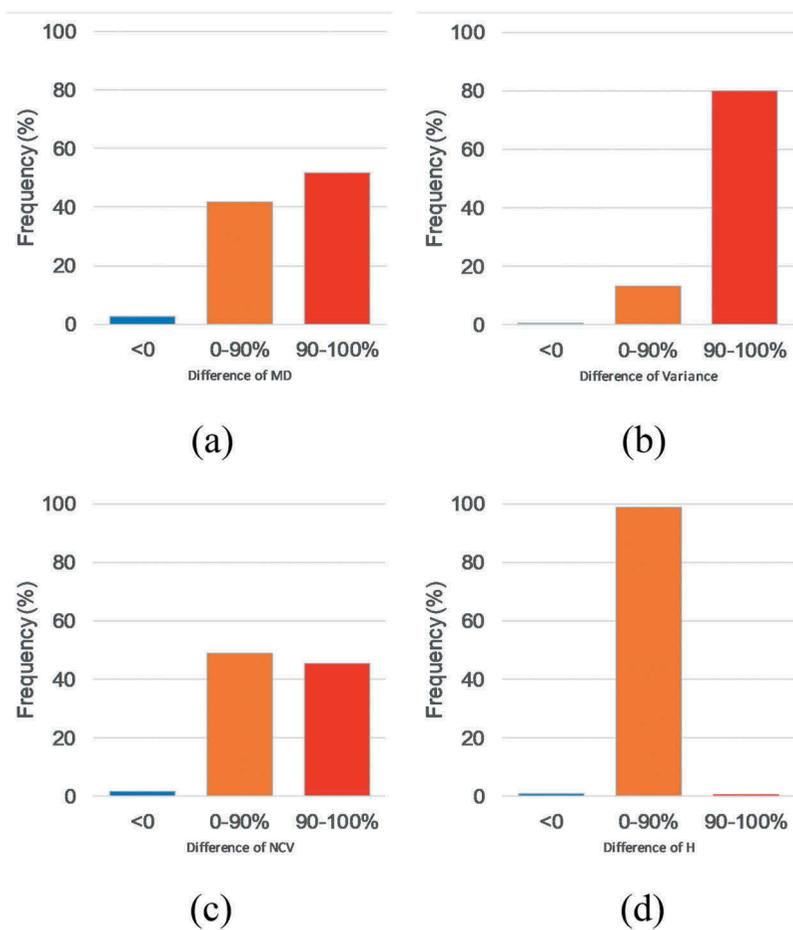


Figure 9. Frequency histogram of differences of four spatial texture indices between two data sets in the real urban area: (a) MD, (b) variance, (c) NCV and (d) entropy.

#### 4.2. DMSP blooming effect in the real urban area

Since blooming effect brings opposite spatial heterogeneity tendency inside and outside of real urban area and introduces fake spatial heterogeneity outside the real urban area, results in the real urban area are extracted for further analysis. In this study, real urban area is defined as the area with NPP-VIIRS DN value  $\geq 1$  which well matches the urban extent derived from Landsat image in 2013. Figure 8 shows the spatial distribution of differences in four spatial texture indices between the DMSP-OLS and NPP-VIIRS data in real urban area. The histogram (Figure 9) shows their frequency statistics. Histograms in Figure 9 suggest that for all the four spatial texture indices, mean deviation (MD), variance, normalized coefficient of variation (NCV), and entropy, there are very few pixels have  $d < 0$  (frequency  $< 3\%$ ), and almost all pixels have  $d > 0$  (frequency  $> 97\%$ ). Thus, in real urban area, spatial heterogeneity of DMSP-OLS data smaller than NPP-VIIRS data is observed in most pixels, suggesting that DMSP-OLS data has lower spatial heterogeneity than NPP-VIIRS data in real urban area.

Results in the sub-region highlighted in Figure 8(a) (Figure 10) shows the majority of pixels are warm colour indicating that in real urban area, blooming effect of DMSP data exist in most cities, which is consistent with the frequency histogram in Figure 9. The results indicate that blooming effect will underestimate spatial heterogeneity within real urban area and is more serious from edge to the centre of cities (red colour areas in Figures 10(a-c)).

Figure 11 shows the relationship between the blooming effect represented by  $d$  (relative differences of four spatial texture indices between two data sets shown in Figure 8) and light intensity represented by the DN value of NPP-VIIRS data. The DN value of NPP-VIIRS data (X-axis) can well depict the profile of real light intensity from the outskirts to the centre of the city. Y-axis represents the severity of blooming effect, i.e. relative difference of spatial indices between NPP-VIIRS and DMSP-OLS data. MD, variance, and NCV show positive relationships with DN value of NPP-VIIRS data, which reflects that blooming effect becomes more serious when nighttime light is stronger. When NPP-VIIRS value  $> 10$ , DMSP-OLS underestimates more than 90% spatial heterogeneity (Figure 11). It means that DMSP-OLS data cannot identify the light intensity variability in the urban centres. On the contrary, NPP-VIIRS data has a good ability of detecting the variability of the brightness in the centre of cities. Among these four

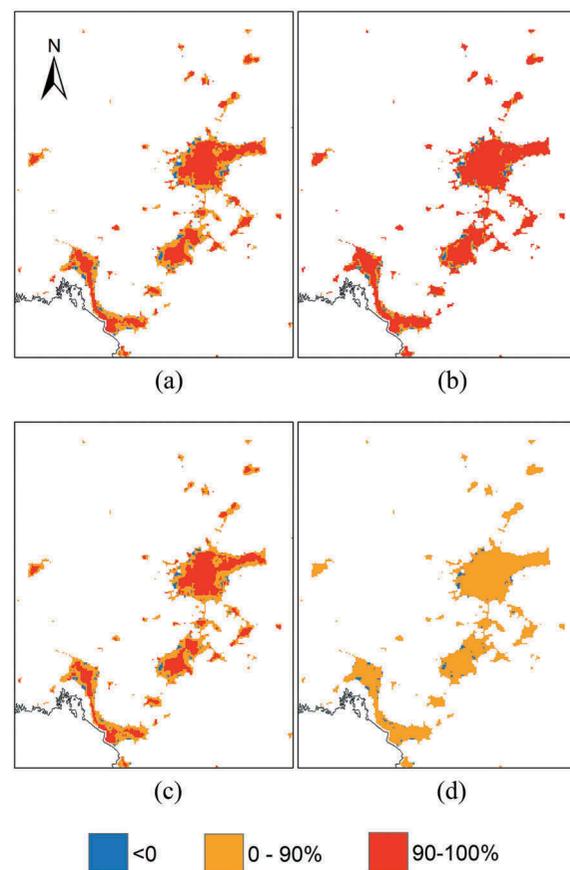
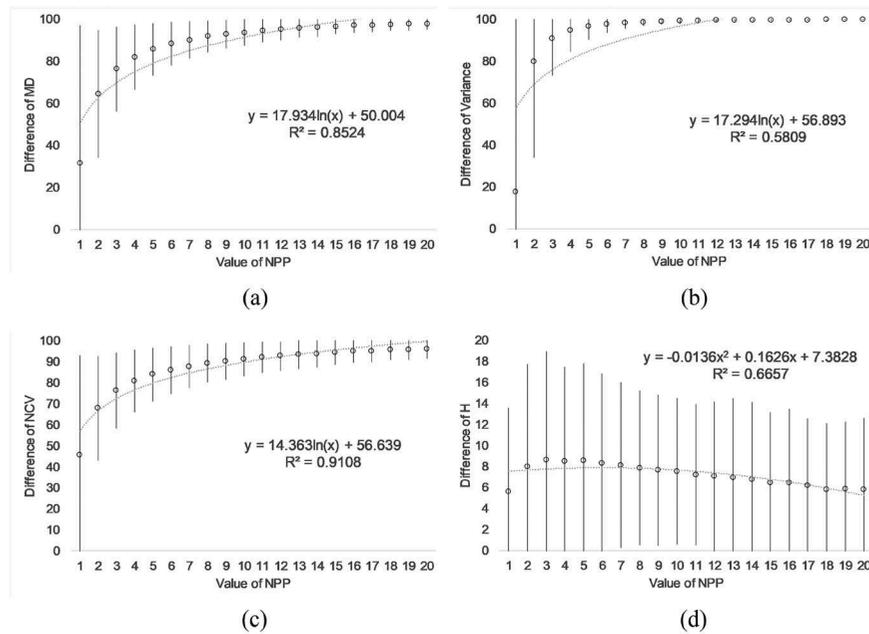


Figure 10. Spatial distribution of differences of four spatial texture indices between two data sets in the real urban area of a sub-region marked in Figure 8: (a) MD, (b) variance, (c) NCV and (d) entropy.

indices, MD and NCV can better describe the severity of blooming effect under different light intensity ( $R^2 > 0.85$ ) than variance and entropy, suggesting that MD and NCV may be better indices to describe the blooming effect of DMSP-OLS nighttime light data.

#### 4.3. DMSP blooming effect in real urban area excluding saturated pixels

The reduction of spatial heterogeneity in the centre of large cities mainly caused by two reasons: blooming effect and saturation of DMSP-OLS data. Saturation, as mentioned in the Introduction section, is one of the three main problems of DMSP-OLS data. It is an effect that sensor could not accurately measure too bright lights due to its 8-bit quantization and low dynamic range, and usually happens in the centre of the big cities where many pixels have the same largest DN value 63 (Bennett and Smith 2017). In the entire mainland China, there are 9% DMSP-OLS pixels within the



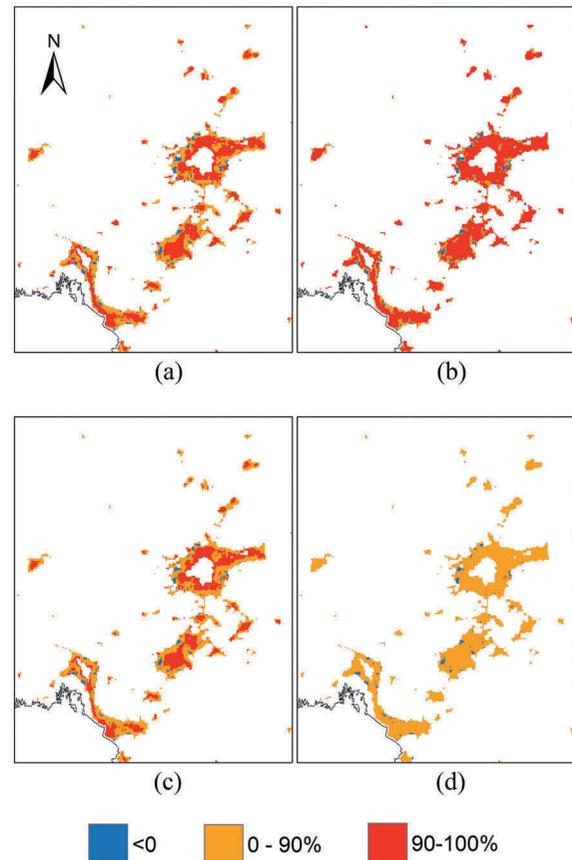
**Figure 11.** Relationship between NPP-UIRS pixel value and the relative differences of spatial texture indices between two data sets: (a) MD, (b) variance, (c) NCV and (d) entropy. Circles indicate the mean relative difference of pixels within a small interval of UIRS-NPP pixel value; error bars represent mean  $\pm$  standard deviation.

real urban area are saturated (DN = 63). This considerable number of saturated pixels may affect the analysis of blooming effect in Sections 4.2 and 4.3.

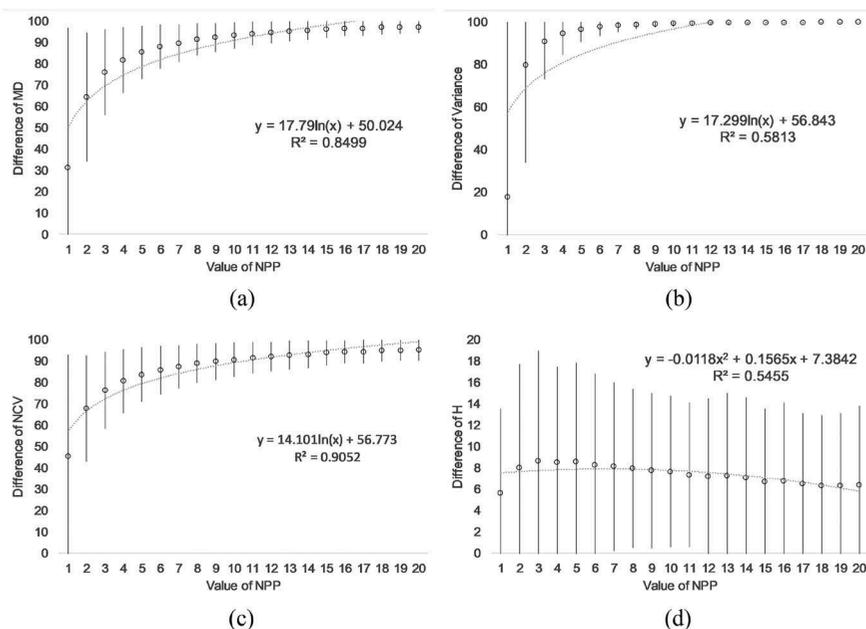
To better qualify blooming effect in city, saturated pixels of DMSP-OLS data were excluded from real urban area of two data sets. Figure 12 shows the results of spatial heterogeneity differences in sub-region highlighted in Figure 8(a) (also in Figure 5(a)) between two data sets after masking out saturated pixels. It is clear that saturated pixels are in the centre of cities. The spatial pattern of blooming effect still exists after excluding saturation part. The relationship between blooming effect and light intensity after excluding saturated pixels (Figure 13) are very similar with that using all pixels (Figure 11). Specifically, DMSP-OLS data underestimates 90% spatial heterogeneity when NPP value >10 due to blooming effect (Figure 13(a-c)). It confirms that blooming effect is more serious towards to brighter regions, normally the centre of cities.

## 5. Conclusion

The study attempted to measure and analyse the blooming effect of DMSP-OLS data at pixel level based on NPP-UIRS data. Two data sets, DMSP-OLS data and NPP-UIRS data, were first resampled, co-registered, de-noised, and relative radiation corrected to make sure these two datasets are comparable.



**Figure 12.** Spatial distribution of differences of four spatial texture indices between two data sets in the real urban area exclude saturation area of a sub-region marked in Figure 8: (a) MD, (b) variance, (c) NCV and (d) entropy.



**Figure 13.** Relationship between NPP-VIIRS pixel value and the relative differences of spatial texture indices between two data sets after excluding saturated pixels: (a) MD, (b) variance, (c) NCV and (d) entropy. Circles indicate the mean relative difference of pixels within a small interval of NPP-VIIRS pixel value; error bars represent mean  $\pm$  standard deviation.

Bright areas of NPP-VIIRS and DMSP-OLS were extracted to represent the real urban area and the over-estimated urban area respectively. Then, a  $3 \times 3$  local window was applied to compute spatial texture indices (variance, mean deviation, normalized coefficient of variation and entropy) to describe the spatial heterogeneity of the two data sets. In this way, blooming effect of DMSP-OLS data could be assessed through comparing the values of spatial texture indices between two data sets.

In real urban area, spatial heterogeneity of DMSP-OLS data is lower than NPP-VIIRS data at most pixels. DMSP-OLS blooming effect reduces spatial heterogeneity in real urban area. In addition, the blooming effect increases with NPP values from the edge of the real urban area to the centre of the city. In the 'buffer zone' outside real urban area (representing the outskirts area where NPP-VIIRS data has no effective bright pixels), spatial heterogeneity of DMSP-OLS data is higher than NPP-VIIRS data at most pixels because blooming effect of DMSP-OLS brings fake bright pixels which enhance spatial heterogeneity. Among these four spatial texture indices, MD and NCV are two better indices to describe the relationship between blooming effect of DMSP and light intensity.

The findings of this study will advance our understanding on the spatial pattern of blooming effect

in DMSP-OLS data and will promote the development of new methodologies to mitigate or remove the blooming effect of DMSP-OLS data in the future.

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## Disclosure statement

No potential conflict of interest was reported by the authors.

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