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Forecasting China's GDP at the pixel level using nighttime lights time series and population images

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China's rapid economic development greatly affected not only the global economy but also the entire environment of the Earth. Forecasting China's economic growth has become a popular and essential issue but at present, such forecasts are nearly all conducted at the national scale. In this study, we use nighttime light images and the gridded Landscan population dataset to disaggregate gross domestic product (GDP) reported at the province scale on a per pixel level for 2000–2013. Using the disaggregated GDP time series data and the statistical tool of Holt–Winters smoothing, we predict changes of GDP at each 1 km × 1 km grid area from 2014 to 2020 and then aggregate the pixel-level GDP to forecast economic growth in 23 major urban agglomerations of China. We elaborate and demonstrate that lit population (brightness of nighttime lights × population) is a better indicator than brightness of nighttime lights to estimate and disaggregate GDP. We also show that our forecast GDP has high agreement with the National Bureau of Statistics of China's demographic data and the International Monetary Fund's predictions. Finally, we display uncertainties and analyze potential errors of this disaggregation and forecast method.

Keywords: nighttime light imagery; gross domestic product (GDP); Holt–Winters smoothing; urban agglomeration; China

1. Introduction

The story of China's rapid economic development since economic reforms in 1978 is widely reported. From 1978 to 2013, China achieved 9.5% growth of average annual gross domestic product (GDP). Economists believe that such fast growth momentum will not radically change throughout the decade until 2020 (Kuijs 2009; Wang, Fan, and Liu 2007; Wang, Zhang, and Ho 2010). China's economic growth directly determines energy consumption and carbon dioxide emission and so greatly impacts not only the world economy but also the global environment and climate change (Cai et al. 2008; Li and Oberheitmann 2009; Liu and Diamond 2005; Wang et al. 2005, 2011; Zhang 2011; Zhu et al. 2005).

Present studies of forecasting China's GDP are mainly conducted on the national scale; however, China's economic development is spatially uneven. Speeds of economic growth in eastern coastal regions were much larger than those in inland regions during the

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past three decades (Keng 2006; Lee et al. 2012). This unbalanced economic development has resulted in a series of social and environmental problems (e.g., energy and housing shortages as well as environmental pollution) (Cao et al. 2014a; Fujita and Hu 2001; Herrerias, Joyeux, and Girardin 2013; Keng 2006). Furthermore, urban agglomerations are replacing traditional administrative units (e.g., provinces and cities) while becoming major phenomena in studying social and economic development (Drennan and Kelly 2011; Enright 2003; Fujita and Thisse 2013). Many urban agglomerations emerged in China with economic development, yet present dependable demographic data for China are mostly reported at the province level. Thus, economic development of China's urban agglomerations cannot be accurately forecast by only using demographic data. To better understand and regulate China's economic development and cope with probable emergent social and environmental problems, China's GDP needs to be forecast at finer geographic scales.

Exponential smoothing is a widely used technique to forecast economic data. In light of the use of a recursive calculation algorithm, exponential smoothing can smooth and forecast time series data without need of establishing parametric models (Gelper, Fried, and Croux 2010; Holt 2004). The Holt–Winters smoothing is an extension of exponential smoothing that was developed for forecasting or smoothing time series data with changing trends or seasonality (Gelper, Fried, and Croux 2010; Holt 2004). Therefore, it can be expected that if China's past total GDPs are spatially disaggregated to each pixel, each pixel will have a set of GDP time series data. Then, the Holt–Winters smoothing can be used to forecast GDP changes inside the pixel area.

The Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) nighttime light imagery (originally designed to collect information about moonlit clouds) has been successfully used to estimate socioeconomic factors (e.g., GDP, electric power consumption, and fossil fuel carbon dioxide (CO_2) emissions) (Cao et al. 2014b; Chen and Nordhaus 2010; Doll, Muller, and Morley 2006; Letu et al. 2010; Lo 2002; Oda and Maksyutov 2011; Shi et al. 2016; Sutton, Elvidge, and Ghosh 2007; Wu et al. 2013; Xie and Weng 2016a, 2016b; Xu et al. 2015). Based on statistical linear relationships between the amount of GDP and brightness of nighttime lights at the national or province/state level, the DMSP-OLS nighttime light imagery has been also utilized to spatially disaggregate GDP and produce global, continental, or national GDP maps with relatively fine spatial resolution (from 1 km × 1 km to 1° × 1°) (Doll, Muller, and Elvidge 2000; Ghosh et al. 2010; Sutton and Costanza 2002; Zhao, Currit, and Samson 2011). In these disaggregation studies, national or province/state total GDP is usually directly distributed to each pixel in proportion to the DN value of the pixel of the nighttime light imagery (Doll, Muller, and Elvidge 2000; Ghosh et al. 2010; Sutton and Costanza 2002; Zhao, Currit, and Samson 2011). However, a certain number of saturated pixels exist in nighttime light time series (NLTS) image products. Consequently, disaggregating GDP only dependent on DN values of NLTS images will result in large under-distribution in urban core areas where many pixels of NLTS images are saturated. Additionally, Zhao et al. (2015a) have found that the actual quantitative correlations between brightness of nighttime lights and the amount of the socioeconomic factors are closer to exponential curves than linear functions. Thus, to accurately forecast each pixel area's GDP changes, it is needed to first develop of a more advanced GDP disaggregation method.

The major objective of this study is, therefore, to forecast China's GDP through 2020 at the pixel level. To fulfill this study objective, we first employ NLTS images in conjunction with gridded population data to spatially disaggregate each province's GDP from 2000 to 2013 to the pixel level. We then use Holt–Winters smoothing to forecast GDP produced in each pixel area through 2020. Next, we exhibit GDP changes from 2013 to 2020 and evaluate our forecast results at different geographic levels. Finally, we show uncertainties and analyze potential errors of the disaggregation and forecast methods.

2. Data

The version 4 DMSP-OLS stable NLTS image products for 2000–2013 were obtained from the National Oceanic and Atmospheric Administration's National Geophysical Data Center (NGDC) (available: http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html; last access 13 December 2016). In most years between 2000 and 2013, there are two separate annual stable light image products derived from two satellites to avoid degradation of data quality due to aging of the satellites/sensors (Elvidge et al. 2009). In this study, we used the annual image product derived from the relatively new satellite if there are two separate products for the same year. For example, in 2000, satellites F14 and F15 simultaneously collected global nighttime lights information; thus, we selected the image product from satellite F15 to spatially disaggregate GDP for 2010 under the assumption that the newer sensor would have less degradation of data quality. Each stable light image product is a composite of all the available cloud-free data for that particular calendar year in the NGDC's digital archive with spatial resolution of 1 km^2. Background noise and ephemeral lights (typically fire and lightning) have been removed from the image products. The DMSP-OLS stable light image composites are 6-bit images. Digital number (DN) values of one annual stable light image composite represent average brightness of nighttime lights of that year except DN value 63 (saturated pixels). Detailed algorithms and processes for the products have been described by Baugh et al. (2010).

The LandScan population dataset for 2008 that was used to assist nighttime light data in disaggregating GDP data was taken from the Oak Ridge National Laboratory. The population dataset is produced by interpolating subnational census population data to a fine spatial resolution (1 km^2) with ancillary datasets like land cover, slope, and roads as well as brightness of nighttime lights. These ancillary datasets are derived from remotely sensed images (e.g., Landsat Thematic Mapper, MODIS, Shuttle Radar Topography Mission, and DMSP-OLS) (Dobson et al. 2000). DN values of the LandScan population dataset represent population counts.

The GDP data for 2000–2015 reported by province were obtained from the National Database established by the National Bureau of Statistics of China (NBSC) (available from: http://data.stats.gov.cn/english/easyquery.htm?cn=E0103; last accessed 13 December 2016). Taiwan, Hong Kong, and Macao were excluded from this study due to their distinct political and economic status from the other Chinese provinces. The GDP data of 2014 reported by 32 cities were also retrieved from the NBSC for validation (see Table 4 for the specific 32 cities). China's total GDP between 2012 and 2020 estimated/predicted by the International Monetary Fund (IMF) (2016) was used to evaluate the accuracy of our forecasts.

3. Methodology

3.1. Disaggregating GDP

In previous studies, GDP (or other socioeconomic data such as electric power consumption and fossil fuel CO_2 emission) was spatially disaggregated to each pixel in proportion to DN value of nighttime light images (Doll, Muller, and Elvidge 2000; Ghosh et al. 2010; Oda and Maksyutov 2011; Zhao, Currit, and Samson 2011; Zhao, Ghosh, and Samson 2012). This disaggregation process can be generalized by a linear function with an intercept of 0 (Equation 1):

$$GDP_{pixel} = GDP_{per\ light} \times DN_l = \frac{GDP_{total}}{SL} \times DN_l \tag{1}$$

where $GDP_{per\ light}$ denotes the amount of GDP represented by one unit of brightness of nighttime lights, DN_l denotes the DN value of a pixel of a nighttime lights image, GDP_{pixel} is the amount of GDP distributed to the pixel, GDP_{total} is the total amount of GDP of a region (e.g., a province/state or a country), and SL is sum light (i.e., the sum of the DN values of all the lit pixels in the region).

DN values in the NLTS images are not radiometrically calibrated and so are incompatible across years. In other words, it cannot be discerned whether changes in DN values are due to actual variations in brightness of nighttime lights or man-made adjustments in the gain value of the sensors. Thus, when multiyear nighttime light images are used for a quantitative comparison study, applying Elvidge et al.'s (2009) Sicily empirical intercalibration method to adjust DN values is an essential preparation. The key of Elvidge et al.'s (2009) Sicily intercalibration method is to suppose that brightness of nighttime lights in Sicily, Italy, has no change across the years that are covered by the multiyear nighttime light images. It is improbable that actual brightness of nighttime lights in Sicily did not experience any changes across chosen years (e.g., 2000–2013 in this study) even though the changes in Sicily are likely to be small compared to those in other places of the world. Thus, DN values across different years are still not completely compatible and errors of DN values have been generated even after performing the Sicily intercalibration (Zhao, Ghosh, and Samson 2012; Zhao et al., 2015b). Although DN values are incompatible across different years, DN values (except 63) in an annual stable light image composite are scaled. The increase/decrease in gain value will lead to a proportional increase/decrease in sum light (i.e., SL in Equation 1) and consequently a proportional decrease/increase in the amount of GDP represented by one unit of brightness of nighttime lights (i.e., $GDP_{per\ light}$ in Equation 1). Whereas no matter how large the change in gain value is, the amount of GDP distributed to a pixel will not be varied because the pixel's DN value will also proportionally increase/decrease with the change in gain value. The changes in gain value cannot influence the distribution of GDP and thus, GDP distributed by the stable light image composites is compatible across years. In the following steps, we process a GDP time series but not a DN value time series so there is no need to intercalibrate the NLTS images.

Zhao et al. (2015a) found that the actual correlations between brightness of nighttime lights and the amount of CO_2 emission are exponential rather than linear. Using such a linear function to disaggregate CO_2 emission will result in over-distributions in suburban areas, under-distributions in urban areas, and very large under-distributions in urban core areas where saturated pixels exist. The application of using nighttime light data to spatially disaggregate socioeconomic parameters is dependent on the same logic that a region with brighter lights at night usually has more commerce and industry and consequently produces greater GDP, consumes more electric energy, and emits more CO_2 (Doll, Muller, and Elvidge 2000; Ghosh et al. 2010; Oda and Maksyutov 2011; Zhao, Currit, and Samson 2011; Zhao, Ghosh, and Samson 2012). Thus, it can be inferred that the correlations between brightness of nighttime lights and the amount of GDP should also be

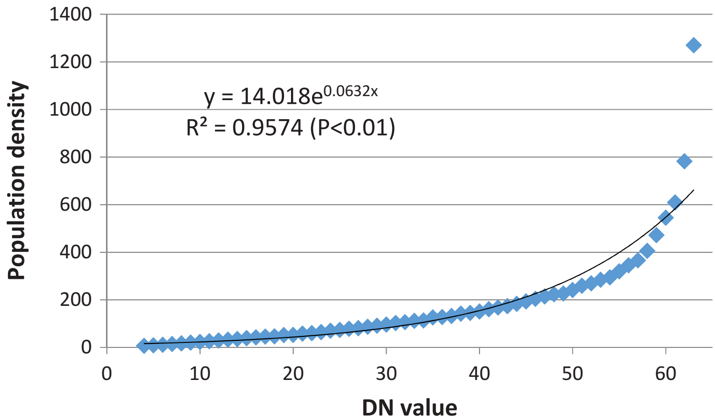

Figure 1. The correlation between DN value of 2001 stable lights imagery and population density (Zhao 2014). For full colour versions of the figures in this paper, please see the online version.

exponential rather than linear. Simply using stable light image data and the linear function to disaggregate GDP is likely to generate similar errors (i.e., over-distribution in suburban areas and under-distribution in urban areas).

In this study, we employed the LandScan population data to help stable light images disaggregate GDP. Figure 1 shows that average population density derived from the LandScan population data has an exponential relationship with nighttime light DN value (Zhao 2014). In suburban areas where the DN values of nighttime lights are relatively small, the population density increases slowly. With progressively higher DN values, however, increase in population density becomes increasingly rapid and finally leads to an extremely large population density in urban core areas with DN value of 63. The relatively large population compensates for the under-valued nighttime light data (i.e., the saturated pixels) in urban areas (Zhao 2014).

We multiplied nighttime light images by the LandScan population data to produce lit-population images and then used Equation 2 to spatially disaggregate GDP:

$$GDP_{pixel} = \frac{GDP_{total}}{SLP} \times DN_{lp} \tag{2}$$

where DN_{lp} is the DN value of a pixel of a lit-population image and SLP is sum lit population (i.e., the sum of the DN values of the lit-population image in a province). Previous studies have proven that luminance of nighttime lights is a sound proxy of economic level (Chen and Nordhaus 2010; Doll, Muller, and Morley 2006; Sutton, Elvidge, and Ghosh 2007; Zhao, Currit, and Samson 2011). Lit population does not correspond to any measurement unit in real life, representing neither people count nor brightness of nighttime lights. It indicates economically weighed-population (Zhao 2014). In other words, if two regions have the same population but different brightness of nighttime lights, the region with brighter nighttime lights has larger lit population and consequently has larger distributed GDP than the one with dimmer nighttime lights. Thus, statistical GDP data obtained from the NBSC were disaggregated from the province level to the pixel level by the lit population and 14 GDP maps for 2000–2013 were produced.

3.2. Forecasting GDP

The Holt–Winters smoothing is also referred to as double exponential smoothing (Gelper, Fried, and Croux 2010). The simplest form of exponential smoothing can be expressed by Equation 3:

$$\begin{aligned}\overline{S_t} &= \alpha \cdot x_t + (1-\alpha) \cdot \overline{S_{t-1}} \\ &= \alpha\left[x_t + (1-\alpha)x_{t-1} + (1-\alpha)^2 x_{t-2} + \cdots + (1-\alpha)^{t-1}x_1\right] + (1-\alpha)^t x_0\end{aligned} \tag{3}$$

where α is the smoothing factor and $0 < \alpha < 1$. Equation 3 shows that a new smoothed value $\overline{S_t}$ is affected by a current observation value x_t and the last-period smoothed value $\overline{S_{t-1}}$, and the effect of the old observation value on a new smoothed value is exponentially declined with period t increasingly updated.

The Holt–Winters smoothing is an extension of exponential smoothing developed particularly to forecast time series data with changing trends. Economists nearly unanimously believe that China will maintain economic growth over 2014–2020 (Holz 2008; Kuijs 2009; Wang, Fan, and Liu 2007; Wang, Zhang, and Ho 2010). Thus, the Holt–Winters smoothing rather than exponential smoothing should be used to forecast GDP through 2020. The Holt–Winters smoothing is given by Equation 4:

$$\overline{S_1} = x_1$$

$$\overline{b_1} = x_1 - x_0$$

and for $t > 1$

$$\begin{aligned}\overline{S_t} &= \alpha \cdot x_t + (1-\alpha)\left(\overline{S_{t-1}} + \overline{b_{t-1}}\right) \\ \overline{b_t} &= \beta\left(\overline{S_t} - \overline{S_{t-1}}\right) + (1-\beta) \cdot \overline{b_{t-1}}\end{aligned} \tag{4}$$

where $\overline{b_t}$ is the estimate of the trend at time t, α is the data smoothing factor ($0 < \alpha < 1$) and β is the trend smoothing factor ($0 < \beta < 1$). A y-step-ahead prediction at time t can be obtained by the following equation:

$$F_{t+y|t} = \overline{S_t} + y \cdot \overline{b_t} \tag{5}$$

In this study, the GDP prediction was performed by the "forecast" package in R (Hyndman 2016). The specific smoothing and trend smoothing factors (i.e., α and β in Equation 4) were calculated by the functions of *HoltWinters* and *forecast.HoltWinters* in the "forecast" package. The optimal values of the two smoothing factors are determined by minimizing the squared one-step prediction error. Since we have produced 14 Chinese GDP maps for 2000–2013, each pixel has 14 GDP time series data. For one pixel, the 14 GDP data were smoothed, and $\bar{S}$ and $\bar{b}$ for each year during 2000–2013 were calculated by Equation 4. The $\bar{S}$ and the $\bar{b}$ for the year of 2013 were then input into Equation 5 to predict GDP from 2014 to 2020. The above process of smoothing and forecasting was conducted for every pixel in China, save for the previously mentioned excluded regions (i.e., Taiwan, Hong Kong, and Macao). Besides "point" forecasts, the "forecast" package also provides interval forecasts to assess future uncertainties. Thus, for each pixel and each year, the forecasting results are two value ranges at the 80% and the 95%

prediction intervals and the mean value of the ranges. Considering the largest probability of occurrence of the mean values other than the values in the ranges, we chose the mean values to produce seven Chinese GDP maps for 2014–2020.

4. Results

Through using the remotely sensed data of nighttime lights and the statistical tool of Holt–Winters smoothing, we forecast that in 2014, China's total amount of GDP is 71,240.43 billion yuan and in 2020 the GDP amount will increase 1.56 times, reaching 111,172.68 billion yuan. Table 1 shows that GDP of different Chinese provinces will increase 1.38 to 1.80 times during the period of 2014–2020. In 2014, Guangdong has the largest amount of GDP, whereas in 2020, Jiangsu will surpass Guangdong becoming the province with the highest GDP. Given the relatively large GDP amounts, rates of GDP increase of economically developed provinces are relatively small. By contrast, economically less developed provinces, mostly located in western areas, have relatively high rates of GDP increase (Table 1). Even so, the disparities of GDP between western and eastern provinces will widen further. For example, Guizhou has the largest increase rate of 1.80 and the increase rate of Guangdong is only 1.47. In 2014, the disparity of GDP between the two provinces is 5856.71 billion yuan, whereas in 2020, this gap will be enlarged to 8288.35 billion yuan.

Figure 2a and b shows predictions of GDP for 2014 and 2020 at pixel level. Since we forecast each pixel's GDP, it was easy to spatially aggregate these pixels and obtain the GDP of any urban agglomeration. At present, the Chinese government still has not issued a clear spatial definition of China's urban agglomerations. Academic definitions and delimitations of Chinese urban agglomerations are also inconsistent. In this study, we used the boundary of Chinese urban agglomerations recently defined by Liu, Derudder, and Wu (2015) to calculate each urban agglomeration's GDP. It needs to be specially stated that these urban agglomerations were defined by the economic and urban situations in 2013. With sustained population migration and urbanization, new cities are likely to be contained in the current urban agglomerations and consequently the extents of the future urban agglomerations may be different from the current ones. Observing present urban development situations of China, Liu, Derudder, and Wu (2015) definition and delimitation of urban agglomerations are still appropriate. We assume that delimitation of the urban agglomerations will not change through 2020.

Based on Liu, Derudder, and Wu (2015) definition, 23 urban agglomerations have formed in China. They are Beijing Tianjin Hebei (BTH), central Anhui (CAH), central Guizhou (CGZ), central Inner Mongolia (CIM), central Plain (CPL), central Shanxi (CSX), central Yunnan (CYN), Chengdu Chongqing (CHC), eastern Fujian (EFJ), eastern Hubei (EHB), eastern Hunan (EHN), Guanzhong Plain (GZP), Harbin Changchun (HAC), Lanzhou Xining (LZX), Liaodong Peninsula (LDP), northern Jiangxi (NJX), northern Ningxia (NNX), Pearl River Delta (PRD), Shandong Peninsula (SDP), Southern Guangxi (SGX), Tianshan Mountains (TSM), western Gansu (WGS), and Yangtze River Delta (YRD). The area of the 23 urban agglomerations is only 18.84% of China's total area (excluding Taiwan, Hong Kong, and Macao), but the 23 urban agglomerations produced 66.17% of China's total GDP (i.e., 47,142.26 billion yuan) in 2014. With the assumption that no new cities are included in the current 23 urban agglomerations, in 2020, the 23 urban agglomerations will produce 72,619.78 billion yuan accounting for 65.32% of China's total GDP by our prediction.

At present, China's economic centers are located in three urban agglomerations: the YRD, the BTH, and the PRD (Liu and Liu 2013). The area of these three urban agglomerations only accounts for 3.50% of Chinese total area, but for 2014, they were

Table 1. Forecast amounts of GDP and comparison with the NBSC's GDP at the province level.

Province	NBSC's GDP in 2014 (billion yuan)	NBSC's GDP in 2015 (billion yuan)	Forecast GDP in 2014 (billion yuan)	Forecast GDP in 2015 (billion yuan)	Forecast GDP in 2020 (billion yuan)	Difference rate for 2014*	Difference rate for 2015*	Increase rate**
Anhui	2084.88	2200.56	2209.40	2436.11	3570.63	0.060	0.107	1.62
Beijing	2133.08	2296.86	2173.31	2371.23	3360.82	0.019	0.032	1.55
Chongqing	1426.26	1571.97	1501.31	1670.15	2514.41	0.053	0.062	1.67
Fujian	2405.58	2597.98	2447.07	2687.91	3892.15	0.017	0.035	1.59
Gansu	683.68	679.03	707.90	780.44	1143.48	0.035	0.149	1.62
Guangdong	6780.99	7281.26	6806.75	7338.13	9995.30	0.004	0.008	1.47
Guangxi	1567.29	1680.31	1661.76	1833.01	2689.51	0.060	0.091	1.62
Guizhou	926.64	1050.26	950.04	1076.15	1706.95	0.025	0.025	1.80
Hainan	350.07	370.28	357.00	393.96	578.78	0.020	0.064	1.62
Hebei	2942.12	2980.61	3162.50	3428.27	4760.00	0.075	0.150	1.51
Heilongjiang	1503.94	1508.37	1605.23	1735.70	2388.22	0.067	0.151	1.49
Henan	3493.82	3701.03	3590.16	3892.57	5405.76	0.028	0.052	1.51
Hubei	2737.92	2955.02	2905.97	3222.64	4806.27	0.061	0.091	1.65
Hunan	2703.73	2904.72	2885.22	3176.33	4632.78	0.067	0.094	1.61
Inner Mongolia	1777.02	1803.28	1915.92	2075.93	2877.25	0.078	0.151	1.50
Jiangsu	6508.83	7011.64	6655.37	7286.17	10,444.22	0.023	0.039	1.57
Jiangxi	1571.46	1672.38	1682.72	1855.53	2719.86	0.071	0.110	1.62
Jilin	1380.31	1427.41	1495.47	1639.18	2358.25	0.083	0.148	1.58
Liaoning	2862.66	2874.34	3073.45	3372.12	4865.56	0.074	0.173	1.58
Ningxia	275.21	291.18	291.99	320.64	464.05	0.061	0.101	1.59
Qinghai	230.33	241.71	240.52	267.27	401.02	0.044	0.106	1.67
Shaanxi	1768.99	1817.19	1852.46	2068.24	3147.69	0.047	0.138	1.70
Shandong	5942.66	6300.23	6057.55	6587.47	9239.72	0.019	0.046	1.53
Shanghai	2356.77	2496.50	2338.06	2485.19	3220.87	−0.008	−0.005	1.38
Shanxi	1276.15	1280.26	1426.48	1540.59	2113.09	0.118	0.203	1.48
Sichuan	2853.67	3010.31	3092.96	3419.24	5051.58	0.084	0.136	1.63
Tianjin	1572.69	1653.82	1637.72	1815.75	2705.86	0.041	0.098	1.65
Tibet	92.08	102.64	89.48	99.41	149.04	−0.028	−0.032	1.67
Xinjiang	927.35	932.48	948.04	1048.32	1550.31	0.022	0.124	1.64
Yunnan	1281.46	1371.79	1338.70	1490.51	2249.80	0.045	0.087	1.68
Zhejiang	4017.30	4288.65	4139.92	4477.97	6169.45	0.031	0.044	1.49

*Difference rate = (Forecast GDP − Official GDP)/Official GDP.
**Increase rate = Forecast GDP in 2020/Forecast GDP in 2014.

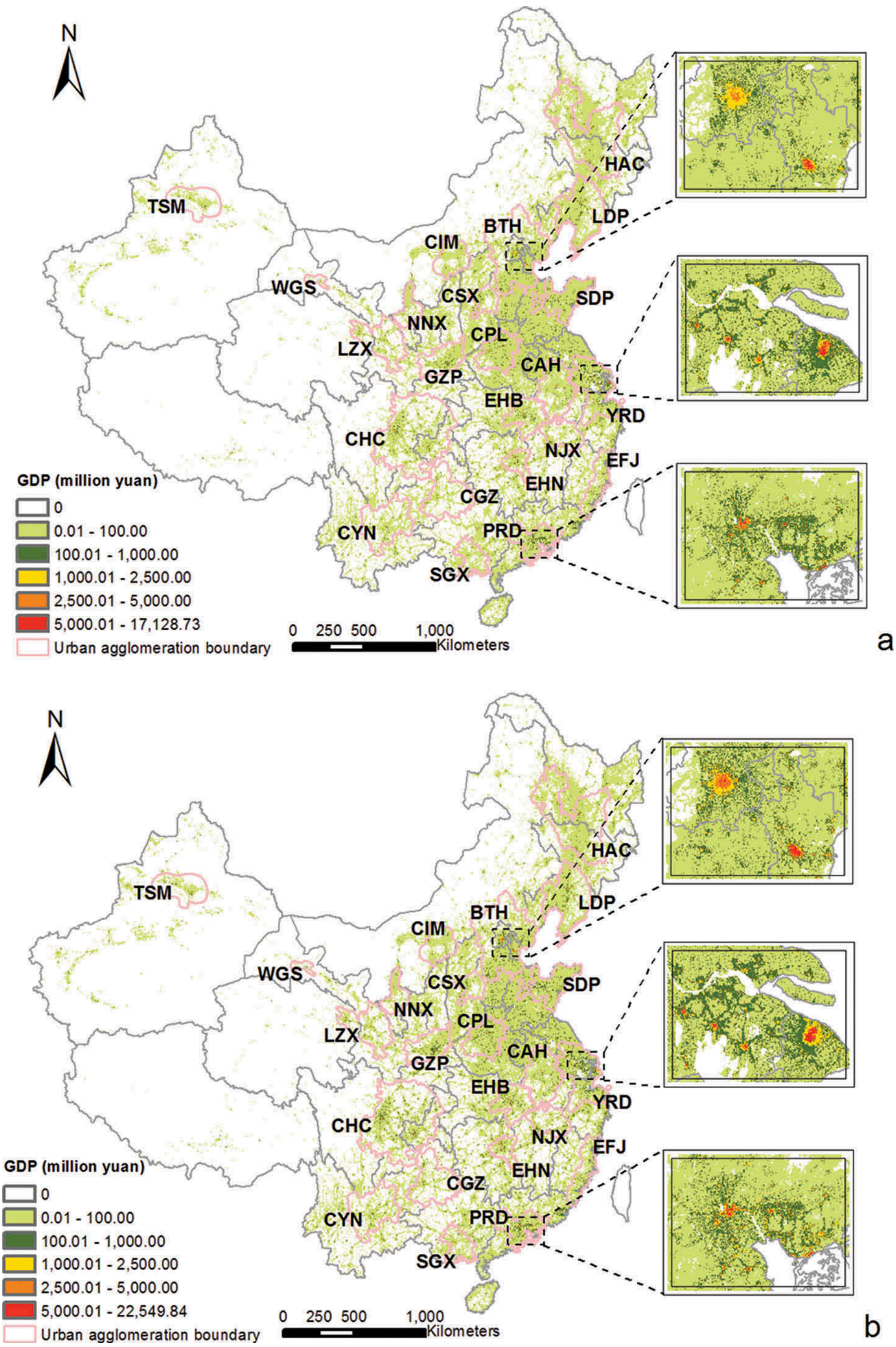

Figure 2. Forecast GDP maps for 2014 (a) and 2020 (b).

forecast to produce 28.12% of Chinese total GDP (i.e., 20,029.32 billion yuan). In 2020, the proportion of GDP produced in the three urban agglomerations will decrease slightly to 26.93%. Using Liu, Derudder, and Wu (2015) delimitation of China's urban agglomerations, the 2014 amount of GDP produced in the CHC is very close to that produced in the PRD, and in 2020, the CHC will exceed the PRD becoming the third largest GDP-production urban agglomeration (see Table 2). Admittedly that the PRD's GDP is bypassed beyond the CHC's GDP in 2020 partly reflects the reality that the pace of economic development in the PRD is slowing down (Liu and Liu 2013). However, a more major reason resulting in the considerably large GDP in the CHC and overtaking the PRD in 2020 is the CHC's large spatial extent, not higher scaled economic activity. The area of the CHC (232,748.22 km^2) is four times larger than that of the PRD (56,602.61 km^2). Cities located in the Sichuan Basin are nearly all included in the CHC that directly results in its massive GDP. However, the spatial GDP productivity (i.e., the amount of GDP produced in 1 km^2 area of land) in the CHC is much smaller than that in the PRD (see Table 2). In 2020, the spatial GDP productivity of the PRD (112.52 million yuan/km^2) is still the second largest in all the 23 urban agglomerations and approximately four times larger than that of the CHC (30.53 million yuan/km^2). Thus, the status of economic centrality of the PRD will not change radically by 2020.

5. Discussion

5.1. Brightness of nighttime lights vs. lit population

Table 3 clearly shows that compared to brightness of nighttime lights, lit population has stronger relationships with GDP at the province level in all the years between 2000 and 2013. At the pixel level, we cannot find a reliable gridded GDP dataset as reference data but analyzes on the problems of saturation and blooming can reveal which variable, brightness of nighttime lights, or lit population is a better proxy of GDP. One of the major drawbacks of stable light image products is that a considerable number of saturated pixels exist in urban core areas (Zhao et al., 2015). These saturated pixels are valued as 63 but their actual values should be much larger than this (Doll 2008). Thus, it can be inferred that GDP in urban core areas is considerably under-distributed when DN values of stable light images are used as the indicator to spatially disaggregate GDP. The problem of saturation is nonexistent in the Landscan population dataset. In the urban core areas with nighttime-light DN values of 63, population densities are exceptionally large (see Figure 1). Thus, if lit population is used as the indicator to disaggregate GDP, the relatively large population can compensate for the under-valued nighttime light data (i.e., the saturated pixels) in the urban core areas.

Blooming is a very common phenomenon in nighttime light imagery where urban peripheries are brightened by urban lights (Imhoof et al., 1997). Through comparison with MODIS land cover type image products, Liu et al. (2016) found that in China, most lit pixels correspond to cropland, forestland, and grassland. Even though DN values of the individual pixels lit by the blooming effect (hereafter, referred as lit nonurban pixels) are smaller than those of the lit pixels in urban areas, the number of such lit nonurban pixels is very large (Liu et al. 2016; Yu et al. 2014). Thus, when brightness of nighttime lights is used as an indicator for disaggregating GDP, a large amount of GDP will be distributed to the rural areas. With the condition that total GDP is determinate, distributing over-large amounts of GDP to rural areas must result in under-distribution of GDP to urban areas.

Table 2. Forecast amounts of GDP of the 23 urban agglomerations.

Urban agglomeration	Area (km^2)	GDP in 2014 (billion yuan)	GDP in 2020 (billion yuan)	Spatial GDP productivity in 2014 (million yuan/km^2)	Spatial GDP productivity in 2020 (million yuan/km^2)
Beijing Tianjin Heibei	175,088.21	6116.15	9523.89	34.93	54.39
Central Anhui	75,743.73	1411.86	2273.28	18.64	30.01
Central Guizhou	87,217.04	653.25	1170.70	7.49	13.42
Central Inner Mongolia	50,868.80	804.42	1184.11	15.81	23.28
Central Plain	58,777.05	2002.32	2900.62	34.07	49.35
Central Shanxi	27,908.92	473.61	677.32	16.97	24.27
Central Yunnan	93,276.50	732.79	1194.80	7.86	12.81
Chengdu Chongqing	232,748.22	4300.06	7106.25	18.48	30.53
Eastern Fujian	51,037.30	2009.15	3165.24	39.37	62.02
Eastern Hubei	54,035.32	1784.47	2881.79	33.02	53.33
Eastern Hunan	28,082.16	1180.40	1775.71	42.03	63.23
Guanzhong Plain	55,675.85	1481.01	2491.54	26.60	44.75
Harbin Changchun	183,583.38	1698.84	2560.84	9.25	13.95
Lanzhou Xining	79,009.65	552.02	882.30	6.99	11.17
Liaodong Peninsula	110,191.11	2871.36	4539.89	26.06	41.20
Northern Jiangxi	46,354.26	886.90	1393.15	19.13	30.05
Northern Ningxia	31,164.43	255.91	402.73	8.21	12.92
Pearl River Delta	56,602.61	4490.48	6368.97	79.33	112.52
Shandong Peninsula	66,978.76	3033.30	4530.04	45.29	67.63
Southern Gangxi	41,915.45	561.19	892.14	13.39	21.28
Tianshan Mountains	64,523.17	384.67	606.38	5.96	9.40
Western Guansu	9473.05	35.42	54.39	3.74	5.74
Yangtze River Delta	99,387.08	9422.69	14,043.29	94.81	141.30

Table 3. Pearson's correlation coefficients of GDP to sum light and sum lit population at the province level.

Year	Sum light	Sum lit population
2000	0.86	0.95
2001	0.86	0.95
2002	0.87	0.97
2003	0.92	0.96
2004	0.87	0.97
2005	0.87	0.97
2006	0.89	0.97
2007	0.89	0.98
2008	0.89	0.97
2009	0.83	0.95
2010	0.83	0.97
2011	0.88	0.96
2012	0.85	0.96
2013	0.87	0.97

Despite the nonzero DN values in nighttime light imagery, population of the areas corresponding to the lit nonurban pixels is very small or even equal to 0. When lit population is used as an indicator, the lit nonurban areas with population of 0 will not be distributed any amount of GDP. If population of a pixel area is not equal to 0, it means that stable human activities exist in this area (e.g., farming) and so it is reasonable to distribute a certain amount of GDP to the pixel even though the pixel is located in a rural area. Hence, jointly using nighttime light imagery and gridded population data can overcome the problems of saturation and blooming existing in the nighttime light imagery and consequently, lit population is a better measure of GDP than brightness of nighttime lights.

5.2. *Comparison with official data*

In this study, we estimated the amounts of GDP from 2014 to 2020 in China. Official GDP data for 2014 and 2015 have been released by the NBSC which provides an opportunity to evaluate accuracy of the estimated GDP data at the provincial geographic scale. It can be seen from Table 1 that absolute values of the error rates of the estimated GDP are all smaller than 0.118 for 2014 and not larger than 0.151 for 2015. Estimate accuracy in the economically developed provinces is particularly high. For example, in 2014 (2015), error rates of Beijing, Shanghai, and Guangdong are only 0.019 (0.032), −0.008 (−0.005), and 0.004 (0.008), respectively. Commerce in these provinces has been highly developed, so economic growth in the areas is more stable and more predictable. This predictability and stability may partly explain the very small error rates in the economically developed provinces as time series GDP data and Holt–Winters smoothing are used to predict future economy.

Table 4 shows error rates of forecast GDP of 32 major Chinese cities for 2014. The average absolute error rate of the 32 cities is 0.203. Absolute error rates of more than two-thirds (22) of the cities are smaller than this average value. In the remaining 10 cities, GDPs of Lhasa and Shenzhen were typically over-forecast and under-forecast, respectively. The GDPs of 2000–2013 were distributed from each province to each pixel. Thus, if economic level of a city (e.g., Shenzhen, Dalian, or Qingdao) is apparently higher than the average level of the province in which the city is located, the city's GDP of 2000–2013 was likely to be under-distributed, leading to a relatively large under-estimation for 2014. On the contrary, if a

Table 4. Error rates of forecast GDP of 32 major Chinese cities for 2014.

City	GDP (billion yuan)	Forecast GDP (billion yuan)	Error rate	City	GDP (billion yuan)	Forecast GDP (billion yuan)	Error rate
Changchun	534.24	472.05	−0.116	Nanchang	366.80	395.01	0.077
Changsha	782.48	752.98	−0.038	Nanjing	882.08	770.42	−0.127
Chengdu	1005.66	1120.53	0.114	Nanning	314.83	359.71	0.143
Dalian	765.56	492.73	−0.356	Ningbo	761.03	681.63	−0.104
Fuzhou	516.92	645.54	0.249	Qingdao	869.21	660.32	−0.240
Guangzhou	1670.69	1142.49	−0.316	Shenyang	709.87	673.29	−0.052
Guiyang	249.73	329.71	0.320	Shenzhen	1600.18	833.62	−0.479
Haikou	109.17	128.93	0.181	Shijiazhuang	517.03	536.17	0.037
Hangzhou	920.62	740.25	−0.196	Taiyuan	253.11	275.14	0.087
Harbin	534.01	512.28	−0.041	Urumqi	246.15	229.38	−0.068
Hefei	515.80	324.41	−0.371	Wuhan	1006.95	1004.64	−0.002
Hohhot	289.41	366.36	0.266	Xiamen	327.36	202.46	−0.382
Jinan	577.06	600.46	0.041	Xi’an	549.26	753.43	0.372
Kunming	371.30	431.32	0.162	Xining	106.58	149.87	0.406
Lanzhou	200.09	205.93	0.029	Yinchuan	138.86	128.21	−0.077
Lhasa	34.75	63.44	0.826	Zhengzhou	677.70	528.97	−0.219

province's economy is relatively rural and the great mass of GDP is derived from farming and livestock, a large part of GDP of the province cannot be directly reflected by nighttime lights. Hence, GDPs of some cities (e.g., Lhasa, Xining, and Hohhot) that, as the political and economic centers of their provinces, have brighter nighttime lights than the other cities in the provinces are likely to be over-distributed for 2000–2013 and consequently to be over-forecast for 2014.

Based on our search, currently reliable predictions for China's GDP were all accomplished at the national level for 2016–2020. Consequently, accuracy evaluation of our estimated GDP data for 2016–2020 can only be conducted at the national level. Table 5 shows comparison results between our estimated amounts of GDP with those of the IMF. By directly comparing our estimations with those of the IMF, the difference rates are in the range of 0.103–0.147 for the years 2014–2020. The NBSC reports that in 2012 and 2013, China's total amounts of GDP are 57,655.18 billion yuan and 63,434.53 billion yuan, respectively, while the IMF does not support those values. The IMF believes that China's actual GDP in 2012 and 2013 should be 53,412.30 billion yuan and 58,801.88 billion yuan, respectively, smaller than the amount reported by the NBSC. Hence, when we selected the IMF's predictions as reference and used the data of 2013, 2012, and even earlier years reported by the NBSC to predict China's future GDP, the relatively large over-estimations have been almost predetermined. For 2012 and 2013, the NBSC's GDPs are both 1.079 times larger than the IMF's GDP. To make the comparison more reasonable, China's total amounts of GDP predicted by the Holt–Winters smoothing for 2014–2020 were divided by the difference coefficient of 1.079. (In our Holt–Winters models, impacts of the fitting data on the forecasts exponentially decline as the year of the data increases earlier than 2013. Thus, we only used the difference coefficients for 2013 and 2012 but did not adopt more difference coefficients for earlier years to adjust the IMF's GDP.) It can be seen from Table 5 that after adjustment by the difference coefficient, the difference rates in China's total amount of GDP between our and IMF's estimations are located in the range of −0.027–0.036 for the years of 2014–2020.

5.3. Uncertainties and errors

At present, there are not a set of gridded population datasets with a sufficiently fine spatial resolution covering the whole period of 2000–2013. In this study, we only used the 2008 LandScan population dataset to assist NLTS images to disaggregate GDP of 2000–2013, which seems to generate relatively large errors. However, previous studies showed that such

Table 5. Comparison with the IMF's GDP at the national level.

Year	NBSC's GDP (billion yuan)	Study forecasted GDP (billion yuan)	IMF's GDP (billion yuan)	Difference rate*	Adjusted difference rate**
2012	57,655.18	–	53,412.30	0.079	0.000
2013	63,434.53	–	58,801.88	0.079	0.000
2014	–	71,240.42	63,613.90	0.120	0.029
2015	–	77,892.11	69,239.05	0.125	0.024
2016	–	84,545.47	74,208.23	0.139	0.032
2017	–	91,200.24	79,540.92	0.147	0.036
2018	–	97,856.47	85,692.36	0.142	0.026
2019	–	104,514.04	92,900.24	0.125	0.001
2020	–	111,172.68	100,817.07	0.103	−0.027

*Difference rate = (Forecast GDP − IMF's GDP)/IMF's GDP.**Adjusted difference rate = (Forecast GDP/1.079 − IMF's GDP)/IMF's GDP.

type of errors generated by the single-year gridded population data are actually much smaller than what we expected (Zhao, Ghosh, and Samson 2012). Brightness of nighttime lights closely correlates to population density (Bagan and Yamagata 2015; Sutton et al. 1997, 2001). In Bharti et al.'s (2011) study, brightness of nighttime lights was used directly as a proxy of population density. In LandScan, the brightness of nighttime lights has been used as an important variable to calculate weights of population distribution. Thus, the population information for different years has been partly reflected by the NLTS images, whereas the single-year LandScan population dataset was mainly used as auxiliary data to reduce the relatively large errors generated by the nighttime light images linearly disaggregating GDP for individual years. Table 3 shows that compared with the Pearson's correlation coefficient between GDP and sum lit population for 2008, the coefficients for the other years are not apparently decreased. This comparison suggests that the use of the single-year population data did not produce apparently adverse impacts on the disaggregation.

It also needs to be mentioned that in this study, we selected 2000–2013 as the training period. With a different training period (e.g., 1998–2013) used, the forecast amounts of GDP will be slightly different from those shown in this paper. In principle, the forecasts should be more accurate with a longer training period. At present, the stable nighttime lights image products cover each year between 1992 and 2013, but in this study, we did not use all the available nighttime light image composites. That is because in Holt–Winters smoothing, exponentially declined weights are put on older data. Data for the years far from 2013 actually have tiny effects on forecast results. Our forecasts were performed at 3757,252 individual pixels, thus using a longer training period (i.e., more than 14 years of NLTS images) will only increase computing burden and cannot effectively improve accuracy of the forecasts.

Once a pixel was not lit during 2000–2013, in our Holt–Winters smoothing forecast, this pixel would not have any chance of becoming a lit pixel and so would be treated as an area without producing GDP during 2014–2020. It can be inferred that with sustained economic development and urban expansion, lit area will become increasingly large from 2014 to 2020. Thus, failing to predict GDP in newly emerged lit areas after 2013 seems a critical shortcoming in our method. Due to the existence of blooming effect, a large area of lit regions is not actual urban areas and so should not be distributed large amounts of GDP (Liu et al. 2016). For the years 2000–2013, we employ population data to reduce the adverse impacts generated by the blooming effect. Besides urban expansion, sustained economic development and population growth can result in nighttime lights in original developed areas being brighter and consequently the blooming-affected regions expand outwardly. Such expansion will lead to some initially unlit pixels to be lit between 2014 and 2020. However, similar to the situation occurring during 2000–2013, such newly lit pixels (i.e., the pixels unlit from 2000–2013 but lit during 2014–2020) are more likely to be generated by the blooming effect but not correspond to newly developed areas (i.e., the areas developed during 2014–2020) and consequently should not be distributed GDP, whereas the newly developed areas are more likely to correspond to the pixels that have been lit during 2000–2013. Once a pixel was lit during 2000–2013 and had a nonzero population in the Landscan dataset, this pixel was likely to be distributed increasingly amounts of GDP with the sustained growth in total GDP of the province during 2000–2013. In the Holt–Winters smoothing model, this growth trend led to larger amounts of GDP distributed to the pixel for the years of 2014–2020, ensuring that the newly developed areas can be distributed increasing GDP. Therefore, not assigning GDP to the newly lit pixels generates a certain degree of errors but the errors should not be large. Additionally, there are a very limited number (less than 0.01% of the count of the pixels distributed GDP) of unlit pixels with nonzero population. The DMSP-OLS has very sensitive capability to detect ground nighttime lights and the blooming effects in the DMSP-OLS nighttime light imagery are plentiful (Doll 2008). Thus, an unlit pixel in the nighttime light imagery mostly corresponds to a remote area lacking stable anthropogenic activities and consequently failing to distribute GDP to the unlit pixel cannot generate large errors even though the pixel corresponds to a nonzero population.

6. Conclusions

In this study, we address a method using lit population as a measure to spatially disaggregate GDP and then apply Holt–Winters smoothing to forecast amounts of GDP at each 1 km × 1 km area from 2014 to 2020. Compared with the traditional approach singly using nighttime light imagery to spatially disaggregate socioeconomic factors, jointly using nighttime light imagery and a gridded population dataset can soundly overcome the problems of saturation and blooming in nighttime light imagery and consequently greatly improve the accuracy of distributing GDP. Using the high-spatial-resolution GDP maps, each province or urban agglomeration's total amounts of GDP in the coming 7 years (2014–2020) can be easily calculated.

Finally, we reiterate that the Holt–Winters smoothing forecasts two value ranges at the 80% and the 95% prediction intervals for each pixel and year between 2014 and 2020. These prediction intervals indicate the likely uncertainties in the GDP forecasts. The amounts of the forecast GDP exhibited in this paper are mean values of the DN value ranges. The lower and upper limit values at the 80% and the 95% prediction intervals together with the 2014–2020 high-spatial-resolution GDP maps produced by the means can all be obtained from the GitHub (https://github.com/thestarlab/data). We welcome our colleagues to further evaluate the quality of this set of GDP maps and use them to study China's economic development in future.

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