



Article Assessing Surface Water Losses and Gains under Rapid Urbanization for SDG 6.6.1 Using Long-Term Landsat Imagery in the Guangdong-Hong Kong-Macao Greater Bay Area, China

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Abstract: As one of the most open and dynamic regions in China, the Guangdong-Hong Kong-Macao

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Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). Greater Bay Area (GBA) has been urbanizing rapidly in recent decades. The surface water in the GBA also has been suffering from urbanization and intensified human activities. The study aimed to characterize the spatiotemporal patterns and assess the losses and gains of surface water caused by urbanization in the GBA via long time-series remote sensing data, which could support the progress towards sustainable development goals (SDGs) set by the United Nations, especially for measuring SDG 6.6.1 indicator. Firstly, utilizing 4750 continuous Landsat TM/ETM+/OLI images during 1986–2020 and the Google Earth Engine cloud platform, the multiple index water detection rule (MIWDR) was performed to extract surface water extent in the GBA. Secondly, we achieved surface water dynamic type classification based on annual water inundation frequency time-series in the GBA. Finally, the spatial distribution and temporal variation of urbanization-induced water losses and gains were analyzed through a land cover transfer matrix. Results showed that (1) the average minimal and maximal surface water extents of the GBA during 1986–2020 were 2017.62 km² and 6129.55 km², respectively. The maximal surface water extent fell rapidly from 7897.96 km² in 2001 to 5087.46 km² in 2020, with a loss speed of 155.41 km² per year ($R^2 = 0.86$). (2) The surface water areas of permanent and dynamic types were 1529.02 km² and 2064.99 km² during 2000–2020, accounting for 42.54% and 57.46% of all water-related areas, respectively. (3) The surface water extent occupied by impervious land surfaces showed a significant linear downward trend ($R^2 = 0.98$, slope = 36.41 km^2 per year), while the surface water restored from impervious land surfaces denoted a slight growing trend ($R^2 = 0.86$, slope = 0.99 km² per year). Our study monitored the long-term changes in the surface water of the GBA, which can provide valuable information for the sustainable development of the GBA urban agglomeration. In addition, the proposed framework can easily be implemented in other similar regions worldwide.

Keywords: surface water mapping; long time series; sustainable development goals (SDG); losses and gains; Google Earth Engine; remote sensing; dynamic type; urbanization

1. Introduction

Terrestrial surface water bodies, which include lakes, rivers, reservoirs, ponds and partially impounded farmland, are a critically important component of water resources for human life and terrestrial ecosystems [1]. Surface water provides and supports diverse ecosystem services for human activities and natural habitats [2].

However, over the past 30 years, the global permanent water area has decreased by 90,000 km² due to human activities and climate change [3]. It is necessary to monitor surface water dynamics to inform water resources protection and regional sustainable development. Among the Sustainable Development Goals (SDGs) proposed by the United Nations in 2015, SDG 6.6.1, which measures "the spatial extent of water-related ecosystem", aims to track changes in different types of water-related ecosystems to support the recovery of already degraded water-related ecosystems and prevent surface water degradation [4,5]. Hence, SDG 6.6.1 is closely related to the monitoring of water-related ecosystems. As in the previous studies of Fitoka et al. and Weise et al., spatial mapping methods of wetlands were developed and their research results were applied to the analysis of SDG 6.6.1 [6,7].

Remote sensing technology can be employed to monitor the spatiotemporal dynamics of surface water bodies in a more large-scale, refined, accurate and fast manner [8–11] compared with conventional spatial measurement and statistic methods [12], as well as to better serve the goal of realizing SDG 6.6.1. In the era of remote sensing big data, monitoring surface water dynamics on a large spatial scale with long time series remote sensing images has become the focus of numerous studies [13–16]. Furthermore, the Google Earth Engine (GEE) Cloud Platform is widely applied to process massive remote sensing data [17] quickly and efficiently, especially for large-scale and long time-series studies [18,19]. Studies, such as those of Wang et al. (2018, 2019 and 2021), Zhou et al., and Li et al., achieved water extraction through the GEE platform and analyzed surface water dynamics at large and regional spatial scales [20–23]. Additionally, the remote sensing data and GEE platform were also utilized to monitor the dynamics of Dongting lake and Baiyangdian lake for reporting SDG 6.6.1, as put forward in the study of Jiang et al. [2] and Wang et al. [21].

At present, the widely used water extraction methods based on remote sensing include the water extraction index, single-band and multiband methods, machine learning methods [24–28], and so on. Among them, the water body extraction index method has the advantages of high efficiency and reliable accuracy [29]. Currently, plenty of water body extraction indices have been proposed to extract water extent. The most popular water body extraction indices include the normalized difference water index (NDWI) [30,31], modified normalized difference water index (MNDWI) [32] and automated water extraction index (AWEI) [33]. These water extraction indices have simple calculation equations and high accuracy, but they also have their corresponding shortages. Combining the advantages of different water indices has proven to be a reasonable solution to this issue [26].

The GBA is one of the most open economically dynamic regions in China and plays a crucial strategic role in China's overall development. Released in February 2019, the central government issued the Outline of the Development Plan for the Guangdong-Hong Kong-Macao Greater Bay Area (http://www.cnbayarea.org.cn, accessed on 17 June 2021), which aims to connect nine cities in the Pearl River Delta of Guangdong Province with Hong Kong and Macao to become an integrated economy and world-class business center. Therefore, the long-term monitoring of surface water dynamics in the GBA is of great significance to the planning and implementation of water-related environmental protection measures for local government departments in this region.

In general, there is a lack of quantitative and systematic research on the long-term spatiotemporal variations of surface water in the GBA, which is a typical region of rapid urbanization. Due to the differences in data sources, temporal coverage, spatial resolution and water extraction methods, the spatial-temporal comparability of current water datasets and analysis are very poor. Additionally, the combination with SDG 6.6.1 in previous studies of surface water is relatively insufficient in regions under rapid urbanization, partly for the proposal of SDGs in 2015. To address these problems mentioned above, this study's main objectives are as follows:

 utilizing all available Landsat TM, ETM+ and OLI data from 1986 to 2020 and the GEE platform, to extract long-term surface water extent based on a multi-index water extraction method to explore its spatial variations and temporal change trends (by OLS-RS method) of surface water extent in the GBA;

- (2) to achieve surface water dynamic type classification and mapping based on multiyear water inundation frequency time-series;
- (3) to analyze the impact of urbanization on surface water losses and gains quantitively from the aspect of realizing SDG 6.6.1 and discuss the possible climate causes for water area changes in the GBA.

2. Materials and Methods

2.1. Study Area

Located in the southern coastal area of China, the GBA (latitude: $111^{\circ}20'E-115^{\circ}24'E$, longitude: $21^{\circ}32'N-24^{\circ}26'N$) is a region across nine cities of Guangdong Province and two special administrative regions, which includes Zhaoqing, Guangzhou, Huizhou, Foshan, Dongguan, Jiangmen, Zhongshan, Shenzhen, Hong Kong and Macao, as shown in Figure 1. The total area of the GBA is approximately 56,000 km². In addition, the GBA is situated in the humid subtropical monsoon climate zone, with abundant rainfall during rainy and hot periods (from April to September); its annual precipitation is approximately 1300~2500 mm, and its annual average temperature is approximately 22 °C [34–36].



Figure 1. Location of the study area: the Guangdong-Hong Kong-Macao Greater Bay Area.

With a total population of more than 86 million people and regional GDP of approximately USD 1668.8 billion at the end of 2020, which was equivalent to 12% of the GDP for all of mainland China, the GBA is the largest and richest economic region in South China. The GBA is also the starting point of the Maritime Silk Road and the gateway of China to the world [37].

2.2. Datasets and Preprocessing

2.2.1. Landsat Data

In this study, we selected Landsat satellite images to extract water areas in the GBA. With a 30-m spatial resolution and 16-day temporal revisit period, all available Landsat 5 TM, 7 ETM+ and 8 OLI surface reflectance images covering the entire GBA from 1986 to 2020 were utilized and processed on the GEE platform for convenience and efficiency. The temporal distribution of image quantities for three remote sensors is shown in Figure 2, which includes scenes with 121/43, 121/44, 122/43, 122/44, 122/45, 123/42, 123/44 and 123/45 as path/row values. The number of images totals 4750, and a rapid decrease in the number of images took place in 1999 due to the launch of Landsat 7. The year 2012 witnessed a dramatic drop in the number of images for Landsat 5 ceased to function, followed by a sharp growth in 2013 caused by the launch of Landsat 8.



Figure 2. The number of available Landsat images in the GBA for TM, ETM+ and OLI sensors per year.

In addition, for each image, we removed the cloud, cloud shadow, and snow/ice according to the pixel quality attributes of the Landsat surface reflectance product, which were generated from the Fmask algorithm [38]. The preprocessed Landsat time series was used to extract the surface water extent in the GBA.

2.2.2. Auxiliary Data

The Joint Research Centre of European Commission (JRC) Monthly Water History (v1.2) data (https://esdac.jrc.ec.europa.eu/, accessed on 28 June 2021), created by Pickens et al. [3], were used as ancillary data for comparison with the surface water extent extracted by MIWDR [26] in the GBA.

The impervious land surface data were used in this study to represent the extent of urbanization. The data is from the annual maps of global artificial impervious area (GAIA) between 1985 and 2018 by Gong et al. [39,40] (http://data.ess.tsinghua.edu.cn/gaia.html, accessed on 28 June 2021). In addition, the mean overall accuracy of GAIA over multiple years (1985, 1990, 1995, 2000, 2005, 2010, and 2015) is higher than 90% and the spatial resolution of GAIA is 30 m.

Moreover, annual rainfall data were collected from the Cas Resources and Environment Cloud Platform (https://www.resdc.cn/Default.aspx, accessed on 28 June 2021) to explore the correlation relationship between surface water area and climate change.

2.3. Methodology

For clarity and brevity, we established an analytical framework to systematically and quantitively characterize the long-term dynamics of surface water in the GBA for reporting SDG 6.6.1 indicator (Figure 3). It is divided into two sections: (1) First, we performed data acquisition, preprocessing and surface water extent extraction on the GEE platform to retrieve long time series surface water results for subsequent dynamics analysis. (2) Second, using the surface water datasets obtained above, we analyzed the changes in surface water from three aspects: (1) The spatial distribution and temporal characteristics of surface water extent were analyzed in the whole GBA and by 11 cities. (2) The annual water inundation frequency time-series for every $30 \text{ m} \times 30 \text{ m}$ pixel in the GBA was calculated, and dynamic type classification and mapping were carried out based on the temporal variation of the WIF. (3) Combined with impervious land surface data and a land cover transfer matrix, the regions with water losses and gains were identified and analyzed for reporting SDG 6.6.1 indicators.



Figure 3. The framework of this study.

2.3.1. Water Extraction Based on Multiple Index Water Detection Rule

In this study, we employed a simple and fast automatic water extraction method, the multiple index water detection rule (MIWDR), developed by Deng et al. [26], to retrieve surface water time series during 1986–2020 in the GBA for subsequent analysis. The method utilized multiple indices, including NDVI, EVI, MNDWI, and AWEI. Equations (1)–(5) of these indices are as follows:

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}}$$
(1)

$$EVI = 2.5 \times \frac{\rho_{NIR} - \rho_{Red}}{1 + \rho_{NIR} + 6 \times \rho_{Red} - 7.5 \times \rho_{Blue}}$$
(2)

$$MNDWI = \frac{\rho_{Green} - \rho_{SWIR1}}{\rho_{Green} + \rho_{SWIR1}}$$
(3)

$$AWEI_{nsh} = 4 \times (\rho_{Green} - \rho_{SWIR1}) - (0.25 \times \rho_{NIR} + 2.75 \times \rho_{SWIR2})$$
(4)

$$AWEI_{sh} = \rho_{Blue} + 2.5 \times \rho_{Green} - 1.5 \times (\rho_{NIR} + \rho_{SWIR1}) - 0.25 \times \rho_{SWIR2}$$
(5)

where ρ_{NIR} , ρ_{Red} , ρ_{Blue} , ρ_{Green} , ρ_{SWIR1} and ρ_{SWIR2} represent the values of the near infrared band, red band, green band, shortwave infrared band1 and band2 in the Landsat Images.

If a pixel meets the following criteria: (AWEI_{nsh} – AWE_{Ish} > -0.1) and (MNDWI > NDVI or MNDWI > EVI), then it is classified as a water body, if not, it is classified as a non-water body. The MIWDR could be implemented quickly through JavaScript codes based on the GEE cloud computing platform. Compared to other relatively complex machine learning methods, this method has the advantages of simplicity, efficiency, high automation, the capacity to quickly acquire the latest surface water information for analysis.

In addition, we assessed the accuracy of surface water results based on MIWDR method by comparing with the actual visual interpretation results from Landsat true color images. The sample points were created randomly (300 random sample points were selected for each imagery in the study) in each Landsat image tile (10 images in total) via the

Create Random Points tool in ArcGIS. These sample points were classified into water and non-water types according to visual interpretation, then a confusion matrix was calculated with the extracted surface water results at the same time. The final accuracy assessment result was presented through overall accuracy and kappa coefficient [21].

Furthermore, we also compared the extracted surface water results with the existing water dataset—the Joint Research Centre of European Commission (JRC) Monthly Water History (v1.2) data in the GBA. The relative error (*RE*) of surface water extent was calculated to measure the accuracy between the two water datasets. The formula to calculate *RE* is as follows:

$$RE = \left(\frac{|S_a - S_e|}{S_e}\right) \times 100\% \tag{6}$$

where S_a respects the surface water area of JRC water dataset, and S_e is the surface water area of the extracted water dataset using MIWDR.

2.3.2. Change Trend Analysis Method

Regression analysis is an important method to explore the statistical correlation relationship between different variables and is also suitable for studying the long-term change trend of land surface variables. In this study, the ordinary least square linear regression (OLS-LR) model was used to conduct regression analysis on the time variable x and the surface water area variable y, which could be expressed by the following mathematical formula [41]:

$$y = a + k\mathbf{x} + \varepsilon \tag{7}$$

In the formula, a is a constant; k is the slope of the linear regression equation; x is the time variable, and ε represents the random error value. This study utilized the least square method to fit the linear relationship between a series of surface water areas and time-series values. The parameter k was used to measure the linear change trend of time-series data. When k > 0, it represents an upward trend; otherwise, it denotes a downward trend. Moreover, the value of k represents the change speed of surface water extent per year. The k is calculated as follows:

$$k = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$$
(8)

$$\bar{x} = \frac{1}{N} \sum_{i=1}^{n} x_i, \bar{y} = \frac{1}{N} \sum_{i=1}^{n} y_i$$
(9)

In Formulas (2) and (3), x_i represents the time value of year *i*; y_i is the surface water area of year *i*, and *N* and *n* represent the total number of observation data points.

Moreover, the goodness of fit test is assessed by using the decisive coefficient R^2 . The closer R^2 is to 1, the closer the whole time-series dataset is to the linear regression line, and the higher the goodness of fit. We applied the OLS-LR over the temporal change analysis in the entire study area as well as 11 cities in the GBA to investigate the surface water extent change trends.

2.3.3. Dynamic Type Classification

Before performing surface water dynamic type classification, we calculated the annual water inundation frequency (WIF) time-series from 2000 to 2020 for each 30 m \times 30 m pixel across the study area, considering the Landsat images' quantity over time (Figure 2).

The WIF index directly indicates the frequency of water body occurrence during a certain period of time. The calculation formula of WIF [21] is as follows:

$$WIF = \frac{\sum_{i=1}^{N} (\varepsilon_i = 1)}{N} \times 100\%$$
(10)

where ε_i represents the corresponding pixel value of the *i*th water map, where 1 is water and 0 is non-water; $\sum_{i=1}^{N} (\varepsilon_i = 1)$ is the total number of observations of water body occurrence, and *N* represents the total number of valid observations at a specific pixel.

Based on the annual WIF time-series of the GBA obtained above, the long time-series dynamic types during 2000–2020 were classified pixel-by-pixel using the mean and range. The thresholds' setting of mean and range was referred to Pickens et al. [42]. The detailed dynamic type classification process for every pixel is shown in Figure 4. Firstly, to reduce annual anomalies, the yearly WIF time-series were smoothed through a three-year average moving window. Secondly, the range and mean of the annual WIF time-series data of each pixel over the period were calculated. The range is the difference between the maximum and minimum value of WIF. In addition, the amount of local extreme values reaching 30% of the range was calculated as the value of WIF change segments. Meanwhile, the permanent and dynamic types of surface water were visualized in RGB color space is visualized according to the WIF change points. The WIF values at the starting position, ending position, and turning position were taken as the values of the red, green and blue channels, respectively. Finally, we achieved surface water dynamic type classification and visualized the spatial distribution.



Figure 4. The workflow of surface water time-series analysis and resulting dynamic types for each $30 \text{ m} \times 30 \text{ m}$ pixel in the GBA. (Transition means change in alternating direction between local maxima and minima value of annual WIF).

2.3.4. Identifying Water Losses and Gains under Urbanization

Considering that the GBA is a typical area of rapid urbanization, this study emphasizes the impact of urbanization on the losses and gains of surface water in the study area. Therefore, we only calculated the conversion between surface water bodies and impervious land surfaces through the land cover transition matrix. The land cover transition matrix is the application of the Markov model in land use and land cover, which can quantitatively measure the transformation of different land use types. Furthermore, in order to analyze the spatiotemporal variation in surface water changes by urbanization, we selected seven periods, including 1986, 1990, 1995, 2000, 2005, 2010 and 2015, to calculate the corresponding surface losses and gains under urbanization.

3. Results

3.1. Accuracy of Extracted Surface Water Bodies in the GBA

A total of 10 images with little cloud coverage (less than 5%) and good quality were selected for accuracy evaluation. These images are evenly distributed every 2–3 years from 1993 to 2020 and cover varied months. As seen from Table 1, the RE (relative errors) of the water area extracted in this study and the JRC water products in the same months are small, ranging from 0.5% to 7.5%, with an average of 4.07%. This indicates that the water area extracted in this study is relatively consistent with the results of JRC products.

Table 1. Comparison between the surface water area extracted in this study and the JRC water datasets.

Sensor	Date	Cloud Cover/%	Water Area Extracted/km ²	JRC Water Area/km ²	<i>RE</i> /%
TM	3 September 1993	0.00	4398.08	4490.74	2.06
TM	3 March 1996	0.00	3776.91	3902.97	3.23
TM	30 December 2001	0.00	4146.16	4420.43	6.20
ETM	14 February 2004	0.00	4006.24	3808.62	5.19
ETM	18 September 2007	1.00	2976.01	2992.04	0.54
ETM	10 January 2009	0.00	4214.95	3922.49	7.46
ETM	20 October 2013	0.00	3837.43	3693.18	3.91
OLI	7 August 2015	2.00	3463.10	3533.15	1.98
OLI	23 October 2017	5.00	3958.55	4250.38	6.87
OLI	18 February 2020	5.00	4247.01	4387.99	3.21

In addition, the overall accuracy and kappa coefficient results of these 10 images are shown in Table 2. The overall accuracy ranged from 89.95% to 96.89%, with an average value of 93.42%, while the kappa coefficient varied between 0.75 and 0.83, with an average value of 0.794, which indicates the accuracy of the surface water extraction results in this study is relatively high.

Table 2. Accuracy assessment results via visual interpretation.

Sensor	Date	Overall Accuracy /%	Kappa Coefficient
TM	3 September 1993	96.21	0.82
TM	3 March 1996	95.02	0.81
TM	30 December 2001	91.86	0.78
ETM	14 February 2004	90.07	0.76
ETM	18 September 2007	89.95	0.75
ETM	10 January 2009	96.62	0.82
ETM	20 October 2013	96.89	0.83
OLI	7 August 2015	94.30	0.79
OLI	23 October 2017	92.43	0.82
OLI	18 February 2020	90.85	0.76

3.2. Spatial Changes in Surface Water in the GBA from 1986 to 2020 for SDG 6.6.1 Monitoring

The spatial distribution of the WIF in the GBA during 1986–2020 is shown in Figure 5, it was divided it into 6 levels: 5-10%, 10-20%, 20-40%, 40-60%, 60-80% and 80-100%. The higher the WIF value is, the more likely the pixel is to be a permanent water body. The

areas of surface water bodies is 1140.62 km², 1179.98.71 km², 1253.96 km², 951.45 km², 823.59 km² and 1889.42 km² under six levels of WIFs mentioned above, and accounts for 19.11%, 15.65%, 16,63%, 12.62%, 10.92% and 25.06% of total water area, respectively. It is also evident that surface water bodies are mainly distributed around the Pearl River Delta and other river networks in the GBA.



Figure 5. Spatial distribution of water inundation frequency from 1986 to 2020. (**a–e**) represent parts of Jinwan District and Macao, Pearl River estuary, Tan River, Dalongdong Reservoir and Sankeng Reservoir, respectively.

When zooming in some typical regions (a, b, c, d and e), it could be seen that the high-WIF area (>80%) tends to be distributed in the center of rivers and lakes, and the WIF in the marginal region of rivers and lakes shows a decreasing trend from inside to outside (Figure 6e). The spatial distribution characteristics are consistent with the natural and hydrological principles of river and lake dynamics, and it is well known that the impact of human activities on water bodies often occurs around surface water Figure 6a,b). In addition, it should be noted that in the interlaced area of river networks, a substantial number of water bodies are distributed in blocks or fragments (Figure 6c), and their WIF values are mostly less than 50%, which could be attributed to the abundance of paddy fields and pits in the region.

3.3. Temporal Changes in Surface Water in the GBA from 1986 to 2020

For the whole GBA, the annual surface water body area calculated under different WIF thresholds from 1986 to 2020 is shown in Figure 7. The permanent surface water bodies (WIF > 75%) did not change much. In contrast, the maximum surface water extent (WIF > 0%) in the GBA demonstrates a significant decreasing tendency after 2001 ($R^2 = 0.8566$, p < 0.0001), with a loss of 155.41 km² per year. Furthermore, the seasonal surface water extent (35% < WIF < 75%) fluctuates slightly over the last 35 years. It also could be seen that the lower the WIF threshold is, the higher the loss rate after 2001.



Figure 6. Surface water area changes from 1990~2020. The first column represents the water inundation frequency (WIF) from 1986 to 2020 for these five subregions. The other four columns represent the composited maximum surface water extent of these areas in 1990, 2000, 2010 and 2020. (**a**–**e**) represent parts of Jinwan District and Macao, Pearl River estuary, Tan River, Dalongdong Reservoir and Sankeng Reservoir, respectively.

The yearly surface body areas of eleven individual cities in the GBA during 1986–2020 showed divergent trends over time (Figure 8). For better separation, we classified these cities into three groups to illustrate their change characteristics according to the range of surface water area. Furthermore, the linear trend lines were added to the line charts corresponding to each city. Among the cities, the surface water areas in Guangzhou, Foshan, Huizhou, Zhuhai, Shenzhen, Hong Kong and Macao show an evident downward trend. Especially for Macao, the linear declining trend in Macao is very significant, with R² of 0.96, but its loss rate is fairly low, with about 0.426 km² per year. It is noteworthy that there are no cities with a significant upward trend here, which reflects that the majority of cities are experiencing a decrease in surface water areas to varying degrees. Therefore, for cities with a rapid downward trend, more attention should be given to surface water protection and recovery.



Figure 7. The temporal variation in the surface water area under different water inundation frequency thresholds in the GBA.



Figure 8. The temporal change and linear trend regression of surface water area for 11 cities in the GBA.

3.4. Dynamic Type Mapping and Analysis in the GBA during 2000–2020

The dynamic type map for surface water variations during 2000–2020 in the GBA is illustrated in Figure 9, in which the color represents varied dynamic types (seen in Figure 4). As seen in some typical enlarged areas of dynamic types, the edge of the lake in subregion A is orange, and the central area of the lake is white, which indicates the surface water around the lake is losing. In contrast, the blue edge of the lake in subregion B presents an expansion trend. Some patches experiencing a dry period (with WIF growing down first and up later) in paddy fields in the subregion C are pink, while the green region of the meandering river streamway (in the subregion D) denotes that it witnessed a wet period in history. The lakes with light gray edges in subregion E experience seasonally stable changes, which could be attributed to the regular hydrological phenology. The paddy fields in subregion F exhibit signs of high-frequency changes, which may be caused by intensive human activities.



Figure 9. Illustration and typical examples of classes of the water dynamics map. Each example has the annual water inundation frequency time series and corresponding R-G-B reduction for a given $30 \text{ m} \times 30 \text{ m}$ pixel. (A–F) represent Loss, Gain, Dry period, Wet period, Stable seasonal and High frequency, respectively.

The statistics of dynamic type classification results are presented in Table A1 in detail and visualized in Figure 10. All water-related areas account for 6.48% (3594.01 km²) of the total area in the GBA, of which 57.46% was dynamic types during 2000–2020. This suggests that most surface water bodies change over the last 20 years instead of remaining unchanged. In addition, the gain, loss, dry and wet periods account for approximately 4–7% of all areas with water, while stable seasonal and high-frequency periods account for approximately 16–18% of all areas with water. The difference in areas indicates that the surface water area experiencing multi-direction changes is greater than that of singledirection changes. In reality, to support the achievement of SDG 6.6.1, areas of loss should be given more attention from local governments and residents.



Figure 10. The total area and proportion statistical results for eight surface water dynamic types: land, permanent water, stable seasonal, gain, loss, dry period, wet period and high frequency.

3.5. Surface Water Losses and Gains under Urbanization in the GBA

The overall spatial distribution of surface water losses and gains is shown in Figure 11A,B. In the two enlarged regions (Figure 11f,g) of water losses, it was found that many cities and towns occupy water bodies in coastal areas and the reclamation of coastal urban zones. In the zoomed region (Figure 11h,i) of water gains, some built-up areas are transformed into water due to the construction of artificial reservoirs and lake parks, like Gongming reservoir and Wenhan Lake Park. In general, the area of water bodies occupied by urbanization is far greater than that restored to water bodies.

Through the land cover confusion transfer matrix, the area of water bodies transformed into impervious surfaces and the area of built-up areas transformed into water bodies in different years were calculated(Figure 12). The surface water losses area shows a significant declining trend from 211.29 km² in 1986 to 2.92 km² in 2015 (Figure 12a), and the surface water restoration area shows a slightly growing trend (Figure 12b), which indicates that more water bodies have been protected in recent years and that more attention has been given to water restoration.



Figure 11. Decreased and restored surface water area caused by urbanization. The upper two rows (f,g) represent the decreased surface water during five periods: 1990~2018, 2000~2018, 2005~2018, 2010~2018 and 2015~2018. The two rows (h,i) at the bottom represent the restored surface water during five periods: 1990~2020, 2000~2020, 2005~2020, 2010~2020 and 2015~2020. The blue area is the surface water in the starting year during the respective periods. (The background image is the median composite of Landsat images with RGB channels: Red: SWIR, Green: NIR, Blue: Green.).



Figure 12. (a) The surface waterbody area degraded to impervious land surfaces during seven periods: 1986~2018, 1990~2018, 2000~2018, 2005~2018, 2010~2018 and 2015~2018. (b) The surface waterbody area restored from impervious land surfaces during seven periods: 1986~2020, 1990~2020, 2000~2020, 2005~2020, 2010~2020 and 2015~2020.

4. Discussion

4.1. Possible Causes for Surface Water Extent Changes

Climate change is an important factor that may affect surface water area. Precipitation is a key component of climatic factors, which has a complicated relationship with surface water extent changes. We briefly analyzed the relationship between precipitation and maximum surface water extent by comparing the changes during 1986–2019. We also calculated the linear correlation coefficient between them (Figure 13). The change trend of precipitation and surface water extent was inconsistent and the linear correlation between them is not significant (p < 0.05), but the change trend was relatively consistent over some short-term periods, which may be caused by extreme precipitation events.



Figure 13. Correlation analysis between mean annual precipitation and maximum surface water area during 1986–2019 in the GBA.

4.2. Comparison with Other Studies

Comparing the surface water area derived in this study with the result of other researchers, it is found that the results are highly consistent. According to the study of Zhao Y L, et al. [43], the surface water area of the GBA in 2015 was 5266.02 km², which was obtained based on remote sensing data used in the Second National Land Survey, China, in 2015 and checked for correctness. While the maximum surface water area of the GBA in 2015 was 5318.80 km² in this study, the difference between the two results was 52.78 km², which further verified the reliability of the surface water results in this study. However, we are not able to compare the temporal variations due to a lack of relevant studies in the GBA.

In addition, the surface water monitoring and analysis method and framework of this study features by efficiency of the GEE platform and serving the goal of SDG 6.6.1. The most important point is that we analyzed the dynamic types of surface water to characterize and visualize the spatiotemporal variations for reporting SDG 6.6.1 in the study area. In comparison with previous studies related to surface water extraction and SDG 6.6.1 [2,21], this study's analytical framework is more refined and comprehensive.

4.3. Implications for SDG 6.6.1 Reporting and Policy-Making

Since the SDG 6.6.1 indicator aims to track variations in different types of water-related ecosystems, informing decision-makers of the extent changes of water-related ecosystems over time, the workflow, framework and analysis of this study are highly consistent with these targets, which might be taken as references for other similar studies related to SDG 6.6.1 reporting and policy-making of regional government for sustainable development.

Additionally, from the surface water extent spatiotemporal variations derived in this study, it is evident that the surface water area in the GBA shows a slow downward trend in recent 35 years and the surface water area keeping losing occupies 7.34% (263.75 km²)

of all water-related area in the GBA. Therefore, more attention should be paid to regions experiencing decreasing trends to pre-empt further loss in surface water resources.

4.4. Limitations and Future Improvements

There are still some limitations and uncertainties in this study.

- (1) The Landsat imagery used in this study is easily affected by clouds, and the GBA is a typical coastal region with frequent cloud coverage. This issue limits the highly frequent monitoring of surface water when it comes to extreme disasters (e.g., extreme precipitation events) in the GBA.
- (2) In regard to surface water verification, we selected ten images for accuracy assessment, the number of images is relatively small and the evaluation of images with a medium or high cloud coverage was not taken into consideration, which could cause some uncertainties to the surface water results.
- (3) The exploration of driving factors of long-term surface water variations is still not enough. We only analyzed the impact of land cover change and precipitation on the surface water changes. Due to low accessibility to more meteorological and hydrological in the GBA and the complexity of mutual influence mechanism between human activities and climate changes, we did not use more datasets to make a comprehensive analysis of the driving forces.

In the future research, we will optimize the data preprocessing procedures to reduce the effects of clouds on the optical remote sensing imagery and introduce other multi-source remote sensing data, such as Sentinel 1/2, HJ, GF and other data with high resolution and quality to better monitor the spatiotemporal dynamics of surface water in the study area. Additionally, we need to apply multi-factor analysis to investigate the driving forces of surface water changes in the GBA more comprehensively. Moreover, we are supposed to integrate.

5. Conclusions

In this study, in order to monitor SDG 6.6.1 indicator, we utilized long-term Landsat images and the MIWDR method to extract surface water extent of the GBA during 1986–2020 on the GEE platform. We characterized the spatial and temporal variations in surface water in the GBA and classified dynamic types of surface water by pixels to explore the features of surface water dynamics in detail. In addition, the surface water losses and gains caused by urbanization were identified and analyzed. The main conclusions are as follows:

- (1) From 1986 to 2020, the average minimal and maximal surface water extents of the GBA were 2017.62 km² and 6129.55 km², respectively. The maximum areas fell rapidly from 7897.96 km² to 5087.46 km², with a loss of 155.41 km² per year, which showed a significant downward trend. The surface water extents calculated by water inundation frequency thresholds greater than 0.35 fluctuate slightly during this period. This denotes that permanent and part of seasonal surface water in the GBA stay relatively stable in the last 35 years. It is noticeable that there exists a slow downward trend in surface water area after 2001.
- (2) The surface water extent in most cities demonstrates a downward trend with varying loss speed. Especially for Foshan, Guangzhou, Zhongshan and Huizhou, the decreasing trend is evident compared with other cities in the GBA. More attention from local government should be given to cities with intense declining trends.
- (3) The areas of permanent water bodies and dynamic water bodies were 1529.02 km² and 2064.99 km², accounting for 42.54% and 57.46% of the total water area, respectively. The statistics reflect that most surface waters are in a changing state.
- (4) The surface body area occupied by impervious land surfaces showed a significant linear downward trend with R² values of 0.98 and 36.41 km² per year, while the surface water restored from impervious land surfaces denoted a slightly growing trend. It

appears that surface water extent is under less pressure induced by urbanization in recent years and has more chances to be restored and protected by human activities.

In addition, we also assessed the water extraction accuracy and possible climate factors for surface water changes. However, due to the uncertainties and limitations that existed in our study, we need to further explore other factors affecting the surface water extent of GBA in following research.

In this study, the long-term surface water time-series datasets and spatiotemporal analysis results could be provided for reference by local governments or related ecological environment protection agencies to assess regional procedures toward achieving SDG 6.6.1 as well as to inform environmental protection policy-makers of the key areas for water conservation and restoration in the GBA. Furthermore, the methodology, analytical framework and remote sensing big data resources available on the GEE could be easily applied in other similar regions worldwide for supporting the SDG 6.6.1 indicator and promoting regional water resources protection as well as management.

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Appendix A

Table A1. The statistics of surface water area for different dynamic types in the GBA.

	Area km ²	Percent of Total Area	Percent of All Water	Class Definition
Land	51865.85	93.52	/	Mean WIF \leq 10% and inter-annual variability \leq 33%
Permanent water	1529.02	2.76	42.54	Mean water percent \geq 90% and inter-annual variability \leq 33%
Stable seasonal	598.26	1.08	16.65	Intra-annual variability with inter-annual variability < 50%
Gain	170.34	0.31	4.74	Land-dominant to water-dominant
Loss	263.75	0.48	7.34	Water-dominant to land-dominant
Dry period	167.55	0.30	4.66	Water-dominant to land-dominant to water-dominant
Wet period	242.04	0.44	6.73	Land-dominant to water-dominant to land-dominant

	Area km ²	Percent of Total Area	Percent of All Water	Class Definition
High frequency	623.05	1.12	17.34	3+ transitions between water-dominant and land-dominant
Multiple transitions	1032.64	1.86	28.73	Dry period, wet period, and high frequency (2+ transitions)
All change types	1466.73	2.64	40.81	Gain, loss, dry period, wet period, high frequency
All dynamic types	2064.99	3.72	57.46	Gain, loss, dry period, wet period, high frequency, stable seasonal
All with water	3594.01	6.48	100	Permanent water, stable seasonal, gain, loss, dry period, wet period, high frequency

Table A1. Cont.

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