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Article

Annual Wetland Mapping in Metropolis by Temporal Sample Migration and Random Forest Classification with Time Series Landsat Data and Google Earth Engine

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Abstract: Wetlands provide various ecosystem services to urban areas, which are crucial for sustainable urban management. With intensified urbanization, there has been marked loss of urban natural wetland, degradation, and related urban disasters in the past several decades. Rapid and accurate mapping of urban wetland extent and change is thus critical for improving urban planning toward sustainability. Here, we have developed a rapid method for continuous mapping of urban wetlands (MUW) by combining automatic sample migration and the random forest algorithm (SM&RF), the so-called MUW_SM&RF. Using time series Landsat images, annual training samples were generated through spectral angular distance (SAD) and time series analysis. Combined with the RF algorithm, annual wetland maps in urban areas were derived. Employing the Google Earth Engine platform (GEE), the MUW_SM&RF was evaluated in four metropolitan areas in different geographical and climatic regions of China from 1990 to 2020, including Tianjin, Hangzhou, Guangzhou, and Wuhan. In all four study areas, the generated annual wetland maps had an overall accuracy of over 87% and a Kappa coefficient above 0.815. Compared with previously published datasets, the urban wetland areas derived using the MUW_SM&RF approach achieved improved accuracy and thus demonstrated its robustness for rapid mapping of urban wetlands. Urban wetlands in all four cities had variable distribution patterns and showed significantly decreased trends in the past three decades. The annual urban wetland data product generated by the MUW_SM&RF can provide invaluable information for sustainable urban planning and management, so as for assessment related to the United Nation’s sustainable development goals.

Keywords: urban wetlands; sustainable cities; field sample migration; remote sensing

1. Introduction

With continuous population growth and rapid economic development, urban areas have expanded significantly worldwide [1,2]. Massive urban expansion has brought about a slew of concerns, such as loss of natural habitat, reduction of biodiversity, and degradation of natural landscapes, posing enormous challenges for urban planning and development [3,4]. Wetlands serve urban areas by contributing to various ecosystem services, including water purification, climate mitigation, recreation, and tourism [5,6]. Targets 11.3 and 11.5 of the Sustainable Development Goals (SDGs) emphasize the necessity of sustainable urban development and ecosystem protection. Wetlands serve a valuable
role in sustainable urban management as an integral component of urban ecosystems [7]. However, rapid urbanization poses a severe threat to the wetland ecosystem, causing wetland degradation and loss in recent decades [8]. Therefore, an exact and consistent mapping of the urban wetland is required for sustainable urban development.

Numerous studies have utilized remote sensing techniques to map wetlands on various scales [9,10]. Nevertheless, studies focusing exclusively on urban wetlands are relatively scarce, owing to the fact that urban wetlands are usually scattered and diverse, with significant fragmentation and heterogeneity, making accurate mapping difficult [11]. Several supervised machine learning techniques, such as the random forest algorithm (RF) and support vector machine (SVM), have been reported to be effective for mapping wetlands [12]. Such supervised algorithms always depend on a large quantity of training data to obtain high-precision results [13]. In general, obtaining adequate training samples through field surveys or visual interpretation is an extremely laborious and time-consuming process [14]. Some useful training samples can be obtained through national research projects, scientific publications, and publicly available datasets. However, these resources were collected at a specific time or location and intended for a specific research goal, making them difficult to utilize directly as samples for mapping urban wetlands. Considering these concerns, the sample migration strategy, which can generate appropriate training samples based on previous data [15], offers great promise for providing sample data for long-term and annual mapping of urban wetlands.

Large-scale remote sensing research has been substantially facilitated by the widespread availability of multiple remote sensing data and the advancement of cloud computing capabilities [16,17]. Landsat has been the most broadly utilized data source for mapping wetlands, owing to its fine spatial resolution (30-m) and temporal resolution (8–16 days) [18]. When all Landsat images are employed, the effects of poor-quality observations can be minimized, resulting in high-quality time series images [19,20]. Such dense data makes it possible to effectively identify the status of wetlands and capture their changes, which can facilitate the development of effective sample migration methods and annual wetland mapping. Combining Landsat time series data with the Google Earth Engine (GEE), a powerful cloud computing platform for remote sensing studies [21], allows us to develop an effective sample migration approach and create long-term maps of urban wetlands on a large scale.

This study has developed a rapid methodology for annual urban wetland mapping and has generated accurate annual urban wetland maps in four metropolises of China from 1990 to 2020, including Tianjin, Hangzhou, Guangzhou, and Wuhan. Employing Landsat images and GEE, we focused on (1) developing the annual mapping urban wetlands (MUW) approach by combining sample migration and random forest algorithm (SM&RF) and so named MUW_SM&RF; (2) testing the MUW_SM&RF method in four metropolis areas in China; and (3) examining temporal changes of urban wetlands in the study areas based on the generated maps. The methodology developed in this study is devoted to providing a reference for delineating urban wetland extent and change at a broader scale, and the resulting maps are expected to benefit the evaluation of SDGs.

2. Materials

2.1. Study Area

Four metropolises in China were selected as study sites, namely Tianjin, Hangzhou, Wuhan, and Guangzhou. The selected cities are located in the Beijing–Tianjin metropolitan region, the Yangtze River Delta, the Triangle of Central China, and the Pearl River Delta, which are representative of the different geographical regions (Figure 1). There are abundant wetland resources in these cities, as well as high urbanization levels. Urbanization and industrialization have led to the expansion of these cities over the past few decades [22]. All of these cities have populations in excess of 10 million, and their urbanization rates exceed 80% and are continuing to rise [23]. The urban boundary of each study site is defined as the area within the latest metropolitan boundary of the city, separating the urban area
from rural lands. These metropolitan boundaries were determined based on geographical knowledge and visual interpretation of the latest Google Earth images.

![Figure 1](image_url)

**Figure 1.** Geographic locations of the four study sites and distributions of field samples in each site. Site (A–D) represent urban area of Tianjin, Hangzhou, Wuhan, and Guangzhou, respectively. The backgrounds in the views are the Landsat 8 OLI images (bands 5, 4, 3 as RGB).

2.2. Data and Pre-Processing

2.2.1. Imagery and Processing

All available 919 Landsat series images from the annual summer months, from June to September between 1990 and 2020, were obtained in GEE, including 566 Landsat 5, 102 Landsat 7, and 251 Landsat 8. To obtain consistent, high-quality images for annual urban wetland mapping, all images were subjected to a series of processes on the GEE. First, the QA band of the image, which flags the pixels disturbed by clouds and shadows, was used to eliminate bad-quality pixels within the image. Then, terrain shadows were removed from each image by utilizing the digital elevation model (DEM) images and terrain algorithm provided by GEE. We used the SLC Gap-Fill algorithm provided by the USGS and implemented it on the GEE to eliminate the scan-line error strips on the Landsat 7 images [20]. Particularly, the temporal aggregation algorithm, which generates
a composite image by calculating the statistics of both images over a defined period [24],
was used to produce high-quality images annually from 1990 to 2020 in this study.

2.2.2. Sample Data

The initial sample data were collected in 2020 from a series of field investigations
and collaborators. The acquisition dates of these field samples provided by collaborators
varied and applied their own described system for classification based on their research
topic. Thus, using images from 2020, we checked and modified these sample data to
maintain their validity through visual interpretation, and they were relabeled with a
uniform format following the definition of urban wetlands in this study, including urban
wetlands (waterbody and vegetated wetland) and non-urban wetlands (land cover types
other than waterbody and vegetated wetland in urban areas) (Table 1). In areas where
sample data were insufficient, we supplemented the sample by utilizing high-spatial
resolution Google images and the visual interpretation approach. Ultimately, a total of
1740 samples were collected across all study sites in 2020, with Tianjin, Hangzhou, Wuhan,
and Guangzhou corresponding 530, 309, 532, and 369 samples, respectively (Figure 1).
Based on the initial sample data obtained in 2020, sample data for the each year from 1990
to 2019 were generated at each study site utilizing the sample migration algorithm (see
Section 3.2) which was developed for this study.

Table 1. The urban wetland classification system used in this study.

| Category I       | Category II        | Description                                                                 | Google Earth Image Example | Landsat Image Example |
|------------------|--------------------|----------------------------------------------------------------------------|----------------------------|----------------------|
| Urban wetland    | Water body         | Natural or artificial surface water body, e.g., lake, pond, river, and canal. | ![Image](image1)          | ![Image](image2)     |
|                  | Vegetated wetland  | Vegetated wetlands with vegetation, such as swamp and marsh                  | ![Image](image3)          | ![Image](image4)     |
|                  | Non-urban wetland  | Other natural and anthropogenic landscapes, e.g., grassland, cropland, and built-up land | ![Image](image5)          | ![Image](image6)     |

2.2.3. Other Public Wetland Datasets

In this study, wetland maps extracted from the National Wetland Datasets of China (CAS_Wetlands) [10] and the National Land Cover datasets of China (ChinaCover) [25] in 2015 were used to compare with the generated result. Both the ChinaCover and CAS_Wetlands datasets were derived from Landsat images using an object-oriented classification approach. Wetlands in the ChinaCover were classified as surface water (lake, river, reservoir/pond) and wetland (swamp, marsh), while the CAS_Wetlands dataset involves more detailed other wetland types, e.g., lagoon, estuarine water, shallow marine water, tidal flat, salt pan, and coastal aquaculture pond. We extracted and re-categorized those wetland types from both datasets to keep the mapping categories consistent with our wetland classes.

3. Methodology

This study developed an annual mapping urban wetlands approach by combining sample migration and RF algorithm, i.e., the MUW_SM&RF. The workflow of this process is shown in Figure 2, and the specific components are as follows:
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This study developed an annual mapping urban wetlands approach by combining sample migration and RF algorithm, i.e., the MUW_SM&RF. The workflow of this process is shown in Figure 2, and the specific components are as follows:

Figure 2. General workflow of the MUW_SM&RF.

3.1. Data Processing and Building Database of Time Series Feature Images

In this study, many features were extracted to enhance the image spectrum information and improve the accuracy of image classification. Three components of K-T transformations [26], including wetness, brightness, and greenness, were calculated from each image. Among these components, the wetness component can highlight the water content information of the image, which is commonly used in mapping wetlands [27]. In addition, several popular spectral indices were measured, including the Nominalized Difference Vegetation Index (NDVI) [28], Normalized Difference Built-up Index (NDBI) [29], Normalized Difference Water Index (NDWI) [30], and modified Normalized Difference Water Index (mNDWI) [31], which are useful in enhancing the information of major landscapes in urban areas, including vegetation, wetlands, water bodies, and urban areas. These indices are defined as Equations (1)–(4). Several texture feature bands were also derived to enhance the texture information, such as Angular Second Moment (ASM), Contrast, and Entropy. All spectral bands and features mentioned above were combined to generate feature images by the temporal aggregation method described in Section 2.2.1. Finally, the image database of time series features from 1990 to 2020 for each of the four study sites was created.

\[
\text{NDVI} = \frac{\rho_{\text{nir}} - \rho_{\text{red}}}{\rho_{\text{nir}} + \rho_{\text{red}}} 
\]

\[
\text{NDWI} = \frac{\rho_{\text{green}} - \rho_{\text{nir}}}{\rho_{\text{green}} + \rho_{\text{nir}}} 
\]

\[
\text{mNDWI} = \frac{\rho_{\text{green}} - \rho_{\text{swir}}}{\rho_{\text{green}} + \rho_{\text{swir}}} 
\]

\[
\text{NDBI} = \frac{\rho_{\text{swir}} - \rho_{\text{nir}}}{\rho_{\text{swir}} + \rho_{\text{nir}}} 
\]
where $\rho_{\text{green}}$, $\rho_{\text{red}}$, $\rho_{\text{nir}}$, and $\rho_{\text{swir}}$ are green, red, near-infrared, and short-wave infrared bands of Landsat images, respectively.

### 3.2. Methodologies for Sample Migrations

#### 3.2.1. Extracting Unchanged Samples from 1990 to 2020 by Temporal Analysis

Using the initial samples in this study (described in Section 2.2.2), we selected samples that have not changed significantly in type between 1990 and 2020 by analyzing their standard deviation of wetness (SD_WET) and the change in the NDVI and wetness values. As shown in Figure 3, a lower SD_WET value indicates a lesser change in land cover type during these decades (Figure 3A), whereas a higher SD_WET demonstrates a higher change probability (Figure 3B, C). Therefore, we can use an SD_WET threshold to divide the initial samples into unchanged and changed parts throughout the whole period. Time series wetness and NDVI were derived from the initial samples between 1990 and 2020 to determine the optimum SD_WET threshold. The variation characteristics of time series wetness and NDVI for each sample type were then analyzed. Finally, the SD_WET threshold was determined to obtain unchanged samples for each study site.

![Figure 3](image-url)

**Figure 3.** Example of the spatial distribution of SD_WET. (A–C) demonstrate the land cover change in the areas with different SD_WET values between 1990 and 2020.

#### 3.2.2. Extracting Unchanged Samples from 1990 to 2020 by Temporal Analysis

With the unchanged samples identified from the preceding step, we selected all water body and vegetated wetland samples among them to analyze their spectral characteristics, and then generated a reference spectral extent of the water body and vegetated wetland for each site. To enhance the difference in spectral information, besides the spectral bands, spectral indices and the main components of K-T transformations were also used. The spectral characteristics of the water body and vegetated wetland in each study site are shown in Figure 4. Compared to a vegetated wetland, the water body has a higher wetness level and a lower NDVI, NDWI, and mNDWI, making it possible to accurately separate them. According to the reference spectral ranges of vegetated wetlands and water bodies,
the average of the ranges was selected as the reference spectral for each type at the four study sites.

![Reference Spectral Comparison](image)

**Figure 4.** The reference spectral of the water body and vegetated wetland on feature bands. (A–D) demonstrate the reference spectral for each type at the four study sites (Site(A–D)).

### 3.2.2. Extracting Unchanged Samples from 1990 to 2020 by Remote Sensing

Using this rule, urban wetland samples were further subdivided into the water body spectrum is greater (Equation (6)). Conversely, when the reference vegetated wetland spectrum is larger, it will be classified as a vegetated wetland. This rule is used to separate the samples into urban and non-urban wetland samples. According to the reference spectral ranges of vegetated wetlands and water bodies, the average of the ranges was selected as the reference spectral for each type at the four study sites.

\[
\theta = \cos^{-1} \left( \frac{\sum_{i=1}^{N} X_i Y_i}{\sqrt{\sum_{i=1}^{N} (X_i)^2 \sum_{i=1}^{N} (Y_i)^2}} \right), \quad SAD = \cos \theta
\]  

(5)

where \( \theta \) represents the spectral angle and \( X_i \) and \( Y_i \) represent the two spectral vectors to be measured, respectively. The variable \( i \) represents the index number of the spectral bands, which varies from 1 to the total number of bands (\( N \)). \( SAD \) is the distance of spectral angle between the spectral vectors \( X_i \) and \( Y_i \), which ranges from 0 to 1.

A sample will be classified as a water body if the SAD between it and the reference water body spectrum is greater (Equation (6)). Conversely, when the SAD between it and the reference vegetated wetland spectrum is larger, it will be classified as a vegetated wetland. Using this rule, urban wetland samples were further subdivided into the water body and vegetated wetland.

\[
SAD(Tar_{T1}, Ref\_Water) > SAD(Tar_{T1}, Ref\_Wetland)
\]  

(6)
where $TAR_{T1}$ represents the spectra of the given sample at time $T1$ and the $Ref\_Water$ and $Ref\_Wetland$ are the water body and vegetated wetland reference spectra, respectively. $SAD(TAR_{T1}, Ref\_Water)$ and $SAD(TAR_{T1}, Ref\_Wetland)$ represent the SAD value for a given sample with the water body and vegetated wetland reference spectra, respectively.

Finally, by combining the unchanged samples and reclassified samples following the above processing, time series urban wetland sample datasets from 1990 to 2019 were generated for each study site. We divided the samples into two groups equally for training and testing.

$$\theta \text{ represents the spectral angle and } X_i \text{ and } Y_i \text{ represent the two spectral vectors measured at time } T1.$$

$$\text{Where } T1 \text{ is the target year; } Wetness_{T1} \text{ is the wetness feature of the image. } TAR_{T1} \text{ represent spectra values measured at time } T1,$$

$$\text{Ref\_Water and Ref\_Wetland are the reference spectra of the water body and the vegetated wetland, respectively.}$$

3.3. Mapping Urban Wetlands and Accuracy Assessment

The RF algorithm is the most commonly used supervised machine learning method in various remote sensing studies, which combines a number of classification trees to obtain an optimal solution to complex problems [35]. It has been widely discussed in the literature and has been proven to be a suitable method for classifying land cover using satellite images at medium and high resolution [14,36]. The GEE platform provides a complete random forest algorithm, which also includes sample collection, feature extraction, and detailed accuracy evaluation parts [37]. Based on RF, annual urban wetland maps from 1990 to 2020 for the four study sites were generated by using time series feature images and training samples.

An accuracy assessment was carried out using all of the testing samples in this study. Specifically, we used a confusion matrix to evaluate the generated classification results, containing four indicators, namely overall accuracy, the Kappa coefficient, and user’s and producer’s accuracy.

4. Results

4.1. Determination of SD_WET Threshold and Sample Migration Results

To determine reasonable SD_WET thresholds for extracting samples of the water body and vegetated wetland not changing in type between 1990 and 2020, we examined the changes in NDWI and wetness for all initial samples (2020) at different SD_WET thresholds.

Figure 5. The decision tree for the classification of the changed samples. $T1$ is the target year; $Wetness_{T1}$ is the wetness feature of the image. $TAR_{T1}$ represent spectra values measured at time $T1$, $Ref\_Water$ and $Ref\_Wetland$ are the reference spectra of the water body and the vegetated wetland, respectively.
an example. Firstly, the threshold selection can be narrowed down to 0.01–0.05. Within this range, samples of all types maintain their spectral characteristics related to NDVI and wetness that they should have, i.e., water body and vegetated wetland samples have higher wetness values (Figure 6A), and NDVI values for water body samples are the lowest (Figure 6B). Accordingly, samples in this range have high purity and have barely undergone a change in type between 1990 and 2020. Then, by analyzing the number of samples of each type within the above range (0.01–0.05), we can determine that the most reasonable threshold is 0.05. Utilizing this threshold will ensure that sufficient samples of each type are obtained (Figure 6C). Using the same approach, the optimal SD_WET thresholds were determined to be 0.04, 0.06, and 0.05 for Sites A, B, and D, respectively.

Figure 6. The variation characteristics of the time series wetness (A) and NDVI (B) for each type of sample with different SD_WET values. (C) shows the changes of sample number with different SD_WET values.
The sample numbers for each type after migration in the four study sites are shown in Figure 7. In 2020, the number of initial samples of each type was more evenly distributed across the four study sites, while the number of samples generated by migration during 1990–2019 has changed, indicating that samples have changed differently over the three decades. Moreover, the amounts of each sample type in the four study sites have various change trends characterized by different SD values from 1990 to 2019.

Figure 7. The number of samples after sample migration in this study. (A–D) show the number of generated samples for the four study sites (Site(A–D)), respectively. The black auxiliary dotted lines show the initial size of samples in 2020. The SDw, SDv, and SDn indicate the standard deviation of the sample number for the water body, vegetated wetland, and non-urban wetland from 1990 to 2020, respectively.

4.2. Accuracy Assessment of Mapping Urban Wetlands

The confusion matrix showed that our annual urban wetland maps from 1990 to 2020 achieved good classification results in the four study sites. As shown in Figure 8, the OA for each year is greater than 87% in all study sites, and the mean values from 1990 to 2020 in four sites are greater than 90.31%. For all study sites, the Kappa coefficient is greater than 0.82 from 1990 to 2020, indicating that the mapping results and ground-truth exhibit a high level of agreement. Moreover, as shown in Figure 9, both PA and UA of both urban wetland types have high values in all study sites, with the mean value of PA and UA for each site being higher than 84.5%.

4.3. Spatial Patterns and Temporal Trends of Studied Urban Wetlands

As shown in Figure 10, urban wetlands dominated by water bodies were widely distributed over the four study sites. The majority of vegetated wetlands are found adjacent to open water bodies. The vegetated wetlands and water bodies in small areas experienced evident changes and thus have lower occurrence frequency. The subset views (Figure 10A–D) show the most representative change of urban wetlands for each study site. In Tianjin (Site A), small water bodies suffered the most severe change (Figure 10A). In Hangzhou (Site B), changes of vegetated wetland have notable spatial heterogeneity (Figure 10B). In Wuhan (Site C), urban wetlands with small areas spreading throughout the city experienced
significant changes (Figure 10C). In Guangzhou (Site D), vegetated wetlands distributed around a larger water body suffered the most severe losses (Figure 10D).

Figure 8. OA and Kappa coefficient of urban wetland mapping in this study. (A–D) show OA and Kappa coefficient of urban wetland mapping in four study sites (Site(A–D)) from 1990 to 2020, respectively.

Figure 9. The UA and PA of each study site. W and V indicate the water body and vegetated wetland, respectively. The points in the graph indicate the UA and PA values from 1990 to 2020. (A–D) present the UA and PA of urban wetland mapping in four study sites (Site(A–D)) from 1990 to 2020, respectively.
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To open water bodies. The vegetated wetlands and water bodies in small areas experienced evident changes and thus have lower occurrence frequency. The subset views (Figure 10A–D) show the most representative change of urban wetlands for each study site. In Tianjin (Site A), small water bodies suffered the most severe change (Figure 10A). In Hangzhou (Site B), changes of vegetated wetland have notable spatial heterogeneity (Figure 10B). In Wuhan (Site C), urban wetlands with small areas spreading throughout the city experienced significant changes (Figure 10C). In Guangzhou (Site D), vegetated wetlands distributed around a larger water body suffered the most severe losses (Figure 10D).

In general, urban wetlands in each city experienced a significant areal decline from 1990 to 2020 (Figure 11). The most remarkable areal reduction of urban wetlands occurred in Tianjin (Site A), with a rate of 67.71% and an average loss rate of about 2.82 km² per year, followed by Guangzhou (35.51% and 5.53 km²) and Wuhan (28.85% and 5.74 km²). The declining trend of urban wetlands in Hangzhou (Site B) is relatively slow between 1990 and 2020, with a rate of 18.93% and the smallest reduction of about 0.57 km² per year.

Figure 10. The occurrence map of urban wetlands during the investigated 31 years for each study site (Site A–D). The value between 1 and 31 indicates the number of urban wetland occurrences from 1990 to 2020. The subset views (A–D) present the detailed changes of urban wetland for each study site with a 10-year interval from 1990 to 2020, respectively. The backgrounds in the views are the Landsat images.

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Figure 11. Area changes of urban wetlands from 1990 to 2020. (A–D) present the area changes of urban wetlands in four study sites (Site(A–D)) between 1990 and 2020, respectively.

5. Discussion

5.1. Comparison of the MUW_SM&RF Product with Other Public Datasets

Figure 12 overlays the products from the ChinaCover, the CAS_Wetlands, and the MUW_SM&RF. The ChinaCover and the CAS_Wetlands had a larger extent of water bodies than the result in this study. This difference can be attributed to the images and method. In this study, the images were generated by the temporal aggregation method rather than at a specific time. Thus the extent of extracted water varied. In addition, vegetated wetlands in this study are more detailed than the results of both the CAS_Wetlands and ChinaCover. Both the CAS_Wetlands and ChinaCover used the object-oriented classification method to identify vegetated wetlands. With a spatial resolution of 30 m, it is difficult to segment small vegetated wetland objects in urban areas. In this study, we generated reliable urban wetland samples by sample migration and used a pixel-based RF algorithm for urban wetland extraction. As a result, the range of vegetated wetlands obtained in this study is more refined.

5.2. Performance of the MUW_SM&RF

In this study, MUW_SM&RF was effective at mapping annual urban wetlands over the long term. By developing an effective sample migration approach, MUW_SM&RF can produce sufficient and high-quality training samples for the classifier and generate annual urban wetland maps. The generated maps allow us to understand the effects of urbanization on wetlands, which is significant not only for the conservation of wetland ecosystems, but also for sustainable urban planning. Additionally, the open-accessed Landsat time series imagery and the computing capability provided by the GEE platform enabled MUW_SM&RF to produce annual and time series urban wetland maps with uninterrupted data in a moderate 30 m spatial resolution.
Figure 12. Urban wetland comparison between urban wetland map in 2015 of this study and other reported datasets including CAS_Wetlands and ChinaCover dataset. (A–D) present the urban wetlands of 2015 in four study sites (Site(A–D)), respectively. The subsets (rectangle scope) are the typical region of four study sites respectively to show the detail of urban wetland results. The backgrounds of the subset views are the latest Google Earth images.

The MUW_SM&RF performed well in mapping annual urban wetlands in the four study sites and can be applied to other cities worldwide. SDG targets 11.3 and 11.5 focus on sustainable urban planning and management and emphasize the importance of urban ecosystem conservation. Annual urban wetlands data generated by MUW_SM&RF offer valuable insights into sustainable urban programming, as well as an important reference for assessing these goals. Additionally, the Wetland City accreditation scheme (Resolution XII.10), sponsored by the Ramsar Convention on Wetlands, encourages cities that value the conservation and proper application of wetlands, as well as highlighting the importance of urban wetlands. MUW_SM&RF can provide an effective method to evaluate the conservation and utilization status of urban wetlands for this scheme.

5.3. Inadequacies of the MUW_SM&RF

The accuracies of the annual urban wetland maps were inevitably affected by some factors. Even though the temporal aggregation algorithm was adopted and most of the
pixels affected by the cloud and shadows were removed from each image, it remains difficult to obtain high-quality images for low-latitude cloud-prone areas (i.e., Site D). Additionally, the MUW_SM&RF may have some shortcomings when it is applied to produce appropriate amounts of samples. If extreme weather events (drought or flood) occur in the study area, the landscapes will be drastically altered, making it difficult for MUW_SM&RF to generate appropriate samples. It will directly affect the accuracy of urban wetland extraction. For example, in 1998 and 2016, the extreme floods in Wuhan (Site C) have greatly changed the pattern of urban wetlands. As a result, the samples of urban wetland in 1998 and 2016 for Site C produced by the MUW_SM&RF were much more uneven than those in other years (Figure 7). To overcome the above shortcoming, we can shorten the detection period, divide the entire time period into several shorter periods, and produce training samples in each shorter period using the MUW_SM&RF to mitigate the effect of extreme weather on change detection.

6. Conclusions

In this study, continuous urban wetland mapping of four metropolises of China, namely Tianjin, Hangzhou, Guangzhou, and Wuhan, was conducted using Landsat time series from 1990 to 2020 by applying an effective approach (MUW_SM&RF) with the support of the GEE cloud platform. The MUW_SM&RF can automatically produce sufficient and high-quality training samples through spectral angular distance (SAD) and time series analysis and generate annual urban wetland maps using the random forest classification. The generated annual wetlands maps had an overall accuracy of over 87%. Compared to previously published datasets, the urban wetlands delineated using the MUW_SM&RF achieved better mapping accuracy, thus demonstrating its robustness for rapid mapping of urban wetlands. The generated annual urban wetland dataset revealed significant declining trends for each city. The MUW SM&RF can be applied to metropolises worldwide, and the annual urban wetland data it generates can offer valuable insights into sustainable urban programming and facilitate the evaluation of related SDG goals.

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