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China's Wetland Databases Based on Remote Sensing Technology

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Abstract: Wetland databases can provide the basic data that necessary for the protection and management of wetlands. A large number of wetland databases have been established in the world as well as in China. In this paper, we review China's wetland databases based on remote sensing (RS) technology after introducing the background theory to the application of RS technology in wetland surveys. A key conclusion is that China's wetland databases are far from sufficient in fulfilling protection and management needs. Our recommendations focus on the use of the hyper-spectral imagery, microwave data, multi-temporal images, and automatic classifications in order to improve the accuracy and efficiency of wetland inventory. Further, attention should also be paid to detect major biophysical features of wetlands and build wetland databases in years after the 1980s in China. Considering that great gap exists between RS experts and wetland experts, further cooperation between wetland scientists and RS scientists are needed to promote the application of RS in the foundation of wetland databases.

Keywords: wetlands; inventory; remote sensing; mapping; China

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1 Introduction

Wetlands, which are landscape features found in almost all climate zones from the tropics to the tundra (Mitra *et al.*, 2005), have been called 'the kidneys of the landscape' and 'ecological supermarkets' to bring attention to the important values (e.g., water storage and groundwater recharge, water quality control, biodiversity, and wildlife support) they provide. However, wetlands have been threatened, degraded or lost because of natural and human actions at alarming rates throughout the world (Zhang *et al.*, 2013). As recognition of their value has grown, the protection and management of wetlands have become the norm in many parts of the world. Therefore, understanding the distribution and area of wetlands is of great significance for wetland conservation as well as wetland management. Global or regional wetland databases can provide the basic data that necessary for the protection and management of wetlands.

Although various global wetland databases exist, obtaining reliable overall estimates of the wetland sizes globally is still difficult. Great uncertainty has limited the estimation of global wetland resources. Previous estimates suggest that the area of global wetlands ranged from 5.3×10^6 to 9.7×10^6 km^2 (Finlayson *et al.*, 1999), but present analyses suggest that previous studies have

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underestimated the area. Finlayson *et al*. (1999) calculated a tentative minimum of 12.8 km^2. Fluet-Chouinard *et al*. (2015) applied the downscaling technique to the Global Inundation Extent from Multi-Satellites (GIEMS) database to produce a new high-resolution inundation map at a pixel size of 15 arc-seconds, termed GIEMS-D15, which represents three states of land surface inundation extents: a mean annual minimum (total area, 6.5×10^6 km^2), a mean annual maximum (1.2×10^7 km^2), and a long-term maximum (1.7×10^7 km^2) (Fluet-Chouinard *et al.*, 2015). A great inconsistency also exists in China's wetland databases (Niu *et al.*, 2009; Gong *et al.*, 2010). For example, Niu *et al*. estimated that coastal wetland area was 1.8×10^4 km^2 while State Forestry Administration (SFA) and National Coastal Zone (NCZ) reported 5.9×10^4 km^2 and 2.4×10^4 km^2, respectively.

Wetland surveys mainly depended on traditional survey methods in the early stage when remote sensing (RS) techniques were not available. Traditional methods have the disadvantage of being time-consuming, high cost, damaging to the wetlands, and time intensive. These challenges have greatly affected the development of wetland databases. The innovation of RS technology has provided strong support for conducting wetland inventtories because of its advantages of time and labor savings, multi-temporal and multi-platform characteristics, and use of visible, infrared and microwave observations. Traditional optical sensors are prone to underestimating areas of wetlands, especially forested wetlands, temporarily inundated wetlands, and wetlands that are covered by clouds (Loveland *et al.*, 2000; Civco *et al.*, 2006). Long-wavelength Synthetic Aperture Radar (SAR; L band) can detect inundation which is obscured by vegetation and clouds, which can help to map inundations and wetlands more accurately at a continental scale (Civco *et al.*, 2006; Schroeder *et al.*, 2010). However, the difficulty of simultaneously observing spatiotemporal variability over large contiguous regions has limited the use of SAR data at a global scale. As a consequence of these limitations, great inconsistencies exist in current wetland databases. Previous studies (Finlayson *et al.*, 1995; Scott *et al.*, 1995; Melton *et al.*, 2013) also suggest that current wetland databases usually focus only on basic location and size information, and lack biophysical features. Therefore, existing wetland databases are far from perfect. Understanding the implication of RS technology in wetland inventories is of great significance for building more perfect wetland databases, as well as for choosing suitable databases for different study purposes.

China supports a large variety of wetland resources, ranking fourth in the world. The total value of wetlands could account for more than half of the annual ecosystem services in China. To promote the sustainable development of national resource environments, it is strategically significant to monitor wetland changes in China. The rapid development of RS technology has made the construction of wetland databases feasible. In China, research on wetland inventories by RS technology started relatively late. Understanding and comparing the research progress of related fields in China and abroad is of great significance to promote the research of wetlands in China. In this paper, we introduce a background theory for the implications of RS for wetland inventories. Then, we compare the application of RS in different types of wetland databases and introduce the development of China's wetland databases. Finally, we discuss some problems that exist in the application of RS in China's wetland databases research and propose directions to take in future research directions.

2 Background Theory

2.1 Data source

The data commonly used in wetland inventories include aerial photographs, multispectral data, hyper-spectral data, Synthetic Aperture Radar (SAR) data, and Light Detection and Ranging (LiDAR) imagery.

Aerial photographs have traditionally been used to map wetlands since the first aerial photography was collected in 1858 (Congalton, 2008). The advantages of aerial photographs include providing long time series of data of surface conditions, flexibility in the timing of data collection, and better spatial resolution than multispectral data (Shapiro, 1995; Morgan *et al.*, 2010). However, they have low spectral resolution, which limits the use in measuring soil moisture, distinguishing inundation in vegetated ecosystems, and detecting small bodies of water and turbid water (Finlayson and Valk, 1995). Another shortcoming is the limited use of auto-classification in aerial photographs (Wright and Gallant, 2007).

Multispectral images (Table 1) are often cheap or free of charge (Hewitt, 1990; Töyrä *et al.*, 2002; Li and Chen, 2005). They also have better spectral and temporal resolution compared to aerial photographs. Therefore, they have been widely used in mapping wetlands since 1972, especially Systeme Probatoire d'Observation de la Terre (SPOT) (Töyrä and Pietroniro, 2005; Davranche *et al.*, 2013) and Landsat (Sader *et al.*, 1995; Huang *et al.*, 2014) data. Landsat Thematic Mapper (TM) 2–4 is useful for the detection of understory vegetation, whereas bands 5 and 7 are helpful for identifying water and freshwater swamps (Congalton *et al.*, 1993; Töyrä *et al.*, 2002). Landsat 8, which was launched in February 2013, will ensure the popularity of Landsat images in mapping wetlands (Roy *et al.*, 2014; Rapinel *et al.*, 2015). SPOT data are capable of differentiating medium and small wetland patches, and detecting flooded wetlands, reeds as well as submerged macrophytes (Töyrä *et al.*, 2002; Poulin *et al.*, 2010). Some multispectral sensors, such as GeoEye and WorldView, can reach a high spatial resolution similar to that of aerial photographs and auto- classification methods can be used in multispectral imagery (Töyrä *et al.*, 2002; Huang *et al.*, 2014) to increase efficiency. Multispectral sensors cover a wide range of spatial resolutions, which is very helpful in wetland mapping. Coarse spatial resolutions (such as Advanced Very High Resolution Radiometer, AVHRR, 1.1 km), which are not typically used to map wetlands on a local or regional scale, can be used to map global scale wetlands, as well as help finer-resolution sensors (Landsat TM, 30 m; SPOT, 8–20 m, *etc.*) to depict hydrologic dynamics because of their better temporal resolution (Zhao *et al.*, 2012; Petus *et al.*, 2013). Other multispectral sensors with finer spatial resolution (such as QuickBird, 2.4 m, and WorldView-2, 0.5 and 1.8 m) can improve wetland mapping accuracy and are increasingly used in wetland mapping (Belluco *et al.*, 2006; Ouyang *et al.*, 2011), but the difficulty and expense of acquiring them (Nagendra *et al.*, 2013) hinder their advance. The limitations of multispectral imagery include the difficulty of obtaining consistent high-quality data due to climate conditions (Costa, 2004; Costa and Telmer, 2007), low accuracy in detecting forest wetlands (Huang *et al*., 2014), and insufficiency for mapping small wetland patches (Ausseil *et al.*, 2007).

Because hyper-spectral data resolve more details than multispectral data, they can better characterize wetlands (Hirano *et al.*, 2003; Schmidt and Skidmore *et al.*, 2003; Klemas, 2011; Zhang and Xie, 2012), including identification of marsh vegetation species and detection of forested wetlands. Silva *et al*. (2008) found that the accuracy of hyper-spectral imagery in mapping aquatic vegetation is between 70% and 96%. Of all the hyper-spectral data, Moderate-Resolution Imaging Spectroradiometer (MODIS) data are the most widely

Table 1 Multispectral imagery commonly used to map wetlands

Name	Spatial resolution (m)	Temporal resolution (d)	Life span
Landsat TM	30 (TIR 120)	16	1982–2011
SPOT 1–23	20 (Pan 10)	26	1986–2009
SPOT 4	20 (Mono 10)	26	1998–2013
AVHRR	1100	0.5	1998–Pres.
Landsat ETM+	30 (TIR 60, Pan 15)	16	1999–Pres.
IKONOS	4 (Pan 1)	3	1999–Pres.
QuickBird	2.4	1-6	2001–Pres.
SPOT 5	10 (SWIR 20, Pan 2.5–5.0)	26	2002–Pres.
Worldview-1	0.55	1.7 (average)	2007–Pres.
GeoEye-1	1.65 (0.41)	<3	2008–Pres.
Worldview-2	1.84 (0.46)	1.1 (average)	2009–Pres.
Pleiades	2 (0.5)	1	2011–Pres.
OLI	30 (Pan 15)	16	2013–Pres.

Notes: Landsat TM means the Landsat Thematic Mapper; SPOT means the Systeme Probatoire d'Observation de la Terre; AVHRR means the Advanced Very High Resolution Radiometer; Landsat ETM+ means the Landsat Enhanced Thematic Mapper Plus; Landsat 8 OLI means the Landsat Operational Land Imager (OLI); TIR means the thermal infrared bands; Pan means the panchromatic band; Mono means the monospectral band; SWIR means the short wave infrared band; Pres. means present used in wetland mapping (Hirano *et al.*, 2003; Hladik *et al.*, 2013). Hyper-spectral imagery is not commonly used in wetland boundaries mapping because of the large data volume (Hirano *et al.*, 2003; Klemas, 2011), image processing challenges (Phinn *et al.*, 1999; Klemas, 2013), poor data availability (Judd *et al.*, 2007; Kokaly *et al.*, 2013), and relatively coarse spatial resolution. The numerous spectral bands of hyper-spectral data increase the amount of information, as well as the time and space challenges of processing images. Sometimes, the use of such high spectral resolution is not necessary. For example, while mapping salt marsh classes, the spectral content of the hyper-spectral imagery was largely redundant and could be produced by multispectral data (Belluco *et al.*, 2006).

The advantages of microwave remote sensing include being able to be used in all weather conditions and at any time of day, and having strong permeability and abundant multi-band as well as polarization information; thus, the focus of wetland mapping has gradually shifted from optical remote sensing to microwave remote sensing (Hall 1996; Martinez and Le Toan, 2007). Since Seasat was successfully launched in 1978, it has shown the ability to detect flooding (Place, 1985; Hess *et al.*, 1995). Many sensors, such as Airborne Synthetic Aperture Radar (AIRSAR) (1993–2004), Spaceborne Imaging Radar (SIR)-C (1994), and Japanese Earth Resources Satellite (JERS) (1992–1998), have been shown to have the capacity to map inundation in forested wetlands (Ormsby *et al.*, 1985; Townsend, 2000; Costa, 2004; Martinez and Le Toan, 2007).

In general, microwave sensors are ideal for estimateing soil moisture and vegetation biomass (Le Toan *et al.*, 1992; Kellndorfer *et al.*, 1998; Martinez and Le Toan, 2007), detecting hydrologic features below vegetation and freeze/thaw events (Hall, 1996; Wilson and Rashid, 2005), and identifying forest wetlands (Dwivedi *et al.*, 1999; Lang *et al.*, 2008). The C-band (3.9–7.5 cm) and L-band (15–30 cm) are the most commonly used microwave wavelengths for obtaining wetland inventories (Kasischke *et al.*, 2003; Bartsch *et al.*, 2007; Lang *et al.*, 2008). L-band is useful for the detection of woodland wetlands (Townsend and Walsh, 1998; Zhang *et al.*, 2013), whereas the C-band is more sensitive in the detection of wetlands with low biomass (Townsend, 2002; Kasischke *et al.*, 2003; Lang *et al.*, 2008). Studies also show that cross polarized data (e.g., horizontal transmitted and vertical received, HV; vertical transmitted and horizontal received, VH) are more sensitive to differences in biomass (Bourgeau-Chavez *et al.*, 2009), whereas horizontal transmitted and horizontal received polarized (HH-polarized) data can be adapted to detect inundation beneath a plant canopy (Hess *et al.*, 1995).

Microwave images are often used in combination with optical images (Li and Chen, 2005; Bwangoy *et al.*, 2010), which usually leads to better results than when they are used alone. For example, Landsat Enhanced Thematic Mapper Plus (ETM+) data and LiDAR Digital Elevation Models (DEMs) can be combined to separate the upper salt marsh from the upland forest, whereas Landsat ETM+ data alone does not give satisfactory results due to mixed pixels (Civco *et al.*, 2006). Habitat characterization (Vierling *et al.*, 2008) and vernal pools detection (Leonard *et al.*, 2012) can be successfully performed by using optical images in conjunction with microwave images.

Microwave data have great potential in wetland mapping. However, the disadvantages including the relatively high expense of obtaining the data, and data processing challenges greatly limit the ability of researchers to fully utilize their potential (Costa, 2004; Silva *et al.*, 2008).

The advantages, disadvantages, and applications of different data sources are provided in Table 2. In conclusion, aerial photographs provide long-time series of data, which can date back to the 1950s. Multispectral images are the most widely used data source due to their relatively high availability of data and low expense. Hyper-spectral data and microwave data both have great potential for obtaining wetland inventories, but their relatively high expense and data processing challenges limit their use. Studies show that no data are adapted to all types of wetland inventories. Therefore, combining different data sources to obtain wetland inventories has become common. Capturing the critical features of the seasonal variation of wetlands with single-temporal images is difficult, which is not beneficial for the extraction of high-precision wetland information. Multi-temporal images can provide more detailed information about wetlands, which can improve the accuracy of wetland classification (Lunetta and Balogh, 1999; Maria *et al.*, 2002). Lunetta *et al.* found that wetland classification accuracy can increase from 69% (single-temporal images) to 88% (multi-temporal images) (Lunetta and Balogh, 1999).

Table 2 Comparison of different data sources

Data source	Example	Spatial resolution	Advantage	Disadvantage	Application
Aerial photographs	Corona, NAPP, NHAP	High	Long time series; better spatial resolution	Expensive; low spectral resolution; limitation of auto-classification	Wetland boundaries mapping
Multi-spectral data	AVHRR	Low	High temporal resolution; automated interpretation can be used	Coarse spatial resolution; low accuracy in detecting forested wetland; difficulty to obtain high-quality data regularly	Global scale wetland mapping; depicting hydrologic dynamics
	SPOT, Landsat TM, Landsat 8	Moderate	Good data availability and low expense; automated interpretation can be used	Insufficient for mapping small wetlands; low accuracy in detecting forested wetland; difficulty to obtain high-quality data regularly	Mapping wetland at local and regional scales
	QuickBird, IKONOS, Worldview	High	High spatial resolutions; automated interpretation can be used	Difficulty and high expense in acquiring data; low accuracy in detecting forested wetland; difficulty to obtain high-quality data regularly	Mapping smaller wetlands
Hyper-spectral imagery	MODIS, AVIRIS, DAIS	Usually low	High spectral resolution; more detailed information	Relatively poor data availability; image processing challenges; insufficient spatial resolution	Identifying plant species; detecting plant biochemical properties and water quality; mapping oiled marsh
Microwave data	Seasat, Radarsat, PALSAR	Usually moderate	All weather; all time; strong permeability; plenty of multi-band; polarization information	Interpretation is less intuitive than that of optical imagery; expensive; processing challenges	Mapping forested wetlands; estimating soil moisture and vegetation biomass

Notes: NAPP means the National Aerial Photography Program; NHAP means the National High Altitude Photography; AVHRR means the Advanced Very High Resolution Radiometer; TM means the Thematic Mapper; SPOT means the Systeme Probatoire d'Observation de la Terre; MODIS means the Moderate-Resolution Imaging Spectroradiometer; AVIRIS means the Airborne Visible / Infrared Imaging Spectrometer; DAIS means the Digital Automotive Image System; PALSAR means the Phased Array type L-band Synthetic Aperture Radar

2.2 Wetland classification

The most widely used classification systems include the Ramsar international wetland classification system, the Cowardin classification system, and the hydrogeomorphic (HGM) classification system (Cowardin *et al.*, 1979; Brinson, 1993; Ramsar Convention Secretariat, 2010).

The Cowardin classification system, which is very comprehensive, has become the foundation of wetland resource registration and management in the United States (Tiner *et al.*, 2015). However, it is a complicated system. Therefore, the Ramsar international wetland classification system is more versatile. Many countries such as Denmark, Finland, Germany, Norway, Sweden, the Netherlands, and the United Kingdom use this system as a foundation for inventorying their wetlands (Tiner *et al.*, 2015). Brinson realized that the Ramsar system did not address hydrogeomorphology (Brinson, 1993), so he developed the HGM classification system to help provide a framework for wetland evaluation. This system focuses on performing functional assessments of wetlands, leading to the possibility that some types of wetlands may overlap (Scott and Jones, 1995; Tiner *et al.*, 2015).

Various classification systems exist in China in order to meet different research purposes. Niu *et al.*, classified wetlands as three broad (coastal wetland, inland wetland, artificial wetland) classes with 14 subcategories (Niu *et al.*, 2009). The national land use and land cover change (LUCC) database classified wetlands as streams and rivers, lakes, reservoir and ponds, swampland, and paddy. Here, we give an example of the first national wetland survey in China (Table 3). The advantage of this classification is that it is simple, in accordance with the customary wetland classification by China's scholars (Gong *et al.*, 2010; Liu *et al.*, 2011). In practice, however, there are some obvious shortcomings. For example, human-made wetlands are incomplete, excluding all other types of wetlands except for reservoirs and ponds. In a national wetland survey, swamp wetlands were divided into too much detail.

2.3 Wetland classification methods

2.3.1 Visual interpretation

Early satellite images were mainly interpreted visually in the identification of wetlands (Nayak *et al.*, 1985).

Table 3 Wetland classification of the first national wetland survey in China

Class	Subclass	Class	Subclass
Coastal wetland	Shallow waters	Lake wetland	Floodplain wetland
	Subtidal aquatic layer		Permanent freshwater lakes
	Reefs		Seasonal freshwater lakes
	Rocky coast		Permanent saline lakes
	Intertidal sandy beach		Seasonal saline lakes
	Intertidal mud beach	Swamp wetland	Moss swamp
	Intertidal salt marsh		Herbaceous swamp
	Mangrove marsh		Swamp meadow
	Coastal saline lakes		Shrub swamp
	Coastal freshwater lakes		Forested swamp
	Estuarine waters		Inland salt marsh
	Delta wetland		Geothermal wetland
River wetland	Permanent river		Freshwater springs or oasis wetland
	Seasonal or intermittent river	Human-made wetland	Reservoirs and ponds

Usually, the accuracy of visual interpretation is higher than automatic classification. In addition, the knowledge and experience of the interpreters can be fully utilized. However, visual interpretation is subjective and time-consuming.

2.3.2 Computer automatic classification

Commonly used automatic classifications include supervised and unsupervised classification. The advantage of supervised classification is that the required classes can be specified, while the disadvantage is that the required classes might not have a unique spectrum. When field data are limited or nonexistent, unsupervised classification is quite valuable. The advantages of unsupervised classification are that it eliminates the time-consuming training phase and that the classes are different units; however, the disadvantage is that some classes may not be needed. In general, supervised classification is used more widely than unsupervised classification.

In complex wetland environments, many different classification techniques are used to improve wetland classification accuracy. These methods include decision trees (Li and Chen, 2005; Wright and Gallant, 2007; Bwangoy *et al.*, 2010; Hladik *et al.*, 2013), random forests (Breiman, 2001), object-based classification (Dronova *et al.*, 2011), support vector machines (SVMs) (Sadeghi *et al.*, 2012), and neural networks (Bao *et al.*, 2011), and so on. 1) Decision trees: the strengths of decision trees include their ability to combine a wide variety of input data (for example, spectral indices; other classification results; ancillary data, such as vegetation maps; and active RS measurements from SAR and LiDAR), high computational efficiency and flexibility. However, if the training data are not reasonable, their use can lead to poor results. 2) Random forests: as a machine learning algorithm, the random forests method adds an additional layer of randomness to bagging by using a random selection of attributes to create splits (Tiner *et al.*, 2015). The class that gets the most 'votes' from each decision tree determines a pixel's classification. The advantages of this algorithm include the following: it has the ability to handle databases with a small number of observations and a large number of attributes. In addition, it is well suited to parallel processing, which is more powerful than a single classifier, and it is insensitive to non-predictive inputs. This algorithm can also easily handle missing attributes. The disadvantages are that this algorithm is not intuitive and it is sensitive to inaccurate training data (Liaw and Wiener, 2002). This algorithm is a popular option for mapping different wetland environments (Kloiber *et al.*, 2014). 3) Object-based classification: one of the advantages of the object-based classification is the ability to overcome difficulties related to pixel-based methods. The object-based classification method involves segmentation that consists of delineating different geospatial data as homogeneous segments (termed 'objects' or 'regions') in satellite images. The object-based classification characteristics are intrinsic to objects (e.g., spectral, textural or geometrical properties) or rely on topological and semantic and thematic properties related to their contextual information (e.g., connectivity or proximity). In contrast to the pixel-based approach, objects are segmented based on both their spatial correlation and thematic similarity. This technique is therefore expected to extract 'real-field' objects with high classification accuracy. This method has been widely used in wetland mapping (Sun *et al.*, 2008; Dronova *et al.*, 2011).

Studies show that there is no single method that can be applied to all conditions. Therefore, using a combination of different methods to improve accuracy has become common. Generally, this approach can overcome the drawbacks of single classification and improve the accuracy (Salem *et al.*, 2005; Töyrä and Pietroniro, 2005).

3 Global/Regional Wetland Databases

Generally, wetland databases can be divided into three categories: wetland maps produced by aggregating historical regional or global maps (e.g., global raster map of wetlands, Global Lakes and wetland Database-3), wetland maps produced from measurements based on satellite imagery (e.g., National Wetland Inventory or wetland data derived from Global Land Cover maps), and remotely sensed inundation databases that detect inundated areas (e.g., Global Inundation Extent from Multi-Satellites). Wetland maps produced by aggregating historical regional or global maps have the advantage of only selecting wetlands for inclusion while excluding other water bodies (Melton *et al.*, 2013) and the ability to fully use different types of data (Mattews and Fung, 1987). However, these databases are static in time, not including seasonal dynamics and may be outdated. Furthermore, some wetlands, such as those in arid or semiarid regions, might be overestimated because the frequency of intermittent wetlands becoming actual wetlands could be extremely rare (Lehner and Döll, 2004). Wetland maps produced from measurements based on satellite imagery capture a more contemporary situation and usually include various wetland types, but they only represent a snapshot in time and do not include seasonal dynamics (Giri *et al.*, 2005; Fluet-Chouinard, 2015). Remotely sensed inundation databases are more up-to-date, allowing at least monthly resolution, and close to global coverage (Melton *et al.*, 2013). Problems with these data include the non-specific measurement of inundation and the limited ability to detect standing water at the surface. Given that saturated and non-inundated wetlands also produce CH_4, detection of these areas is also important, especially in module simulation.

3.1 Wetland maps produced by aggregating historical regional or global maps

Most global wetland databases are produced by aggregating historical regional or global maps. Multi-source data have been used to obtain this type of wetland databases. For example, the Wetland Map of the World Conservation Monitoring Center (WCMC), which are broadly based on 1∶1 000 000 map and wetland directories prepared by the World Conservation Union and partners. By integrating three independent global maps of vegetation, soil properties, and inundation, Mattews and Fung (1987) derived a global raster map of wetlands with 1° × 1° resolution. The Global Lakes and Wetland Database (GLWD) was mapped by aggregating seven existing wetland maps (e.g., WCMC and the Digital Chart of the World (DCW)) (Lehnera and Döll, 2004).

Usually, the classification systems of this kind of databases are relatively simple (Dugan 1993; Lehnera and Döll, 2004; Melton *et al.*, 2013; Fluet-Chouinard, 2015). The classification of DCW only includes permanent water bodies, intermittent water bodies, and wet sands and makes no distinction between rivers, lakes, and reservoirs (Lehnera and Döll, 2004). GLWD-3 includes lakes, reservoirs, rivers, and nine other types of wetlands (Lehnera and Döll, 2004; Fluet-Chouinard, 2015).

Some automated or self-automated classification methods were used in producing this type of wetland maps. Lehnera and Döll used a method similar to a decision tree to produce the GLWD wetland map (Lehnera and Döll, 2004). They first applied individual decisions to generate a single polygon based on three different data sources; then, they used visual inspections and other decisions to link to other polygons according to other databases.

Although these databases have the disadvantage of overestimating some wetlands, being static in time, and having no specific time stamp available, they provide important reference data for wetland conservation. DCW provides a comprehensive global vector database and the best source of vector data for many areas of the world (Lehnera and Döll, 2004). GLWD indicates the most extensive total wetland area among six water-related global land cover maps (Nakaegawa, 2012).

3.2 Wetland maps produced from measurements based on satellite imagery

Many regional wetland databases have been produced from measurements based on satellite imagery. For example, the Canadian Wetland Inventory (CWI) and the National Wetland Inventory (NWI) of the United States. Some global land cover maps can be regarded as wetland databases because wetlands are usually included in these databases. We compare different wetland databases in Table 4.

The CWI was established in 2002 to provide a uniform approach to produce a reference map of wetlands for national reporting (Fournier *et al.*, 2007; White *et al.*, 2015). The CWI is still in progress (White *et al.*, 2015). Based on the Landsat and Radarsat platforms (Li and Chen, 2005; Fournier *et al.*, 2007), the CWI used a five-class system to map wetlands (Fournier *et al.*, 2007).

Based on manual aerial photo interpretation, the NWI has a target map unit (TMU) of 0.2 ha. The classification includes wetland systems, classes, subclasses, water regimes, and special modifiers (Dahl *et al.*, 2009). In general, it provides a readily available nationwide data source that is used by local, state, federal agencies, and private industry (Wilen and Bates, 1995). Field data show that all non-forested wetlands on the NWI map were correctly identified, with an accuracy of 96.9% in upland areas. The lowest level of accuracy was 90.7% (forested wetlands). However, studies have also shown that the NWI often underestimates the size of wetlands (Stolt *et al.*, 1995).

There are five types of global land cover databases that are widely used: 1) the University of Maryland (UMd) 1 km land cover maps; 2) the International Geosphere-Biosphere Programme Data and Information System (IGBP-DIS) DISCover databases; 3) the global land cover databases produced by Boston University (i.e., MODIS databases); 4) the global land cover databases produced by the European Commission's Joint Research Centre (i.e., GLC2000 databases); and 5) the global land cover databases produced by the European Space Agency with global cooperation (i.e., Globcover 2005 and Globcover 2009 databases). These land cover databases include various classifications, and wetlands are usually represented as 'open water' and 'permanent wetlands' (such as in the IGBP-DISCover databases and MODIS databases). These databases have the advantage of being applicable to the analysis of the dynamic change of wetlands because they can be used to identify the land use/cover change in wetland areas, whereas databases that only include wetlands can only be used to identify the change area. Another advantage is that automatic classification methods can be used (e.g., UMd used the decision tree method to map global land cover based on AVHRR and NDVI data). However, these maps have struggled to produce accurate high-resolution representations of the extent of wetlands (Giri *et al.*, 2005; Ning *et al.*, 2012), and large inconsistencies exist in the different databases (Hansen and Reed, 2000; Giri *et al.*, 2005).

With the development of RS, a stable data source has become available, which is a great convenience in updating wetlands maps. Additionally, the specific time stamp available on wetland maps produced from measurements based on satellite imagery and automatic computer classifications can be used to improve efficiency.

Table 4 Comparison of different wetland databases

Name	Main data source	Classification	Method	Reference
CWI	Landsat and Radarsat images	Five class system including bog, fen, marsh, swamp and shallow water	Visual interpretation combined with some computer-automated methods	Li and Chen, 2005; Fournier *et al.*, 2007; White *et al.*, 2015
NWI	Aerial photographs and multispectral imagery	Classification includes wetland systems, classes, subclasses, water regimes, and special modifiers which is modified according to the Cowardin classification system	Visual interpretation	Stolt and Baker, 1995; Dahl *et al.*, 2009
Global land cover maps	AVHRR, MODIS, SPOT, *etc.*	These land cover databases include various classifications and usually wetland are represented as 'open water' and 'permanent wetland'	Automatic classification methods (e.g., decision tree)	Hansen and Reed, 2000; Giri *et al.*, 2005; Ning *et al.*, 2012

Notes: CWI means the Canadian Wetland Inventory; NWI means the National Wetland Inventory; AVHRR means the Advanced Very High Resolution Radiometer; MODIS means the Moderate-Resolution Imaging Spectroradiometer; SPOT means the Systeme Probatoire d'Observation de la Terre

However, these maps have the shortcomings of being static in time and not including seasonal dynamics, and the accuracy needs to be improved in the future, especially on the global scale.

3.3 Remotely sensed inundation databases

Using multisource data (e.g., data from the Special Sensor Microwave/Imager, radar backscatter from the European Remote Sensing, Advanced Microwave Instrument scatterometer, and visible and near-IR reflectances from AVHRR), the Global Inundation Extent from Multi-Satellites (GIEMS) has quantified the extent of inundation for each month from 1993 to 2004 (Fluet-Chouinard, 2015), and the classification system includes lakes, rivers, wetlands, and irrigated agriculture (Prigent *et al.*, 2007). An automatic classification method called the multisatellite method (Prigent *et al.*, 2007) was used to create this database. As a remotely sensed inundation product, GIEMS has the advantages of being more up-to-date, with monthly temporal resolution, and having close to global coverage. The disadvantages include non-specific measurement of inundation, i.e., no information about the depth of water ponding, and ambivalence to the type of water body (Melton *et al.*, 2013). Additionally, GIEMS appears to classify many small lakes as inundated land (Walker *et al.*, 2005) and underestimates inundated areas in some forested areas, such as western Siberian (Schroeder *et al.*, 2010) and eastern Amazonia (Miller *et al.*, 2007).

The development of RS technology provides more data sources and more classification methods for constructing wetland databases. From Table 5, we can see that the global/regional wetland databases are continuously improving. By using multi-source RS data and auto-classification methods, wetland databases have a higher temporal resolution and are more up-to-date. Various global wetland databases can be used for different purposes according to different needs. Although there are many global wetland databases, great inconsistencies exist in the current wetland databases.

4 China's Wetland Databases

Wetlands research and inventory in China started in the early of the 1950s, mainly leading by Northeast Institute of Geographic and Agroecology, Chinese Academy of Sciences through filed survey. The research topics mainly included inventory, classification, formation and evolution, ecological protection, pollution control, wise use and management of wetlands (Zhao, 1999). Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences is now the leading research institute in comprehensive limnology and watershed research, concentrating on the Yangtze River Basin, western region, and southeast coastal zone. The 'Mire Map of China' which was the first wetland map in China was published in 1999. Although it is paper version, it provides a great reference value for wetland research. Then, the development of RS technology provided great support for the establishment of wetland databases in China (See 4.2).

4.1 Mire map of China

Based on historical maps and field validation, Wang edited the 'Mire Map of China' in 1999 (Wang *et al.*, 2004). The map scale was 1∶4 000 000 and shows forty years' investigations of mire which mainly done by scientists of Northeast Institute of Geography and Agroecology, Chinese Academy of Sciences. The types, characteristics, formation, and distribution of 396 pieces of mire in China were described in detail in this map.

Table 5 Comparison of three types of wetland databases

Class	Example	Advantage	Disadvantage
Wetland maps produced by aggregating historical regional or global maps	WCMC GLWD	Use various data sources; usually includes various wetlands types	Outdated; overestimates some wetlands; being static in time; no specific time stamp is available
Wetland maps produced from measurements based on satellite imagery	CWI NWI	Captures a more contemporary situation; auto-classification methods can be used; specific time stamp is available; usually includes various wetlands types	Only represents a snapshot in time and does not include seasonal dynamics; accuracy needs to be improved
Remotely sensed inundation databases	GIEMS	More up-to-date; allows at least monthly resolution; close to global coverage	Non-specific measurement of inundation and they are limited to detecting standing water at the surface

Notes: WCMC means the Wetland Map of the World Conservation Monitoring Center; GLWD means the Global Lakes and Wetland Database; CWI means the Canadian Wetland Inventory; NWI means the National Wetland Inventory; GIEMS means thee Global Inundation Extent from Multi-Satellites

The publication of this map not only have important theoretical and practical significance in promoting the rational exploitation of China's mire but also have an important contribution to study of the world's mire.

4.2 Wetland maps produced from measurements based on satellite imagery

4.2.1 Marsh database in China

Based on the 15 years' data accumulation of marshland during the seventh, eighth, and ninth five-year-plan periods, a database on the dynamic distribution of marsh lands using Landsat images from 1986, 1996 and 2000 were established (Zhang, 2002; Niu *et al.*, 2009). Visual interpretation, combined with field survey validation were used in the image processing, and the map scale was 1∶10 000 (Zhang, 2002). Users can query part of the data by visiting http://www.marsh.csdb.cn/index.html.

4.2.2 Chinese wetland map

Using Landsat data and visual interpretation, Gong *et al.* mapped Chinese wetland map with three broad (coastal wetland, inland wetland, artificial wetland) classes and 15 subcategories (tide zone/shallow/beach, marine marshes, estuarine water, estuarine deltas/sandy islands, lagoons; rivers, flood, plain wetlands, lakes, inland marshes; reservoirs/ponds, artificial river channels, seawater fish farms and salt flats, rice and paddy fields, landscaping and recreational water bodies, other) in 2010 (Gong *et al.*, 2010). The classification scheme is consistent with the Ramsar wetland classification system. Studies (Gong *et al.*, 2010) show that from 1990 to 2000, inland wetland dropped from 3.2×10^5 to 2.6×10^5 km^2, coastal wetland reduced from 1.4×10^4 to 1.2×10^4 km^2, while artificial wetland increased from 2.3×10^4 to 3.5×10^4 km^2. This database is of great significance for wetland conservation and scientific management in China. But it may underestimated the size of coastal wetland and artificial wetland (Niu *et al.*, 2009; Gong *et al.*, 2010).

4.2.3 Wetland survey by State Forestry Administration

The publication of 'China's Marshes' (Zhao, 1999) provides a useful reference for the State Forestry Administration to organize a national wetland resources survey. From 1995 to 2003, the State Forestry Administration did a detailed national survey of lakes, bogs, rivers, coastal wetlands, and reservoirs that larger than 1 km^2 mainly by filed survey. From 2009 to 2013, the State Forestry Administration organized the second national wetlands survey. The minimum survey unit was 8 ha. The vegetation, hydrology status etc. of wetlands were also surveyed in the first and second survey. RS technology (China-Brazil CBERS images and visual interpretation) was widely used in the second survey. These wetland surveys can provide basic data for wetland conservation and management, which with no doubt have great values. However, related wetland geographic maps were not public, hindering our understanding of spatial distribution and wetland changes across the country to some extent.

4.2.4 National land use and land cover change database

Using high-resolution RS images and visual interpretation, Liu *et al*. established a national-scale LUCC database in China in the early 1990s and this LUCC database has been updated every 5 years (Liu *et al.*, 2002; 2003; 2010). Up to now, a 1∶100 000 national LUCC vector database and a 1-km grid database have been completed for five stages: the late 1980s, 1995, 2000, 2005, and 2010 (Liu *et al.*, 2002; 2005; 2010). And interpretation results were checked out with extensive field surveys and other historical data such as Statistical Yearbook of China and tabular data from field sites.

The LUCC data was produced with a perspective of land use development and utilization while wetland mapping is aimed to obtain information on wetland locations. The difference in mapping goals led to different classification systems and different results. For example, meadow wetlands are classified as wetlands in the wetland mapping while they are classified as grasslands in LUCC mapping. Niu *et al*. (2009) found that the wetland area estimated by LUCC mapping is smaller than that of their wetland mapping. These data are public and are quite useful in identifying the land use/cover change in wetland areas in China.

A growing number of data sources and RS methods are used in obtaining wetland inventories, leading to an increasing abundance in wetland databases in China. The wetland databases of China are becoming more and more comprehensive and detailed. RS technology has become an important supplementary method to develop a wetland inventory, which greatly improves the efficiency. Overall, China's wetland databases are far from sufficient in fulfilling protection and management needs.

Therefore, the full use of RS to develop wetland databases in China requires further research. Here, we conclude with the problems that exist in China's wetland databases.

(1) Most wetland databases are limited to the use of optical remotely sensed data, and few have attempted to use the hyper-spectral imagery and microwave data. In addition, visual interpretation combined with the field survey is still the main method to inventory wetlands at the national scale although many automatic classifications have been developed.

(2) Current inventories in China mainly focus on the basic location and size of each wetland and lack major biophysical features, such as vegetation conditions, soil moisture, and water quality. For example, soil moisture is an important factor that influences greenhouse gas emissions from wetlands. With the development of RS technology, all of these features can be detected. Although RS technology has been widely used to detect these features on many scales, these features were rarely included in wetland databases.

(3) Great inconsistencies exist between different wetland databases in China. Therefore, the accuracy of wetland databases in China is still need to be improved in the future. In addition, an inundation wetland database is lacking in China.

(4) The wetland databases in China mainly focus on years after 1980s. However, large area of wetlands have been destroyed since the 1950s. For example, large area of marsh were reclaimed as farmland in the Sanjiang Plain in the 1950s (Yan *et al*., 2016). The 'Learn from Dazhai in Agriculture' movement (1964–1978) of China transformed numerous landscapes and filled countless lakes, wetlands, and coastal areas for crop production with little regard for topographic, climatic, and socioeconomic conditions (Liu *et al*., 2010). Establishing a wetland database before the 1980s is needed in order to better understand wetland changes in China.

5 Conclusions

China, the country hosts a large area of natural wetlands, has experienced a decline of wetland area since the second half of the 20th century. Therefore, establishing more accurate and more perfect wetland databases is of great significance for wetland conservation and management. Given existing conditions and problems with China's wetland databases, the proposed key points and future developments should focus on the following goals:

(1) Considering that hyper-spectral/microwave data include more detailed information of wetlands, more attention should be paid to these data to obtain more detailed wetland features such as vegetation condition. Automated or semi-automated methods should be considered in a national or larger scale. Many automated or semi-automated methods have been successfully used in updating regional inventories. These methods can be extended to a larger scale in order to improve efficiency.

(2) Future inventories should focus not only on the basic location and size of wetlands but also pay attention to the major biophysical features. These supplementary data will provide the basic information for wetland monitoring and conservation, as well as for environmental protection.

(3) Most importantly, the information in wetland databases should be more accurate. Special attention should be paid to temporal changes in future wetland inventories. Researchers can choose suitable temporal images/methods or use multi-temporal images, and conduct field verification after collecting data from aerial photographs and satellite imagery in order to get more accurate information. Also, an inundation wetland database should be established in China in order to better understand wetland changes.

(4) Attention should also be paid to build wetland databases in years after the 1980s in China. Aerial photographs are available now to get the information of wetlands in an early stage. Both interpretation of aerial photographs and reconstruction by model are good choices to establish China's wetland databases before the 1980s.

(5) RS technology is playing an increasingly important role in wetland surveys. However, great gap exists between RS experts and wetlands experts. Therefore, further cooperation and communication between wetland scientists and RS scientists are needed to promote the application of RS in the foundation of wetland databases and to improve the efficiency of wetland surveys.

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