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Monitoring spatiotemporal changes of marshes in the Sanjiang Plain, China

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ABSTRACT

The marshes have undergone dramatic loss in the Sanjiang Plain since the 1950s. This paper analyzed the spatiotemporal changes of the marshes using the transition probabilities index, loss rate, and landscape indices. We also used a trajectory analysis method to trace every location of marshes over multiple points in time and to quantitatively estimate the impact of human activities on the marsh changes since the 1950s. This study indicates that the marsh area declined sharply by 79.4% (approximately 2.99 million ha) from 1954 to 2015. A large area of marsh was reclaimed as cultivated land from 1954 to 2015. The changes in the related landscape indices showed the large-scale loss of the marsh area and marsh fragmentation in the study period. Human activities were the dominant factor (87.86%) that influenced the marsh changes in the Sanjiang Plain during the last 60 years compared with natural factors. These findings can provide valuable information for better understanding wetlands changes and implementing sustainable management strategies for wetlands (such as wetland restoration).

1. Introduction

As “the kidneys of the landscape” and “ecological supermarkets”, wetlands play a significant role in performing ecosystem services, such as water quality control, biodiversity conservation and wildlife support (Baker et al., 2006; Davranche et al., 2010). However, wetlands have been threatened, degraded or lost at alarming rates because of natural and human actions worldwide (Dugan, 1992; Fluet-Chouinard et al., 2015). Degradation or loss of wetlands can lead to decreased biodiversity and ecosystem service, soil erosion, increased major greenhouse gas emission, and reduced water supply (Dugan, 1992; Finlayson et al., 1999). Restoration approaches for wetlands are necessary to enhance both the biodiversity and ecosystem services in places where the wetland area is lost (Liu et al., 2013). One of the key issues in wetland restoration is to clarify the spatiotemporal changes of wetlands and disturbing causes. Distinguishing the relative role of human factors from natural factors in terms of their impact on wetland changes is vital for understanding wetland changes and implementing sustainable management strategies for wetlands.

A bitemporal detection method is a common method to analyze land use and land cover changes (LULCC) in different time periods (Liu et al., 2005a; Liu et al., 2010; Muttitanon and Tripathi, 2005). It is usually needed to recover the history of LULCC and to link the spatiotemporal changes to natural and human factors. Trajectory analysis can recover the history of LULCC and relate LULCC to natural and human factors (Wang et al., 2013; Yan et al., 2016b; Zhou et al., 2008). In addition, it can effectively analyze the trends of LULCC over time (Mertens and Lambin, 2000; Wang et al., 2012). Some studies have applied a trajectory analysis method to assess LULCC over time (Mertens and Lambin, 2000; Swetnam, 2007; Wang et al., 2012, 2013; Yan et al., 2016b; Zhou et al., 2008) and quantitatively study the effect of human and natural factors on LULCC (Wang et al., 2012; Yan et al., 2016b). Trajectory analysis was used to better understand marsh changes and study the impact of human activities on the marsh area changes in this study.

As the core part of wetlands, marshes are frequently or continually inundated with water and have emergent soft-stemmed vegetation adapted to saturated soil conditions. Based on the Ram-

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sar Classification system, Chinese scholars classify wetlands in the Sanjiang Plain, which includes the largest freshwater marshy wetland in China, as rivers, lakes, marsh, and paddy fields (Liu et al., 2013). This paper focuses on marshes and its related LULC types in the Sanjiang Plain.

Since the 1950s, marshes have undergone dramatic area loss and landscape fragmentation because of large-scale reclamation in the Sanjiang Plain. Many studies have evaluated spatiotemporal changes of marsh in some portions of the Sanjiang Plain or over the whole region (Li et al., 2002; Liu et al., 2013; Song et al., 2014; Wang et al., 2006; Zhou et al., 2009), but these studies mainly focus on years after the 1970s. Several studies have investigated the LULCC in the Sanjiang Plain since the mid-1950s (Liu et al., 2004a; Liu et al., 2014; Song et al., 2008; Wang et al., 2011). However, their classification system was relatively coarse (e.g., they did not separate marsh from wetland) to study marsh changes, and these studies paid less attention to changes in the landscape patterns of marshes. Considering large-scale reclamation began around the mid-1950s and reclamation mainly focuses on marsh conversion into croplands, it is necessary to examine the spatiotemporal changes in marshes in detail from the mid-1950s. Additionally, it is necessary to link the spatiotemporal changes to natural or human factors to better understand marsh changes in the study area. Based on multi-source data, including topographic maps, Landsat MSS (Multispectral Scanner), TM (Thematic Mapper) and OLI (Operational Land Imager), we separated marsh and paddy fields to analyze the dynamic change in marshes. Additionally, we studied the space configuration and fragmentation characteristics in the Sanjiang Plain from 1954 to 2015 using the landscape pattern indices. Additionally, a trajectory analysis method was used to trace the marsh changes for every location and to quantitatively study the effect of human activities and natural factors on marsh changes.

In this study, our objectives are as follows: (1) to analyze the land use and land cover change of marshes in the Sanjiang Plain from 1954 to 2015, (2) to study landscape change characteristics of marshes from 1954 to 2015 using the landscape pattern indices, and (3) to trace the paths of marsh changes and quantitatively separate the effect of human activities and natural factors using a trajectory analysis method.

2. Materials and methods

2.1. Study area

The Sanjiang Plain (Fig. 1) (45° 01′ 05″–48° 27′ 56″ N, 130° 13′10″–135°05′26″ E), a floodplain in northeastern China that encompasses the largest freshwater marshy wetland in China, is formed by alluviation of Amur, Ussuri and Songhua Rivers. The Sanjiang Plain covers an area of approximately eleven million hectares, covering twenty-three counties. The average annual temperature ranges from 1.4 to 4.3 °C in this area, and the warmest month is July, with a maximum average temperature of 22 °C, while the minimum average temperature is approximately −21 °C in January. The average annual precipitation is between 500 and 650 mm in the Sanjiang Plain. Located at mid-high latitudes, the Sanjiang Plain is sensitive to climate change. In addition to extensive human activity, it has also been experiencing natural disturbances, such as drought, flooding (Yan et al., 2001; Zhang et al., 2002) and global warming (Qian and Leung, 2007; Song et al., 2009).

2.2. Data sources and handling

The data sources of our study mainly include topographic maps (Zhang et al., 2006), Landsat MSS (Multispectral Scanner) images, Landsat TM (Thematic Mapper) images (Liu et al., 2005a; Liu et al., 2003; Zhang et al., 2006), and CBERS-1 (China-Brazil Earth Resources Satellite 1) data (Liu et al., 2003; Zhang et al., 2006). In addition, we used Landsat OLI (Operational Land Imager) images to update the LULC maps to 2015. Using the Cellular Automata (CA) model, the LULC map was reconstructed in 1954 based on topographic maps and other auxiliary data, and the accuracy was validated with aerial photos (Zhang et al., 2006). The Beijing 1954 Krasovsky_Albers projection was used to integrate different spatial data in our study. The standard methodology was used to produce LULC maps in other years (Liu et al., 2003; Liu et al., 2005b; Liu et al., 2010; Zhuang et al., 1999). One disadvantage of the post-classification comparison method is that the error of each individual classification will be amplified during spatial comparisons. To reduce the error caused by the post-classification comparison method, we delimited the outline of LULCC by comparison of the data source in different periods. We drew the line of LULCC by comparing remote sensing images in different times (Liu et al., 2005b). For example, we produced the LULC map in 1986 by comparing TM images between 1976 and 1986 with the references from the LULC map in 1976. More detailed data sources and methodology were described in our previous publications (Liu et al., 2005a; Liu et al., 2003; Yan et al., 2016b; Zhang et al., 2006; Zhuang et al., 1999).

Integrating multi-source data to obtain historical LULC maps is an economically feasible way to analyze LULCC in many cases. However, one problem with checking the classification accuracy is the lack of related historical land use data (Wang et al., 2006). To ensure the accuracy of our data, extensive field survey data, historical data consisting of aerial photos, Heilongjiang Statistical Yearbook and field site data, and interviews with local people as well as experts were used to check the interpretation accuracy in the study area (Liu et al., 2005a; Liu et al., 2003; Liu et al., 2010). For example, we performed extensive field surveys in 1999/2000 and 2015. Considering that marshes are always located in a remote area where traffic is usually not very convenient, unmanned aerial vehicle (UAV) images were also used to validate the accuracy of our interpretation results in 2015. UAV images are relatively new for acquiring high-resolution remote sensing measurements of Earth surface (Hugenholtz et al., 2013). For example, UAV aerial photos, flown at an altitude of 215 m can produce images with a resolution of 5–6 cm (Rango et al., 2009). UAV images have been used to monitor forest (Saari et al., 2011), rangeland (Rango et al., 2009), and soil erosion (Wang et al., 2016) in recent years. The detailed information provided by UAV images (Fig. 2) was used in this study to validate and correct the interpretation results. Unmanned aerial vehicles can reach places where humans cannot reach, which is convenient for marsh surveys. For example, UAVs can detect marshes that we cannot see due to forest barriers in our field validation. In our study, a battery-powered quadrocopter type Phantom 3 Professional (DJI, Shenzhen, China) was used to acquire the UAV images (Fig. 2) in the airborne campaign in September 2015. The quadrocopter has four rotors with a weight of 1280 g, and it can maintain flight for 23 min (Wang et al., 2016). Visual interpretation, which was the main method to produce LULC maps in our study, may be labor intense and time consuming, but it can ensure high accuracy of the LULC result. With 1990–2000 as an example, the average LULC classification accuracy was 92.9%, and the LULCC detection accuracy was 97.6% (Liu et al., 2005b).

2.3. Data analyses

2.3.1. Transition probabilities index

The transition probabilities matrix P_{ij}^t (Eq. (1)) was used to analyze LULCC between periods in our study (Yang et al., 2014):

$$P_{ij}^t = \left(S_{ij}^t / S_i^t\right) \times 100\%, \quad (1)$$