QUANTIFYING THE IMPACTS OF URBANIZATION ON MANGROVE FORESTS IN CHINA

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ABSTRACT: Mangroves grow in tropical and subtropical coastal areas, which have enormous ecological significance to environment. China has experienced rapid urbanization especially in coastal areas. Since 1970s, there has been great efforts to protect mangrove ecosystem by establishing nature reserves. This study explores the association between urbanization and mangroves changes in China in 1973-2015, the effectiveness of conservation policy was also identified. Existing satellite-derived datasets were employed to present the changes in mangroves and urbanization. Results showed that the conservation policy and establishment of nature reserves have made great achievements to mangrove conservation and restoration. After the 1990s, mangroves were relatively stable in the regions where experienced rapid urban expansion.

1. INTRODUCTION

Mangrove forests are a group of shrubs and trees that live in the coastal intertidal zones in the tropical and subtropical regions between mainly between latitudes 30° N and 30° S (Giri et al., 2011). Mangrove forests provide unique ecological environments that can protect coastline against flood waves and Tsunamis, and filter pollutants from water. Mangrove forests are productive ecosystems that serve as breeding grounds for marine species, such as fish, shrimp, crabs, and other shellfish. They also provide fuel and building materials for local communities (Giri et al., 2008). The remaining mangrove forests are under pressure from both natural and anthropogenic forces (Alongi, 2002; Giri et al., 2008; Giri et al., 2011). The natural forces mainly include climate change, sea level rise and hydrological alterations. However, the conversion of mangrove forests to aquaculture, aquaculture and urban construction are major anthropogenic causes of deforestation. There has been an increasing interest in the urbanization's impact on mangroves. The impact of urbanization of mangroves has already been studied by many researchers using qualitative analysis. Lee et al. (2006) indicated impervious surfaces can modify the hydrological and sedimentation regimes, and the dynamics of nutrients and chemical pollutants, which influence the structure and function of coastal wetlands. As remote sensing technique has been widely applied in mangrove investigation using various machine learning methods, several researches extracted land-use and land-cover change from satellite imageries and calculated the area of conversion from mangrove forests to other land use type, such as mudflat, agriculture, aquaculture, and urban construction (Buitre et al., 2019; Liu et al., 2018; Jia et al., 2014; Thomas et al., 2017; Wan et al., 2018; Wan et al., 2020; Zhang et al., 2018). Ai, Ma, Zhao and Zhang (2019) conducted correlation analysis and revealed the influence of urban expansion on mangroves in Guangdong, China. As highlighted by Vaz (2014), the decrease in mangroves is highly correlated with urban expansion in Mumbai, India.

However, there is a lack of regional quantitative studies on exploring the impact of urbanization on mangrove cover in China. This study aims to comprehensively investigate the associations between urbanization and mangrove changes, and the effectiveness of conservation policy and nature reserves in China since 1970s.

2. METHODS

2.1 Study area

Mangrove forests in China are located in tropical and subtropical coastal areas, spanning latitudes 18°12′ to 28°25′ N and longitudes 108°01′ to 121°30′ E. The study area is mainly located in the Southeast coastal regions, including the provinces of Zhejiang, Fujian, Guangdong, Hainan, Taiwan, and regions of Guangxi Zhuang Autonomous Region (referred as Guangxi), Hong Kong, and Macau. The extent of mangroves has subtropical and tropical monsoon climates. Guangdong Province has the largest cover of mangroves, followed by Guangxi and Hainan Province. More than 20 mangrove nature reserves were established in China since 1970s. Figure 1 shows the spatial distribution of total mangroves in China from 1973 to 2015 and approximate location of 25 nature reserves.

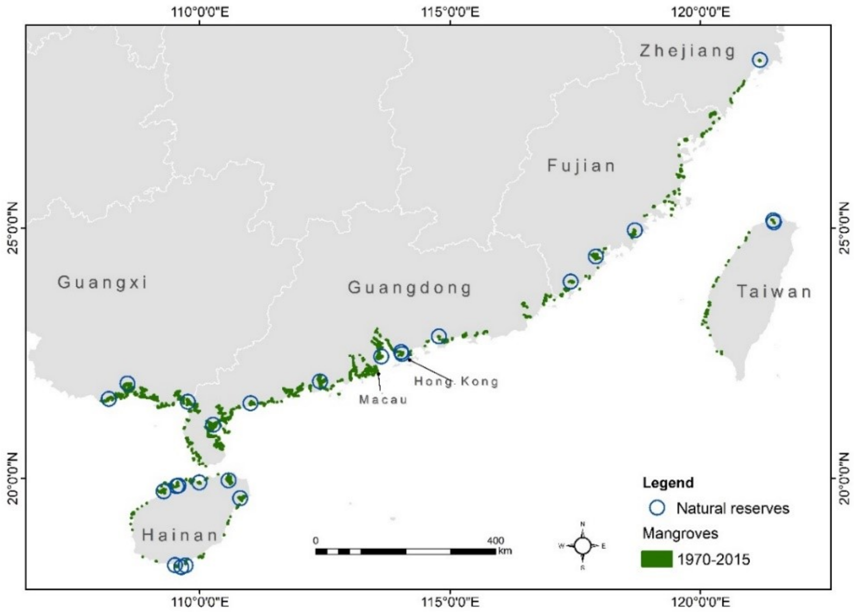

Figure 1. The spatial distribution of total mangroves in China from 1973 to 2015

2.2 Datasets

The datasets of mangrove forests in China were obtained from Jia et al. (2018), which present the spatial distribution of mangroves in 1973, 1990, 2000, and 2015. The datasets were interpreted from Landsat images, with overall accuracies 78%, 87%, 89%, 94% and kappa coefficients 0.71, 0,78, 0,85, 0.91, respectively. The Global Human Settlement Layer (GHSL) produced GHSL built-up datasets (Corbane et al., 2019) and GHSL population datasets (Freire et al., 2016), which is derived from Landsat image collections. In this study, these two datasets covering mangrove extent were collected to represent the urbanization in 1975, 1990, 2000, 2014. The GHSL built-up datasets are at 30-m spatial resolution. GHSL population datasets are at 9 arcsec resolution, which depicts the number of residential population estimates per cell. The urbanization was characterized by analyzing the built-up areas and population density. GHSL datasets in 1975 and 2014 were used to represent built-up and population in 1973 and 2015.

2.3 The association rules mining technique

Association rules mining (ARM) is a popular machine learning and data mining method to discover correlation or patterns in large database. Agrawal, Imieliński and Swami (1993) firstly introduced ARM to analyze sales transactions and explore customer's purchasing behaviour. Then, it has been widely used in many fields, traffic crashes, hydrology, disease, climate, urban study (Mennis and Liu, 2005; Xu et al., 2018; Zhong et al., 2019).

Let $I = \{ i_1, i_2, i_3, \dots, i_n\}$ be a set of all items and $T = \{ t_1, t_2, t_3, \dots, t_m\}$ be a set of transactions in database, each transaction t contains a subset of the items in I. An association rules can be expressed as the form $X \rightarrow Y$, where X and Y are disjoint itemsets, i.e., $X \in I$, $Y \in I$, $X \cap Y = \varnothing$. X is called antecedent or left-hand-side and Y is consequent or right-hand-side. In the market basket analysis, the rule $X \rightarrow Y$ indicates that people who buy X are also likely to buy Y.

As shown in equation (1), equation (2), equation (3), Support, confidence, and lift indicators are used to evaluate and measure the quality of rules. Support measures how frequently the itemset appears in the dataset and the significance or importance of an itemset. Mathematically, support is the probability of co-occurrence of itemsets X and Y. Confidence is the conditional probability of occurrence of the Y in a transaction given that it also contains X. Lift is defined as the ratio of the observed joint probability of X and Y to the expected joint probability if they were statistically independent. A lift value greater than 1 means that the occurrence of X has increased the probability of the presence of Y. If X and Y are independent, the lift value will be 1. The rules with greater support, confidence and lift values indicate stronger associations.

$$Support(X \rightarrow Y) = P(X \cup Y) \quad range: [0, 1] \tag{1}$$

$$Confidence\ (X \rightarrow Y) = \frac{Support\ (X \rightarrow Y)}{Support\ (X)} = \frac{P(X \cup Y)}{P\ (X)} \quad range: [0, 1] \tag{2}$$

$$Lift\ (X \rightarrow Y) = \frac{Support\ (X \rightarrow Y)}{Support\ (X) \times Support\ (Y)} = \frac{P(X \cup Y)}{P(X) \times P(Y)} \quad range: [0, \infty] \tag{3}$$

In this study, the association rule mining was conducted at grid level. Each grid contains the attribution of outside or inside nature reserve, the changes in built-up areas and mangrove forests, and the population density for corresponding period. As the changes in built-up areas and mangrove forests, and the population density data are numeric data, they were converted to categorical data type. As shown in Table 1, each indicator was classified into several categories, which regarded as items i in the association rule mining, the grid with the combination of categories was considered as one transaction t. The threshold values for Support, Confidence and Lift were set as Support > 1%, Confidence > 30%, Lift > 1. Association rule mining was conducted for 1973-1990, 1990-2000, 2000-2015 three period.

Table 1. Indicators and categories used in association rule mining

Indicator	Abbreviation	Category	Definition
Nature reserves	NR	NR0	Outside nature reserve
		NR1	Inside nature reserve
Built-up areas change	BUC	BUC0	No built-up
		BUC1	Increase <10 ha
		BUC2	Increase ≥10 ha
Mangrove change	MC	MC0	Chang ± 10 ha
		MC1	Decrease ≥ 10 ha
		MC2	Increase ≥ 10 ha
Population density	PD	PD0	No people or <10 people/km^2
		PD1	≥ 10 people/km^2

3. RESULTS AND DISCUSSION

3.1 Mangrove changes in China

As presented in Jia et al. (2018), a dramatic decrease of mangroves occurred from 1973 to 1990, after which the rate of decrease slow down gradually from 1990 to 2000. Then, there was a gradual rise from 2000, reaching 22419 ha in 2015. Overall, the areal extent of mangroves dropped from 488012 ha to 22419 ha over the period from 1973 to 2015. The areal extent of gained, lost and intact mangroves over different periods in China were also shown in Figure 2. Between 1973-2015, there was a total loss of 40434 ha of mangrove forests in China. The decrease in mangrove extent was offset by a gain of 14932 ha of new mangroves, resulting in a net change of 25501 ha and gross change of 55366 ha. There were also 7741 ha mangrove maintained from 1973 to 2015. Comparing the three periods, 1973-1990 had the largest net loss, of 37618 ha, followed by 1990-2000 with 13161 ha lost. The mangrove loss was much greater than the mangrove gain during 1973-1990 period. From 2000 to 2015, the area of mangrove gain exceeded mangrove loss, showing an increase trend of net change in mangrove extent.

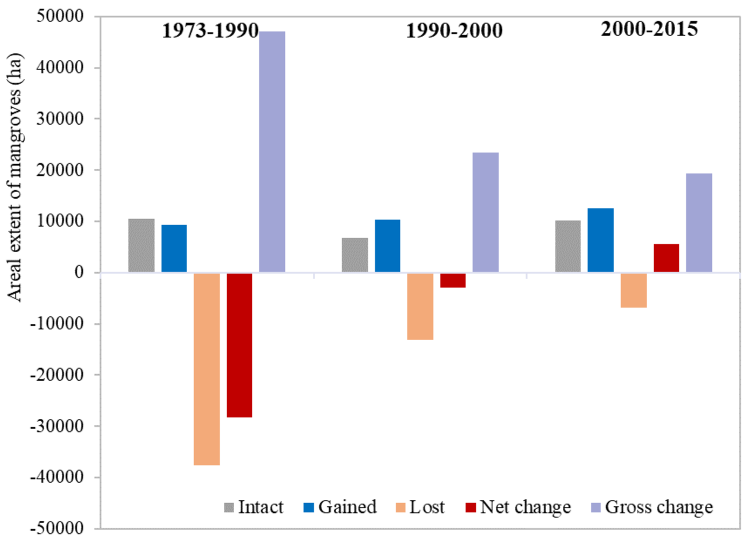

Figure 2. Net changes and gross changes (gained, lost) in mangrove extent for different periods

3.2 Associations between urbanization and mangroves changes

Selected association rules with a confidence level of higher than 0.55 during the whole period were shown in Table 2. From 1973-1990, Rule #1{BUC1, NR1, PD1}→{MC0} indicates that inside or near nature reserves, if the built-up increased slightly (<10 ha) and population density in 1990 is larger than 10 people/km2, it is likely that the mangrove forests changed little (± 10 ha) during this period. Rule #1, 2 show the strong association between NR1 and MC0. These rules indicate that mangrove changed slightly inside or near nature reserves, even rule#1, 2 involve the circumstances of built-up areas increased slightly and large population density. During 1990-2000, the association between BUC1 and MC0 is discovered based on rule# 7, 8, 10. The association between BUC2 and MC0 is more significant with higher confidence values. All the rules involved NR0 shows the strong association between NR0 and MC0, which means mangrove changed slightly outside nature reserves in 1990-2000. During 2000-2015, Rule# 11, 12 show the strong association between BUC2 and MC0, which is the same as the rules for 1973-

1990 and 1990-2000 periods.

Table 2. Association rules between urbanization and mangroves

Rule ID	Policy	Urbanization	Mangroves	Confidence	Period
1	NR1	BUC1, PD1	MC0	0.571	1973-1990
2	NR1	BUC1	MC0	0.558	
3	NR0	BUC2, PD1	MC0	0.752	1990-2000
4	NR0	BUC2	MC0	0.75	
5	NR0	PD0, BUC2	MC0	0.742	
6	NR0	PD1	MC0	0.643	
7	NR0	PD0, BUC1	MC0	0.624	
8	NR0	BUC1	MC0	0.62	
9	NR0		MC0	0.619	
10	NR0	PD1, BUC1	MC0	0.617	
11	NR0	BUC2, PD1	MC0	0.752	2000-2015
12	NR0	BUC2	MC0	0.75	
13	NR0	PD0, BUC2	MC0	0.742	
14	NR0	PD1	MC0	0.643	
15	NR0	PD0, BUC1	MC0	0.624	
16	NR0	BUC1	MC0	0.62	
17	NR0		MC0	0.619	
18	NR0	PD1, BUC1	MC0	0.617	

4. CONCLUSIONS

In this study, the association between urbanization and mangroves changes was investigated in China, the role and effect of conservation policy was also investigated. The results show that: (1) For 1973-1990 period, the conservation effort of nature reserves has been evaluated. Within the protected areas, the mangroves changed slightly and built-up areas gained little. However, outside the nature reserves, mangrove reduction occurred where even no built-up area and no settlement exist, and mangroves were stable in rapid urbanization regions; (2) For 1990-2000 period, in general, mangroves changed slightly outside the nature reserves no matter the degree of urbanization process, it may be due to the fact that people raised their awareness of protecting mangroves and wetlands; and (3) For 2000-2015 period, mangroves increased dramatically, which may due to the implementation of mangrove conservation and restoration. Same as last period, mangroves were stable outside the nature reserves, which is more significant where the built-up areas increased a lot.

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