URBAN LAND USE LAND COVER CHANGE AND ITS DRIVERS: A CASE STUDY OF ZHANGYE CITY IN NORTHWEST CHINA

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ABSTRACT

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Comparing to the central and east coastal regions of the country, China's northwest is less developed. However, land use and land cover (LULC) changes in this region are also worthy of study because of its resource scarcity and thus its sustainability. The objective of this study was to analyze the LULC changes in Zhangye City over the past 17 years and determine the major drivers of these changes, by integrating remote sensing derived land use/cover information with socio-economic analyses. The Landsat imagery was processed for every two years from 2001 to 2017 in Google Earth Engine environment, and then classified into land use and land cover maps using the random forest classification method. To improve accuracy, NDVI, NDWI, DEM and GLCM were incorporated in the classification. These LULC maps were then used in change detection analysis to quantify the rate of urban expansion and land use changes. The resulting land use change matrices were then used in logistic regression model to determine key socio-economic factors. The correlations between LULC changes and published policies were further analyzed to understand policy implications. The results confirmed the following: a) The Zhangye city went through a dramatic land use change from 2001 to 2017; b) Its urban built-up, water surface, cropland, grassland and forest areas all increased at the cost of surrounding bare lands; and c) The city planning and national government’s five-year plan were the main drivers of urban expansion and economic growth, while environmental regulations determined the cropland, grassland and forest expansions. The findings from this study seem to suggest that Zhangye should focus on ecological conservation, environment restoration, and eco-tourism as a pillar of local economic growth.

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CHAPTER 1: INTRODUCTION

With the rapid urbanization around the globe, more than half of the world's population lives in cities, and this trend is likely to continue in the coming decades (United-Nations, 2019). Population growth in urban areas leads to serious environmental problems, including water quality degradation and air pollution (Maimaitijiang et al., 2015) and further effects on ecosystem services (Kuang et al., 2016). Land use and land cover (LULC) change with continued urbanization is a global issue with paramount socio-economic and environmental implications (Maimaitijiang et al., 2015). To promote sustainable development, the Joint International Land Use/Cover Change Project of the International Geosphere & Biosphere Program (IGBP) and the International Human Dimensions Program (IHDP) on Global Environmental Change undertook the monitoring, interpreting, modeling, and prediction of LULC change extensively at global and regional scales (Land Use and Cover Change. International Project Office & International Human Dimensions Programme on Environmental Change, 1999).

During the past several decades, most metropolitan areas in China have experienced unprecedented expansion, mainly due to economic growth, overall population growth and emerging trends of immigration from rural to urban areas (Kuang et al., 2016). The urban population in China grew from 453.0 million (35.88%) in 2000, 658.5 million (49.23%) in 2010, and 803.6 million (57.96%) in 2017 (World Bank, 2019). As in other parts of the world, the Chinese urbanization process is also characterized by regional differences and inequalities, which are mainly caused by economic developments. The region of this study, Northwest China, is generally considered as the least developed part of the country; its urban population is comparatively much lower than those in the eastern and central regions of the country. Even in the least developed Northwest China, the urban population increase is drastic (from 31.4% in 2000 to 52.1% in 2017).

However, the rate of increase is much less than the averages of the whole country (National Bureau of Statistics of China, 2019). Furthermore, the inequalities of urbanization are also existed across different provinces in Northwest China, and even more evident within provinces. For example, among the 12 prefecture-level cities in Gansu Province, the difference of the ratio of urban to total population in 2017 was as large as 2 - 3 folds (Gansu Development Yearbook, 2018).

Northwest China contains three provinces (Shaanxi, Gansu, and Qinghai) and two autonomous regions (Xinjiang and Ningxia), with a total population of around 95 million within an area of about 3.04 million square kilometers. Generally speaking, the Northwest China has the least population density compared to other regions of the country. Besides, most of the Northwest China are in arid and semi-arid regions, and the water resources are comparatively scarce. The shortage of water resources and low population density limit the economic development of this region. In 2005, Northwest China's GDP accounts for 4.43% of total national GDP, while in 2018, this number increased only to 5.74% (National Bureau of Statistics of China, 2019). As mentioned above, slow economic development limited the urbanization of Northwest China, which, in turn, affected the regional development. Thus, in 2001 the Central government put forward the China Western Development policy to help improve the development of western China, including the Northwest China.

The primary area of this study, the Heihe River Basin (HRB), administratively covers parts of three provinces, Qinghai, Gansu, and Inner Mongolia. HRB is the second largest inland river basin in the arid region of Northwestern China, with an area of approximately 1,432,000 km^2 (Li et al., 2013). The upper reaches of the river basin are mainly in the Qilian Mountain area. The middle reaches, the major part of the basin, is in the middle part of the Hexi corridor, an arid region with a series of oases distributed along the river. These are mainly the areas belonging to the prefecture cities of Zhangye and Jiuquan of Gansu Province. The largest and most famous oasis in the Heihe River Basin is the Zhangye oasis, which has been cultivated for more than 2000 years (Li et al., 2015). The mean annual runoff of the Heihe River is approximately $15.8*10^8$ m^3(Li et al., 2013). Because of this relatively abundant water resources, this river has become a significant water resource of the region and, therefore, its middle reaches become an important commodity grain base in northwestern China. The lower reaches of HRB are mainly in the Ejin Banner, a small oasis but essential ecological and economic region belonging to the Inner Mongolia Autonomous Region.

Zhangye Region's administration system was converted from a prefecture to a prefecture-level city by the State Council in 2002 when the implementation of China Western Development Policy started. Since then, Zhangye began to enter into a very rapid economic development period as well as the continuous increase of population and the expansion of farmland (Hu et al., 2015). The prefecture-level city Zhangye is the only region entirely within the HRB. The dramatic increase in water consumption in the middle reaches of HRB resulted in a sharp decline in the amount of water entering the downstream areas, leading to the drying up of two-terminal lakes and the death of riparian *populus euphratica* forests in the Ejin Banner region (Cheng et al., 2014). To restore the deteriorated ecosystems, the Ecological Water Diversion Project (EWDP) was implemented since 2000 (Hu et al., 2015). To reallocate the limited water resources rationally, it is crucial to understand the characteristics of LULC changes in the regions belonging to Zhangye City, particularly the Zhangye oases. Substantial efforts have been made (Cheng et al., 2014 & Hu et al. 2015) to study the most significant LULC change using Landsat TM/ETM images of 2000, 2007 and 2010, and found the continuous farmland expansion (about 12% during those 12 years) in the middle reaches of HRB; They also stressed some critical effects on the Zhangye oases after the implementation of EWDP and the importance of LULC changes study in the promoting of the policy. Studies (e.g., Chen, 2018) have also shown that there is an increasing trend in cropland, forest and grassland in central counties of Zhangye during 2001 to 2016, some clear trends of urbanization (the urban area of Zhangye increased 41.5 km^2) and its effects on the change of regional cultivated lands. Another study by Cao et al., (2015) stressed the impact of human activities on the LULC changes of the middle reaches of HRB during 2002 to 2011 and concluded that the Ganzhou district of Zhangye did have an increase in built-up land, transportation, and water, and the entire district experienced a transformation to non-agricultural land uses. Xiao & Xiao (2003) discussed the history of the Heihe River Basin and the drivers for its changing oasis. Liao, Wang, & Xue (2012) addressed the oasis evolution along the entire HRB during the past fifty-five years, including the driving factors. They found that there is an increasing growth in vegetated areas after 2000 along with an increase in surface water area, where both human and environmental factors contributed to the change.

Previous studies mentioned above are just a few examples of LULC changes and urbanization in the Heihe River Basin. There have been several case studies on the trend of urban expansion in China, but the majority of them focused on eastern, central, and southern parts of the country, the more developed regions and most significant urbanized regions of the country; few concerned about the Northwest China and even fewer focused on its arid regions including the Heihe River Basin. Furthermore, most studies used only a few images of high-resolution satellite imagery, such as Landsat TM/ETM, for the trend analysis of 10 to 20 years, mainly because those data, data products, and relevant powerful data processing tools (such as the Google Earth Engine) have only become freely available in the past few years. As I stressed (and will stress again later), Heihe River Basin, especially its middle reaches, the Zhangye Oases, is not only important and interesting from a historical perspective but also for local, provincial, and nationally in the present day. The few studies on LULC changes and urbanization for the Zhangye region conducted so far either lack a continuous long-term trend based on high-resolution satellite images available recently or lack a comprehensive analysis concerning the driving forces like socio-economic development and policy implementation. It is the aim of this study to fill these gaps, focusing on a more apparent trend of LULC changes among some districts and counties of Zhangye, and a clearer understanding of the driving factors behind these changes, particularly, the effect of government policies on the urban expansion

Various techniques are commonly used for analyzing land use/cover changes. Remotely sensed data holds an advantage in monitoring and detecting land cover change because of the broad spatial coverage, high time resolution, and wide availability (Zurqani et al., 2018). Long-term satellite images are essential to help us understand land cover dynamics and are significantly useful for detecting changes in cropland and urban expansions. Previous studies on vegetation change detection concentrated on using two or more dates of Landsat images at intervals of five or ten years. Since the USGS made their entire Landsat archive freely available to the public in 2008, several studies on continuous long-term forest change monitoring were reported (Zurqani et al., 2018). The Landsat archive contains more than three decades of earth observation images and provides a unique opportunity to monitor successive annual land cover changes at high spatial and temporal resolutions (Huang et al., 2017). There are wide varieties of classification methods and techniques adopted for land use and land cover analyses from remote sensing data, such as decision tree algorithms (Friedl and Brodley, 1997), support vector machines (Petropoulos, Kalaitzidis, & Prasad Vadrevu, 2012), random forest algorithms (Teluguntla et al., 2018; Zurqani et al., 2018), and several other machine learning algorithms (Xiong et al., 2017). However, generating remote sensing classification products required specialized and often expensive software, which may present particular hurdles to research and conservation programs (Jacobson et al., 2015). Moreover, there is a need for easily created inexpensive datasets that can be confidently be used in conservation planning (Watson et al., 2014).

The Google Earth Engine (GEE) is a new cloud-based platform designed for researchers to access high-performance computing resources and extensive geospatial data online (Gorelick et al., 2017). It contains more than forty years of free satellite data that researchers can easily use without downloading them in the first place. Google Earth Engine has deployed many servers around the world that the scientific community could use for parallel processing of satellite images and algorithms (Dong et al., 2016). Jacobson et al. (2015) identified anthropogenic land cover from high-resolution imagery across East Africa using the Google Earth platform. Dong et al. (2016) mapped paddy rice planting area in northeastern Asia with Landsat images, phenology- and pixel-based paddy rice mapping (PPPM) algorithm, and the GEE cloud computing platform. Huang et al. (2017) classified the land covers in Beijing in 2015 using Landsat images with GEE cloud calculation and mapped its major LULC changes. Xiong et al. (2017) produced accurate reference cropland layers of continental Africa based on time series of Moderate Resolution Imaging Spectroradiometer (MODIS) normalized difference vegetation index (NDVI) data using GEE cloud computing. Teluguntla et al. (2018) mapped a 30-m cropland extent over Australia and China from Landsat-8 data by using a pixel-based supervised random forest machine learning algorithm executed on the GEE cloud computing platform. Zurqani et al. (2018) produced the land cover maps over the Savannah River basin using random forest classification method based on GEE.

The logistic regression model has been widely used to detect the drivers for land use and land cover change in various landscapes in different geographical and climatic regions. In previous studies, Wu (1998) used the logistic regression model on Chinese cities and found that accessibility and socioeconomics were the main factors of urban development in Guangzhou after the reforms. Verburg et al. (2004) applied this model to cities in the Netherlands. They concluded that expansions of residential, industrial or commercial, and recreational land were driven by a combination of accessibility measures, spatial policies, and neighborhood interactions. Similarly, Braimoh and Onishi (2007) employed a logistic model regression and identified the driving factors that were responsible for residential and industrial or commercial development in Lagos, Nigeria. In this study, the logistic regression model is applied as well to locate the main driving factor of urban expansion among social-economic factors.

The objective of this study is to map land use and land cover changes and analyze its driving forces in the Zhangye City over the past 17 years by integrating remote sensing derived land use/cover data with socio-economic data. The main efforts of this thesis are to (1) produce a time series land use and land cover data from 2001 to 2017 using a new geospatial technology of GEE and Landsat satellite data; (2) produce a series of land use and land cover conversion matrix and analyze the driving forces to LULC changes with the socio-economic data; (3) apply the spatial logistic regression to model the probability of LULC conversion as a function of spatial independent variables.

CHAPTER 2: STUDY AREA AND DATA

2.1 Study area

Zhangye City (centered at about 100°27′11″E, 38°55′55″N) is located in the central Gansu Province along the Hexi Corridor in northwestern China (Figure 1), with a total area of 38,592km^2 (Bureau of Statistics of Zhangye, 2017). Zhangye City governs one district (Ganzhou) and five counties (Linze, Minle, Gaotai, Shandan, and Yugur Autonomous County of Sunan) in its administrative level. Its urban core is located at the Ganzhou district, where streams, sunlight, and fertile soil make it an important agricultural center in the middle reaches of HRB. The mean temperature from May to September is 7.31 °C (Bureau of Statistics of Zhangye, 2017).

The Heihe River originates in the mountain cryosphere in the Qilian Mountains and flows northward and disappears in terminal lakes in the Gobi Desert (Li et al., 2018). The landscape of Heihe River Basin changes from glaciers and alpine biomes in the upstream region to steppes and agricultural ecosystems in the midstream region to riparian ecosystems surrounded by vast areas of desert in the downstream region (Li et al., 2013). This study focused on the midstream region, including Zhangye City, Gansu Province.

According to Zhangye's Statistical Yearbook in 2001, the total population of Zhangye City was around 1.25 million and the urban residents were 230,274. In 2017, the population of Zhangye City decreased to 1.22 million, while the city residents increased dramatically to 562,500 (Table 1). It is clear from these numbers in Table 1 that Zhangye City has gone through the process of urbanization during the past seventeen years. Along with the urbanization process, Zhangye City has become a region where the agricultural income has become predominant compared to other income sources including the industries and tourism, which have dramatically increased after 2009.

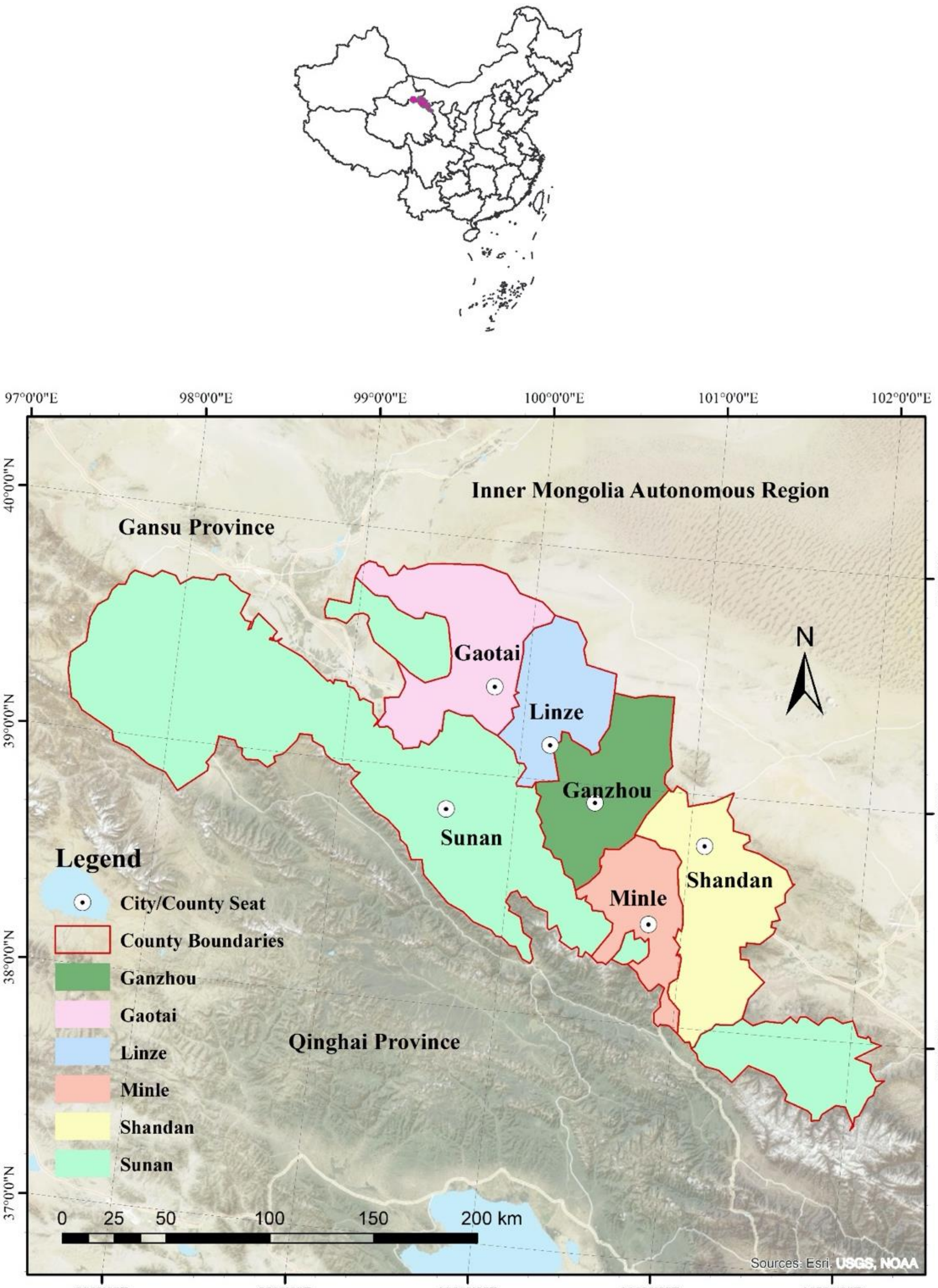

Figure 1. The study area – Zhangye City and its districts.

Compared with the built areas in the Zhangye region in 2001, the current built-up areas have been expanded dramatically during the last seventeen years (Table 1), indicating a considerable expansion of urban areas at Zhangye City. Additionally, the agricultural production had increased from 3.9 billion RMB in 2001 to 17.8 billion RMB in 2017. Therefore, it is crucial to study the urban expansion and its driving factors as well as agricultural land use change in this region.

Table 1. Summary of social-economic data in Zhangye City from 2001 to 2017

Economic data	Unit	2001	2005	2009	2013	2017
Population	100,000Person	12.57	12.70	13.03	12.10	12.29
City resident	100,000Person	2.30	3.13	3.57	4.68	5.62
Non-city Resident	100,000Person	10.27	9.58	9.46	7.41	6.67
Temperature/ Avg Year	°C	7.12	6.85	7.55	7.65	7.78
Precipitation/Avg Year	mm	164.20	229.47	204.58	179.07	250.20
GDP	billon RMB	6.88	11.08	19.21	33.60	40.41
Average income of city residents	RMB	5239.00	7314.00	10153.00	15877.00	23309.00
Average income of non-city residents	RMB	2931.00	3947.00	4989.00	8465.00	12612.00
Agricultural production	billion RMB	3.90	5.89	9.13	15.49	17.81
Food Production	1000 tons	735.55	873.04	1029.11	1280.39	1376.39
Industrial added value above designated	billion RMB	0.75	1.50	4.56	7.05	4.18
Industrial Total value above designated	billion RMB	2.15	4.19	11.30	26.46	24.37
Built area - accomplished	10,000 m^2	73.6	87.84	131.25	365.71	411.31
Total Number of tourists	100,000Person	0.25	8.13	11.22	66.27	25.99
Water usage	100 million ton	21.81	23.41	24.41	24.02	21.71
Tourist income	1 million RMB	110.00	290.00	415.00	3580.00	15730.00
Road Mileage/	kilometers	1837.00	1968.00	2625.00	10862.00	
People with at high school diploma	100,000Person	1.29	1.63	2.29	2.81	3.21

2.2 Data collection and processing

2.2.1 Remote sensing images and processing

GEE is a cloud-based platform that makes it easy to access high-performance computing resources to process geospatial datasets online (Gorelick et al., 2017). GEE provides researchers seamless satellite data imagery free of charge. Moreover, there is no need to download the data. GEE facilitates a quick analysis platform using Google's computing infrastructure. Pre-processed Landsat images are available through GEE and can be used to assess LULC changes. GEE provides online access to Landsat archives of the U.S. Geological Survey (USGS).

Landsat images for the years of 2001, 2005, 2009, 2013, and 2017 were selected based on the availability for the study area in GEE (Table 2). All the Landsat images were selected from the surface reflectance products. All the Landsat data have been atmospherically corrected. To improve the classification accuracy of the land use and land cover results, additional indices were introduced, including the normalized difference vegetation index (NDVI) and a normalized difference water index (NDWI) thirty-two-day composite, as well as the Digital Elevation Model (DEM).

Table 2. Details of the Landsat images used in this study (Spatial Resolution as 30 meters)

Data Layer	Source	Year
USGS Landsat 5 Surface Reflectance Tier 1	GEE data provided by USGS	2001,2005,2009
USGS Landsat 7 Surface Reflectance Tier 1	GEE data provided by USGS	2013
USGS Landsat 8 Surface Reflectance Tier 1	GEE data provided by USGS	2017
Landsat 5 TM Collection 1 Tier 1 32-Day NDVI Composite	GEE data provided by Google	2001,2005,2009
Landsat 7 Collection 1 Tier 1 32-Day NDVI Composite	GEE data provided by Google	2013
Landsat 8 Collection 1 Tier 1 32-Day NDVI Composite	GEE data provided by Google	2017
Landsat 5 TM Collection 1 Tier 1 32-Day NDWI Composite	GEE data provided by Google	2001,2005,2009
Landsat 7 Collection 1 Tier 1 32-Day NDWI Composite	GEE data provided by Google	2013
Landsat 8 Collection 1 Tier 1 32-Day NDWI Composite	GEE data provided by Google	2017
SRTM Digital Elevation Data	GEE data provided by NASA/USGS/JPL	2000

2.2.2 Socio-economic data

Socio-economic data and policy information were also collected for this study (Table 3). First, the five-year plan information by the National Development and Reform Commission that aims for the western development were collected. These five-year plans are from the 11th to the 13th, the first one being published in 2006, and the latest being published in 2016. The provincial-level data and policies were also collected, such as five-year plans and population census. The 10th to the 13th five-year plans of Gansu province were published by Gansu Province’s People's Congress from 2001 to 2016. Other provincial policies included the Gansu’s 2000 and 2010 population census published by Gansu’s provincial census office. Furthermore, five-year plans published by the Zhangye People's Congress, from the 10th to the 13^{th,} were collected. Some municipal level data were collected for this study, such as the Zhangye Statistical Yearbook from 2001 to 2017 published by the Bureau of Statistics of Zhangye. 2001, 2005, 2009, 2013 and 2017 Statistical

Yearbook corresponded to the date when Landsat images were available. Finally, Zhangye's masterplan for 2004-2020 and Zhangye's masterplan for 2012-2020 published by the Bureau of Natural Resources of Zhangye were also obtained.

Table 3. Descriptions of the socio-economic data used in this study

Title	Published Year	Level of governance
The 11th Five-Year Plan for the Large-scale development of western China	2006	National
The 12th Five-Year Plan for the Large-scale development of western China	2011	National
The 13th Five-Year Plan for the Large-scale development of western China	2016	National
The 10th Five-Year Plan for National Economic and Social Development of Gansu Province	2001	Provincial
The 11th Five-Year Plan for National Economic and Social Development in Gansu Province	2006	Provincial
The 12th Five-Year Plan for National Economic and Social Development of Gansu Province	2011	Provincial
The 13th Five-Year Plan for National Economic and Social Development of Gansu Province	2016	Provincial
Gansu Province Population Census in 2000 and 2010	2002. 2012	Provincial
The 10th Five-Year Plan for National Economic and Social Development in Zhangye Prefecture	2001	Municipal
The 11th five-year plan for national economic and social development in Zhangye City	2006	Municipal
The 12th Five-Year Plan for National Economic and Social Development in Zhangye City	2011	Municipal
The 13th Five-Year Plan for National Economic and Social Development in Zhangye City	2016	Municipal
Zhangye Statistical Yearbook 2001, 2005, 2009, 2013, and 2017	2002, 2006, 2010, 2014, 2018	Municipal
Zhangye Masterplan 2012-2020	2014	Municipal
Zhangye Masterplan 2004-2020	2004	Municipal

CHAPTER 3: METHODOLOGY

3.1 Land use and cover classes and training samples

In this study, seven land use-cover classes were identified: 1) Grassland, 2) Forest, 3) Cropland, 4) Water Body, 5) Built-up, 6) Barren Land, 7) Glacial and Snow. In this study, the wetland was treated as water body class. The classification system is consistent with the first level of the classification scheme developed in the HRB by Wang et al. (2014).

An accurate training/validation sample set is essential in land use and land cover classification using remote sensing data (Congalton, 1991). In this study, about 1100 sample polygons were selected manually from high-resolution Google Earth imagery for the years of 2001, 2005, 2009, 2013, and 2017, and these samples were selected independently from each other. For each year, the sample pixels were selected evenly from all seven (7) land cover types except for snow and glacial since they are masked out in the first place when processing the satellite imagery. A total of 60% of the training samples were randomly selected for image classification and the remaining 40% were retained for validation.

3.2 Image classification method and accuracy assessment

GEE provides various built-in classification methods. Supervised machine learning classifiers such as Classification and Regression Trees (CART), Support Vector Machines (SVM), and Random Forest (RF) are progressively used to classify remotely sensed data. After comparing the three classification algorithms' performance for the study area with the same training data, and the RF classifier algorithm performed the best result. Similar findings have been reported by Belgiu and Csillik (2018). Furthermore, the RF classifier has been effective in the classification accuracy even when applied to analyze data with strong noise (Zurqani et al., 2018). Therefore, in this study, the RF classifier algorithm was used to classify the Landsat data in the study area.

RF is an ensemble classification algorithm, which uses bootstrap aggregating or "bagging" to create a classification using multiple decision trees. There are only two parameters that an RF classifier requires: the number of classification trees the RF classifier desired and the number of prediction variables used in each node to make the tree grow (Rodriguez-Galiano et al., 2012). In this study, the number of classification trees are 500, and the number of prediction variables are 5, in addition to that, the bagging fraction is 0.75, the bagging fraction is the fraction of input to bag per tree.

Accuracy assessments are useful and practical techniques to determine how well the selected classification method produced the land use and land cover maps (Zurqani et al., 2018). Following the previous studies (Congalton, 1991; Teluguntla et al., 2018; Zurqani et al., 2018), a confusion matrix of land use and land cover maps was calculated to evaluate the classification accuracy of the results using producer's accuracy, user's accuracy, overall accuracy, and Kappa coefficient (Foody, 2002).

Figure 2 below presents a detailed flowchart of the procedures in this study. The first step of this model is clipping the Landsat images by the study boundary, DEM, NDVI, and NDWI data layers. Snow or glacial cover pixels on the imagery are then masked out based on the pixel quality index that the Landsat Surface Reflectance Tier 1 product provided for each image. The pixel quality attributes generated from the CFMASK algorithm (Google, n.d.). The surface texture information was derived using the Gray-Level Co-Occurrence Matrix (GLCM). The GLCM method is used for calculating entropy, contrast and angular second moment (ASM) data by Landsat 5 and Landsat 7's Band 1-3; Landsat 8's Band 2-4. Among the three surface texture information variables, ASM is a measure of homogeneity of an image, the entropy is a measure of the randomness of the image texture, and the contrast is a measure of the image contrast presents in an image (Hall-Beyer,2017). The GLCM features were added into the random forest (RF) classifier for land cover classification. Selected training samples were used as inputs into the RF classifier algorithm for classification.

Finally, the long-term time series of LULC change products in Zhangye City were thus derived from the Landsat data using the RF classification method through the GEE platform, taking validation samples to evaluate the accuracy. Therefore, the masked out the glacial and snow regions are put into the classification results as Snow/Glacial land use-cover class. These land use and land cover products were analyzed to quantify and detect changes in the ArcGIS environment (Esri, 2018).

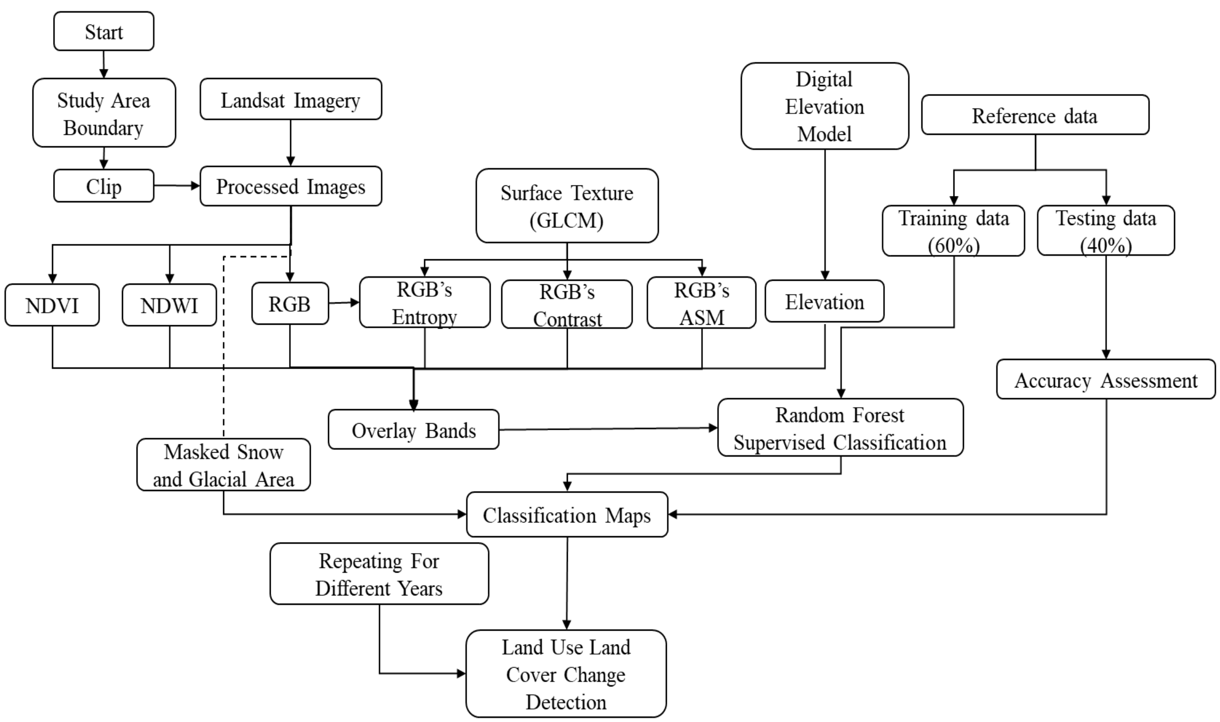

Figure 2. Flowchart of the land use and land cover classification with GEE platform.

3.3 Logistic regression modeling

3.3.1 Logistic regression model

To analyze the drivers for urban expansion in Zhangye City, the logistic regression model was implemented. Because the model is designed to understand the possibility of converting a non-urban area to an urban area. Therefore, the dependent variable of this model was set up as a number, which is given to pixels that their land use types were converted from non-built-up to built-up, while the number 0 is given to the other pixels that their land use type remains the same. The logistic regression model is in the form of (Liu, Yue, & Fan, 2011):

$$\text{logit}(Y) = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + e, \text{ and}$$

$$P(Y = 1) = \frac{\exp(\hat{\beta}_0 + \sum_{i=1}^{n} \hat{\beta}_i x_i)}{1 + \exp(\hat{\beta}_0 + \sum_{i=1}^{n} \hat{\beta}_i x_i)},$$

where the P (Y =1) represents the probability of the conversion from non-built-up to built-up while the odds of P (Y = 1)/[1 / P(Y = 1)] is the ratio of the probability that Y = 1 to the probability that Y ≠ 1. The natural logarithm of the odds is called logit (Y), where x_i are explanatory variables, and logit (Y) is a linear combination function of the explanatory variables. Parameters β_i are the regression coefficients to be estimated in this study.

The hat notation is used to indicate estimated values. Regression coefficients $\hat{\beta_i}$ imply the contribution of explanatory variables to LULC changes. A positive $\hat{\beta_i}$ value means that the increase in the explanatory variable increases the probability of the pixel's land use will be transferring from non-built-up to built-up, and a negative $\hat{\beta_i}$ value means that the decrease in the explanatory variable decreases the probability that the pixel's land use will be transferring from non-built-up to built-up. In addition, it is worth mentioning in this model, and some explanatory variables were chosen distance to somewhere, such as road or railroad. Since the majority of railroad or highway were built far away from the city center, the decrease in distances related explanatory variables will have an increase in the probability of the pixel's land use being transformed from non-built-up to built-up class.

When applying the logistic regression model, first step is to resample the Landsat data at the spatial resolution from 30 m to 270 m to reduce the spatial dependence. Studies (e.g., Liu, Yue, & Fan, 2011) showed that the resampled spatial resolution can still achieve a good fitting model result. Because Zhangye has a relatively large area that the majority land cover type is non-urban and mostly mountains or desert, which are far away from the city center and county town center, pixels far away from these centers are highly unlikely to be converted to built-up. To focus on how the pixels are converted to built-up from other land use type and reduce the total number of input pixels to the model, this logistic regression model was performed to detect the possibility of non-urban pixels being converted to urban pixels through six 10-km circles around each county town center and the major urban center (Ganzhou) of Zhangye. All pixels inside these 10-km circles are used in this model as input.

3.3.2 Dependent and explanatory variables of logistic regression model

3.3.2.1 Dependent variables

As mentioned above in Section 3.3.1, the dependent variable Y is a presence or absence event where Y=1 refers to a non-urban land use pixel being converted to urban land use pixel and Y=0 means the other possibility of land use change or no change at all (Liu, Yue, & Fan, 2011). Here, based on the land cover classification results and further land use and land cover change detection, there is a breakpoint for the Zhangye City in 2009. From the LULC change detection result, this year is a starting year of dramatic urban expansion in Zhangye city. In addition to that, the initial Masterplan of Zhangye City was published in 2004 for 2004-2020, and the city government updated it with the masterplan of 2008-2020 published in 2009. It was replaced with a 2012-2020 Zhangye's masterplan in 2014.

Furthermore, in 2008 the central government of China published the Chinese economic stimulus program that aims to minimize the impact of the global financial crisis on the economy during the 2008 economic crisis. It contains a 4 trillion RMB fund to mainly invests in basic infrastructures of China. Some part of this fund was used to invest in the Northwest Chinese' basic infrastructures and urbanization process. Combining with the classification results, three binary dependent variables Y_1, Y_2, and Y_3 were created for the years of 2001-2009, 2009-2017 and 2001-2017. Therefore, this model was run three times for three different periods.

3.3.2.2 Explanatory variables

Table 3 shows 16 different explanatory variables of logistic regression model and their descriptive statistics. At first, the influence of accessibility to converting a non-urban land use pixel to urban land use pixel was explored through measuring several Euclidean distances to different objects such as distance to roads, distance to railroads, distance to the railway station, distance to the long-distance bus station, and distance to water (including river, lakes, wetlands and reservoirs.

Previous studies (e.g., Liu, Yue, & Fan, 2011) discussed the influence of distance of local central business district (CBD) and sub-city center, and it proves that pixels closer to CBD center are more likely to be converted to urban land use. In this study, since Zhangye is relatively small and it is a third-tier city in China, it does not hold an actual CBD land or a city subcenter. Therefore, I introduced the accessibility of public services, and it represents the probability of a non-urban pixel that will be converted to an urban pixel with its distance to local government location.

Since Zhangye has five counties and one district, it makes Zhangye has six different local government locations. Therefore, six 10-km radius circles were drawn around them. One government location located in Ganzhou district is the municipal government location and five counties' government locations for counties. Furthermore, the distance to public parks and tourist attractions in Zhangye City were also taken into account as a driving factor of LULC changes since

Zhangye's government has tried to promote tourism by building more public urban areas for additional lodging, food, and shopping. The distance to government and distance to parks are also calculated by Euclidean distances.

Second, two neighborhood indices were included in the logistic regression model to capture the potential influence of its intermediate neighborhood because of spatial interaction (Braimoh and Onishi, 2007; Verburg et al., 2004). The neighborhood indices, UrbanD and AvailD, were computed by the total number of urban and developable pixels around the central pixel in a nine by nine window. Here, the available land cover is defined as the grassland, forest, cropland, and bare land. Therefore, the UrbanD value would equal the total number of urban pixels within the nine by nine window since each pixel is assigned as 0 or 1 as its land use type, whether it is non-built-up or built-up. The higher number of UrbanD, the more urban pixels are around it. The AvailD number are the same design except it is on the opposite, the higher number of AvailD, more available land to convert within the nine by nine window.

Then, the market variables were taken into consideration in the logistic regression model. According to the economic data from the yearly published Statistical Yearbook by Zhangye government, some important information like the gross domestic product, total industry value and agricultural production at the end of the model period were collected. Moreover, the increased gross domestic product, total industry value and increased agricultural production during the model period were also included in the model.

Finally, a proxy variable to assess the effectiveness of planning control (PLAN) was adopted to quantify the impacts of zoning on LULC changes. The changing structure of urban space is influenced greatly by the zoning, which to a large extent, encourage or limit certain kinds of new land use (Cheng and Masser, 2003; Wu, 1998). In this study, Zhangye's Masterplan is the spatial policy. A value of 1 was assigned to planned urban areas, and 0 was assigned to planed non-urban areas based on Zhangye's Masterplan. Unlike other variables in this model, the PLAN is a categorical variable.

Figure 3 is a detailed flowchart of how the logistic regression model works. The first step of this process is to assign social data spatially. In essence, the gross domestic product (GDP), agricultural production (AG), industry total value (ITV) and city masterplan were chosen from our socio-economic dataset. Based on GDP, AG, and ITV, the increased GDP, increased AG and increased ITV were calculated based on each year's value. These calculated data, along with the city masterplan, are put into the logistic regression model as four explanatory variables. These entries are spatially assigned with Zhangye's county polygons.

For the city's masterplan, it was extracted using the ArcGIS (Esri, 2018). It is then georeferenced by the existing boundary shapefile. The locations of water bodies were collected by double-checking the land cover classification products and the OpenStreetMap (https://www.openstreetmap.org). Moreover, the locations of parks, governments, railway stations, bus stations, roads, and railway were also collected by the OpenStreetMap and Google Maps.

From the classified land cover products, the urban and non-urban areas were extracted for the two neighborhood indices discussed above; and then the distance of each spatial location to its nearest urban pixel was calculated through the extracted urban area. All data entries were resampled to change the spatial resolution from 30m to 270m. Finally, the logistic regression model was performed using R studio when all the required input data were prepared as one raster file. In this study, every pixel within a total of six circles of the 10 km radius at Ganzhou district and five county town centers was selected for model input points.

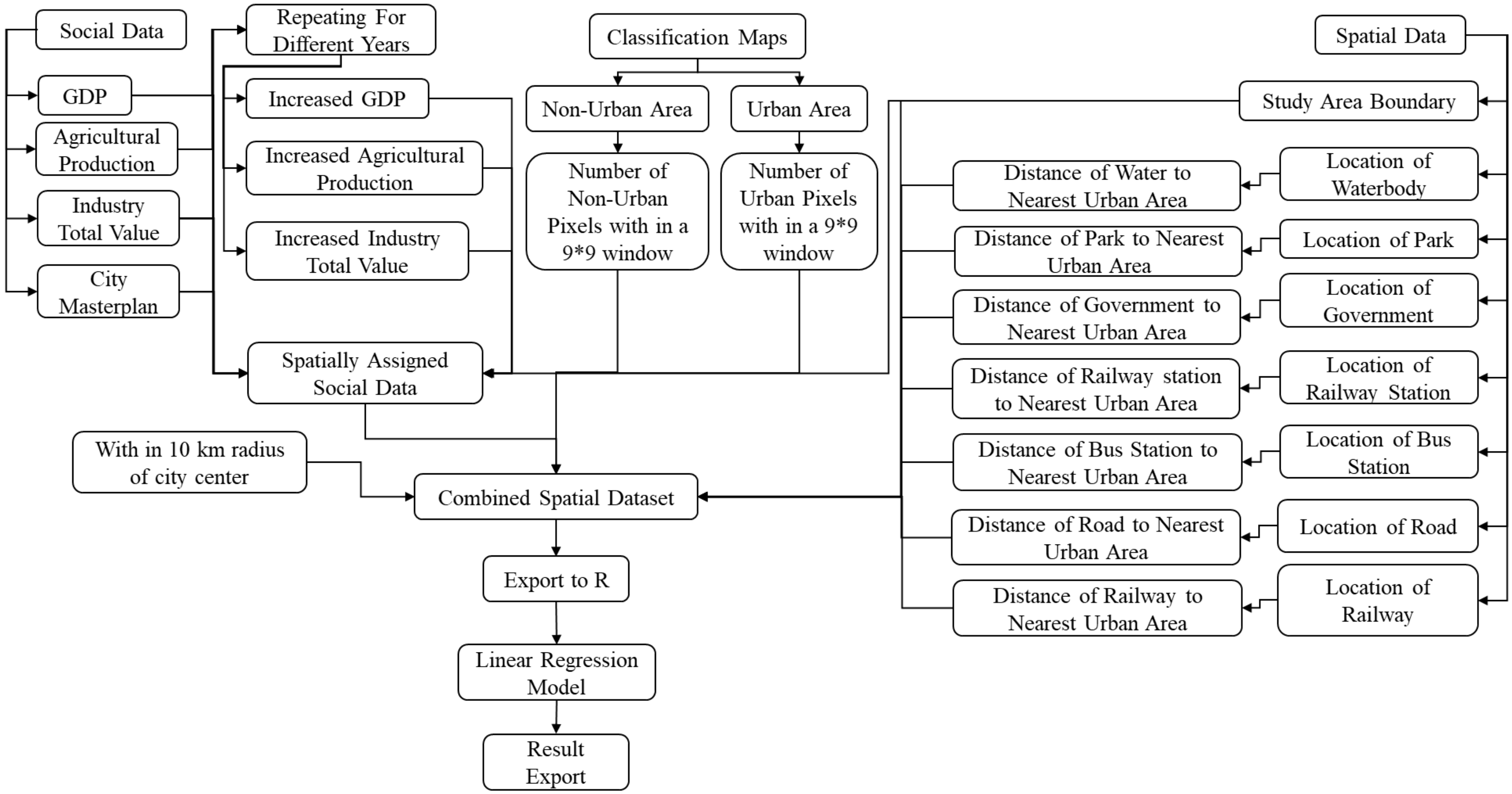

Figure 3. Flowchart of logistic regression model in this study

Table 4. Statistics of different explanatory variables of logistic regression

Name	Explanation	2001-2017				2001-2009				2009-2017			
		Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD
parkD	Distance to park(km)	0	51.16	12.89	13.41	0	51.16	12.89	13.41	0	51.16	12.89	13.41
waterD	Distance to waterbody(km)	0	11.65	3.74	2.53	0	11.65	3.74	2.53	0	11.65	3.74	2.53
GoverD	Distance to government (km)	0.08	10.09	6.67	2.54	0.08	10.09	6.67	2.54	0.08	10.09	6.67	2.54
roadD	Distance to road (km)	0.003	8.28	1.29	1.47	0. 003	8.28	1.29	1.47	0. 003	8.28	1.29	1.47
railD	Distance to railroad (km)	0.006	58.81	12.38	16.83	0.006	58.81	12.38	16.83	0.006	58.81	12.38	16.83
RailSD	Distance to railway station(km)	0.03	60.14	15.01	16.35	0.03	60.14	15.01	16.35	0.03	60.14	15.01	16.35
BusSD	Distance to long-distance bus station(km)	0.09	82.57	50.94	24.42	0.09	82.57	50.94	24.42	0.09	82.57	50.94	24.42
UrbanD	Number of Urban Pixels around the pixel	0	81	7.44	13.44	0	81	7.44	13.44	0	81	7.99	14.92
AvailD	Number of Pixels around the pixel in that could be converted to Urban	0	81	72.98	14.4	0	81	72.98	14.4	0	81	71.86	16.89
IGDP	Increased Gross Domestic Product during the time period	1.83	14.41	5.95	4.44	0.89	5.47	2.21	1.69	0.89	5.47	2.21	1.69
IITV	Increased Industry total value during the time period	1.92	8.74	3.99	2.6	1.06	3.68	1.72	1.01	0.63	5.06	2.27	1.72
IAG	Increased Agricultural production during the time period	0.67	4.95	2.38	1.44	0.17	2.13	0.92	0.66	0.5	2.83	1.46	0.79
GDP	Gross Domestic Product at the end year of time period	2.1	17.39	7.18	5.37	1.17	8.46	3.43	2.62	2.1	17.39	7.18	5.37
ITV	Industry total value at the end year of time period	2.01	9.43	4.28	2.82	1.28	4.37	2	1.22	2.01	9.43	4.28	2.82
AG	Agricultural production at the end year of time period	0.83	6.59	3.07	1.96	0.33	3.76	1.61	1.18	0.83	6.59	3.07	1.96
Plan	Planned as built-up area (1) or not (0)	0	1	0.02	0.15	0	1	0.02	0.15	0	1	0.02	0.15

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Assessment of land cover classification accuracy

The land use and land cover classification maps produced using random forest classification method for the years of 2001, 2005, 2009, 2013, and 2017 in a total of seven land cover categories were presented in Figure 4. As shown in Tables 5, the overall accuracies were 96.19% (2001), 94.99% (2005), 95.61% (2009), 95.55% (2013), and 94.69% (2017), respectively. The Kappa coefficients were 95.51% (2001), 94.12% (2005), 94.81% (2009), 94.72% (2013), and 93.72% (2017), respectively. The results showed that the classification accuracy is high even though the user's accuracy of forest class and the producer's accuracy of barren land class exhibited relatively lower values as compared to the other land cover categories. Generally speaking, it proved that the GEE's plug-in classifier algorithm, such as the random forest method is a useful tool for researchers to perform accurate land use and land cover classification.

The land cover classification method proposed in this study uses the RF supervised classification algorithm combined with several vegetation indices and DEM data within the GEE platform. The RF algorithm accurately classified the heterogeneous land cover in Zhangye City. The Google Earth Engine is faster compared to other software locally, particularly when the study area is vast, and a machine learning classification method is used. Furthermore, using GEE can save relevant researchers much more precious time on processing Landsat images and their computer storages on downloading these original data. In this study, every classification only requires about one to two hours to finish the classification process. As the random forest classifier is built-in the GEE, it would allow the researchers to use it very easily with high accuracy.

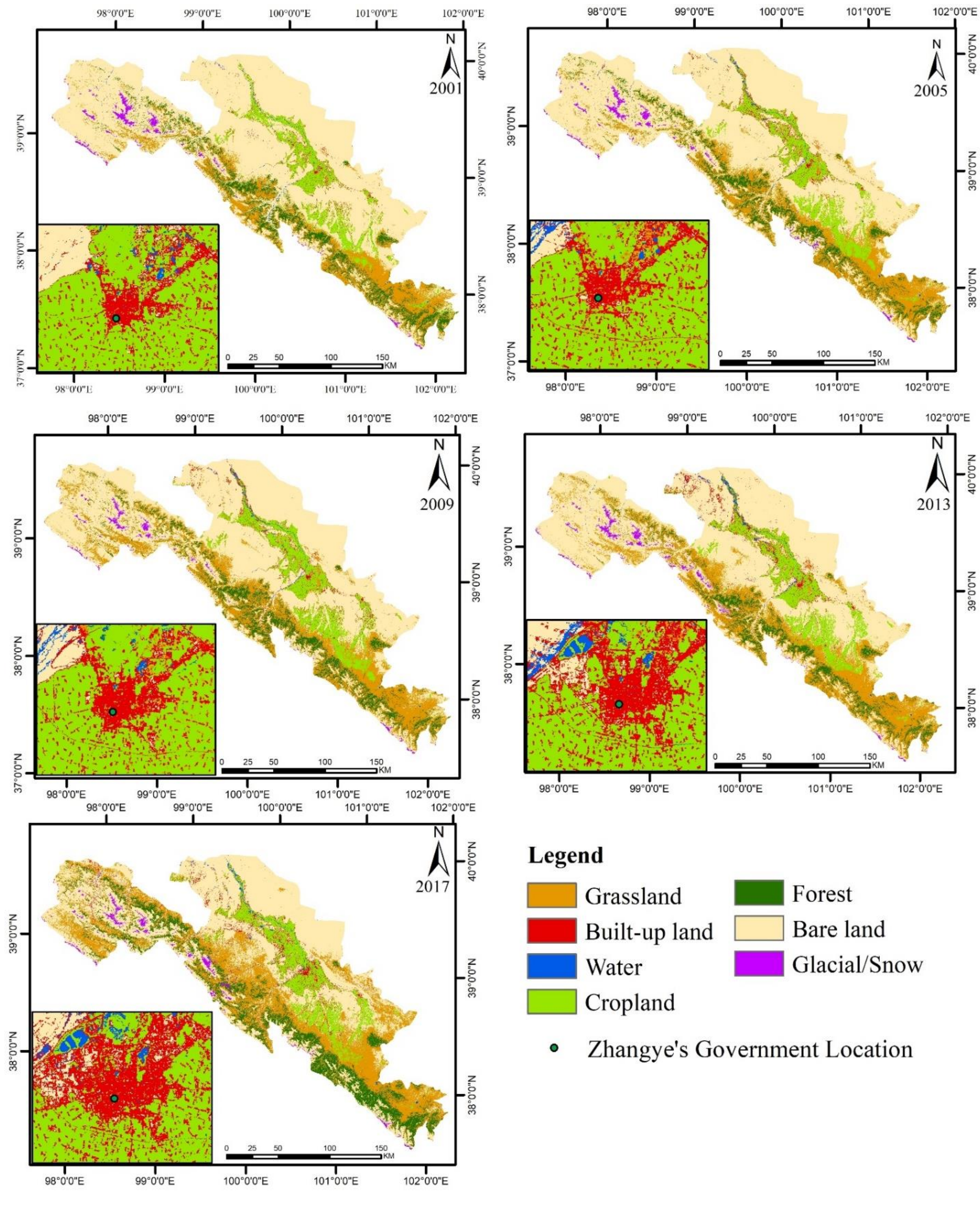

Figure 4. Land use and land cover classification results from 2001 to 2017 in Zhangye City

Table 5. Producer's, user's and overall accuracy and Kappa coefficient for land cover classification.

Year of 2001

Land Cover Type	Grassland	Built-Up	Water Body	Cropland	Forest	Bare Land	Glacial/ Snow	User's Accuracy	Producer's Accuracy
Grassland	108	11	0	7	2	16	0	75.00%	83.08%
Built-Up	3	265	4	21	0	103	0	66.92%	94.64%
Water	0	3	131	0	0	8	0	92.25%	97.04%
Cropland	14	1	0	530	0	3	0	96.72%	94.98%
Forest	5	0	0	0	108	0	0	95.58%	96.43%
Bare Land	0	0	0	0	2	549	0	99.64%	80.03%
Glacial/Snow	0	0	0	0	0	7	83	92.22%	100.00%
								Number of Samples	1984
								Overall Accuracy	96.19%
								Kappa Coefficient	86.49%

Year of 2005

Land Cover Type	Grassland	Built-Up	Water Body	Cropland	Forest	Bare Land	Glacial/ Snow	User's Accuracy	Producer's Accuracy
Grassland	176	5	0	17	4	11	0	82.63%	79.28%
Built-Up	10	295	0	6	0	66	0	78.25%	97.04%
Water	0	3	229	0	0	4	0	97.03%	100.00%
Cropland	7	1	0	463	0	0	0	98.30%	95.27%
Forest	29	0	0	0	81	0	0	73.64%	92.05%
Bare Land	0	0	0	0	3	524	0	99.43%	86.33%
Glacial/Snow	0	0	0	0	0	2	148	98.67%	100.00%
								Number of Samples	2084
								Overall Accuracy	94.99%
								Kappa Coefficient	90.13%

Year of 2009

Land Cover Type	Grassland	Built-Up	Water Body	Cropland	Forest	Bare Land	Glacial/ Snow	User's Accuracy	Producer's Accuracy
Grassland	130	0	0	25	0	5	0	81.25%	87.25%
Built-Up	2	301	1	12	0	17	0	90.39%	99.34%
Water	0	2	164	1	0	2	0	97.04%	98.80%
Cropland	1	0	0	458	0	0	0	99.78%	92.34%
Forest	11	0	0	0	163	0	0	93.68%	100.00%
Bare Land	5	0	1	0	0	520	0	98.86%	95.59%
Glacial/Snow	0	0	0	0	0	0	40	100.00%	100.00%
								Number of Samples	1861
								Overall Accuracy	95.61%
								Kappa Coefficient	94.28%

Year of 2013

Land Cover Type	Grassland	Built-Up	Water Body	Cropland	Forest	Bare Land	Glacial/ Snow	User's Accuracy	Producer's Accuracy
Grassland	301	13	0	12	8	27	0	83.38%	89.85%
Built-Up	2	373	0	20	0	58	0	82.34%	93.95%
Water	0	2	236	8	0	2	0	95.16%	98.33%
Cropland	8	7	2	246	0	2	0	92.83%	86.01%
Forest	24	0	0	0	197	0	0	89.14%	96.10%
Bare Land	0	2	2	0	0	331	0	98.81%	78.44%
Glacial/Snow	0	0	0	0	0	2	78	97.50%	100.00%
								Number of Samples	1963
								Overall Accuracy	95.55%
								Kappa Coefficient	87.76%

Year of 2017

Land Cover Type	Grassland	Built-Up	Water Body	Cropland	Forest	Bare Land	Glacial/ Snow	User's Accuracy	Producer's Accuracy
Grassland	188	15	0	20	21	30	0	68.61%	89.10%
Built-Up	0	334	1	12	0	50	0	84.13%	92.52%
Water	0	7	278	8	0	10	0	91.75%	98.93%
Cropland	4	1	0	544	0	5	0	98.19%	92.99%
Forest	13	0	0	0	213	0	0	94.25%	91.03%
Bare Land	6	4	2	1	0	211	0	94.20%	68.95%
Glacial/Snow	0	0	0	0	0	0	35	100.00%	100.00%
								Number of samples	2013
								Overall accuracy	89.57%
								Kappa coefficient	87.26%

In Figure 4, the primary spread of forest and grassland is along the Qilian Mountains, while the agricultural lands and urban areas were mainly distributed along the Heihe River. This finding is consistent with the reference land use and land cover map that was obtained by the traditional visual interpretation method (Wang, Hu, & Li, 2011). Based on the land use and land cover classification results in 2001 and 2017, Zhangye City had dramatically expanded in all directions, especially towards the south and west (Figure 4).

4.2 Land use and land cover change

The distribution of land cover classification in Zhangye City for each year is listed in Table 6. It is noticeable that considerable changes occurred in the land use and land cover in Zhangye City from 2001 to 2017. Over the whole study period of 2001-2017, here are some highlights:

(1) The total area of cropland increased from 3269.79 km^2 in 2001 to 4132.33 km^2 in 2017, an increase of about 862 km^2 or 26.38% of the total cropland area in 2001 (Table 6), particularly for the Ganzhou District and Shandan County (Figure 4). Further details will be presented in the following section.

(2) The built-up and urban areas' expansion was almost continuously increasing over time, with a total area increased by approximately 580 km^2 or 76.23% of the total built-up area in 2001. Particularly during the two periods of 2009-2013 and 2013-2017, the urban areas increased significantly, with total area increased by 203 km^2, or 25% of the total built-up area in 2009 and 342 km^2 or 32% in 2013.

(3) The forest and grassland along the Qilian Mountains expanded significantly as some barren-land regions in the mountains had returned to green by planting more trees and new grassland since some ecosystem protection policy was implemented. The area of forest, therefore, dramatic experience increase, with total area increasing from 4076.8 km^2 in 2001 to 5075.24 km^2

in 2017.

(4) The barren land area increased by 351.52 km^2 between 2001 and 2005, and this area experienced substantial change between 2005 and 2009, with a decrease of 1851.24 km^2, a 2710 km^2 overall reduction from 2001 to 2017 (Table 6). This decrease indicated Zhangye government achieved to convert unused barren-land to vegetated surfaces and urban areas, and detailed analysis will be presented in the following section. According to Zhangye's statistical yearbook, the total water usage of Zhangye City is around 2,200 million tons per year from 2001 to 2017, with no more than 2,400 million tons. This finding is very impressive that the local government can expand the green area without additional water usage.

(5) Another noticeable change in the land cover classification product is the surface water area, which is with an increase of approximately 216 km^2 between 2001 and 2017. Among the study period of 2009-2013, the total area of water bodies increased by about 95 km^2, which is equivalent to 69.73% of the total water body area in 2009; and this area increased by 89 km^2 in 2017, 38.25% of the total water body area in 2013 (Table 6). This increase was greatly attributed to the several new reservoirs and lakes, as well as restored wetlands near Zhangye City. Besides, many old reservoirs' surface area increased dramatically. However, the area of glacier and snow cover changed slightly, indicating that the glacial preservation in Zhangye city implemented quite well.

Table 6. Changes in area (unit: km^2) and its percentage (unit: %) of different land covers in Zhangye City from 2001 to 2017

Year	Parameter	Built-up	Water	Cropland	Grassland	Forest	Bare Land	Glacial
2001	Area	530.26	116.22	3086.11	5895.74	2916.03	26583.16	479.13
	Percent	1.34	0.29	7.79	14.89	7.36	67.12	1.21
2005	Area	559.96	141.62	3293.81	7522.58	2614.65	25009.43	464.62
	Percent	1.41	0.36	8.32	18.99	6.60	63.14	1.17
2009	Area	668.63	157.08	3797.97	8225.91	2849.17	23581.11	326.80
	Percent	1.69	0.40	9.59	20.77	7.19	59.54	0.83
2013	Area	822.14	203.09	3676.22	8904.45	2232.80	23249.59	518.36
	Percent	2.08	0.51	9.28	22.48	5.64	58.70	1.31
2017	Area	1071.06	220.96	3726.06	10585.38	4562.69	18993.98	446.52
	Percent	2.70	0.56	9.41	26.73	11.52	47.96	1.13
2001-2005	Area change	29.69	25.40	207.70	1626.84	-301.38	-1573.74	-14.51
	Percent	5.60	21.85	6.73	27.59	-10.34	-5.92	-3.03
2005-2009	Area change	108.67	15.46	504.15	703.34	234.52	-1428.31	-137.83
	Percent	19.41	10.92	15.31	9.35	8.97	-5.71	-29.66
2009-2013	Area change	153.51	46.01	-121.74	678.54	-616.37	-331.52	191.57
	Percent	22.96	29.29	-3.21	8.25	-21.63	-1.41	58.62
2013-2017	Area change	248.92	17.87	49.84	1680.93	2329.89	-4255.61	-71.84
	Percent	30.28	8.80	1.36	18.88	104.35	-18.30	-13.86
2001-2017	Area change	540.79	104.74	639.95	4689.65	1646.66	-7589.18	-32.61
	Percent	101.99	90.12	20.74	79.54	56.47	-28.55	-6.81

Table 7. The transition matrix of land use and land cover results between 2001 and 2017 (unit: km^2)

Year	2001	Grassland	Built-up	Waterbody	Cropland	Forest	Bare Land	Glacial/Snow
2017	Grassland	3782.63	54.66	24.96	372.89	558.46	5791.78	0.0009
	Built-up	8.89	154.20	7.45	111.99	2.02	783.49	3.02
	Water body	6.34	10.07	54.83	21.02	6.81	115.86	6.04
	Cropland	83.23	239.63	7.23	2475.77	5.11	915.10	0.00
	Forest	1856.76	3.12	1.38	12.36	2144.81	544.25	0.0054
	Bare land	143.59	68.47	18.66	91.99	175.39	18322.86	173.02
	Glacial/Snow	14.30	0.11	1.70	0.09	23.42	109.84	297.05

Table 7 presented the transition matrix for land use and land cover maps in Zhangye City between 2001 and 2017. The increase in cropland is mainly attributed to a decrease in bare land and grassland areas. Approximately 934.57 km^2 of bare land and 158.13 km^2 of grassland were converted into cropland because of more than ten years of reclamation of new agricultural fields. The newly reclaimed cropland was mainly located in the transition zone between the oasis region and bare land area, such as the desert. Similar findings had been reported by Hu et al. (2015). However, a dramatic increase in cropland land use resulted in the severe overexploitation of groundwater and increasing water consumption of surface water from the Heihe River (Cheng et al., 2014). Thus, more rational management of water resources and water-saving practices were implemented to decrease water consumption in the midstream areas of HRB.

The total area of built-up increased significantly over the study period. The expansion in built-up areas mainly occurred at the expense of cropland and bare land; approximately 106.81 km^2 of farmland and 998.81 km^2 of bare land were converted into built-up land (Table 7), mainly occurring at the Ganzhou District (Figure 4).

The areas of the forest increased significantly between 2001 and 2017 (Table 9), which was primarily transformed from the bare land and the grasslands in front of the Qilian Mountains (Table 7). From 2001 through 2017, the total areas of bare land and grassland that were converted into the forest were 776.31 km^2 and 1345.12 km^2, respectively. The total area of grassland increased substantially throughout the study period of 2001 to 2013 as large areas of bare land transformed into grassland; while during the years of 2013 to 2017, the grassland areas decreased to some extent, which might be attributed to an increase in farmland and forest areas (Tables 6 and 7).

The surface area of water bodies increased slightly between 2001 and 2009, while from 2009 through 2017, the spatial extent of water bodies expanded significantly. Approximately 198.42

km^2 of bare land was transformed into water bodies over the whole study period (Table 7). The primary causes of the sudden increase in water surface land use are firstly related to the implementation of an Ecological Water Diversion Project (EWDP) in 2000 by the Chinese government. Since the implementation of EWDP, the wetland area could be captured in the land use and land cover product in 2009 while not detected in 2001 and 2005. Compared to the land use and land cover products from 2001 through 2009, a large area of surface water and wetland were identified in 2003 due to the implementation of water-saving practices and new wetland conservation project in 2008, which is within the framework of EWDP (Hu et al., 2015).

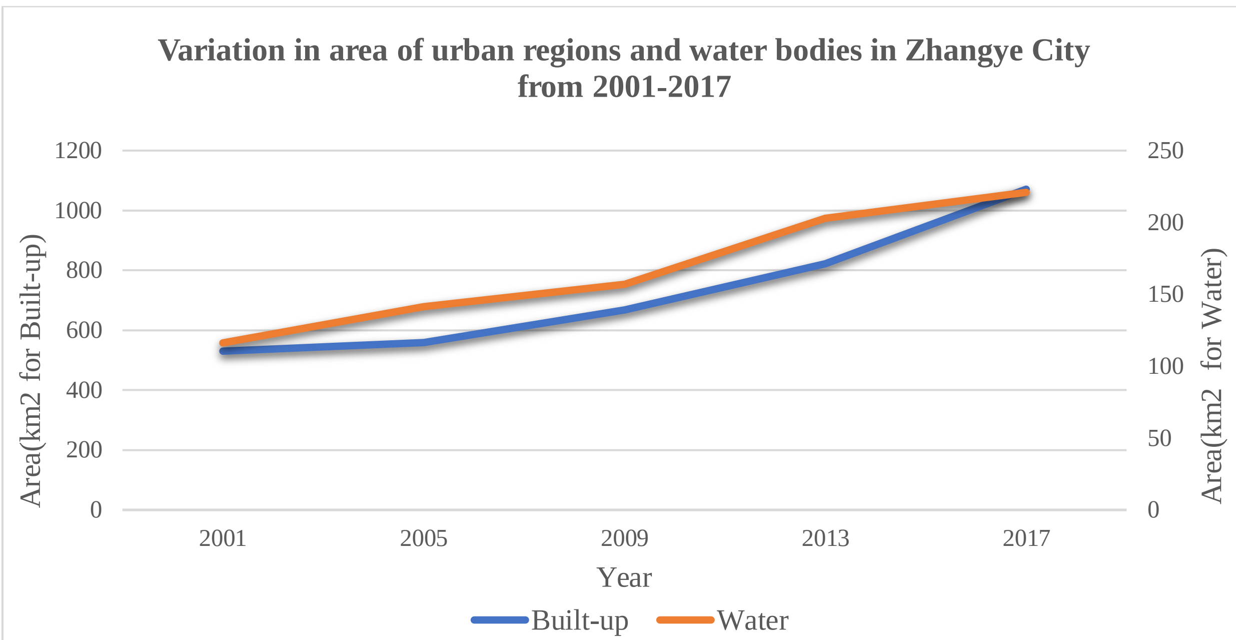

Figure 5. Variation in area of urban regions and water bodies in Zhangye City from 2001-2017

Figure 6 shows an increasing trend in cropland and green area (including grassland and forest) from 2001 to 2017 in Zhangye City. The results shown in Figure 6 indicate that the cropland increased less compared to the green land. The grassland area dramatically increased from 2013 to 2017, which is associated mainly with the expansion of surface water area and afforestation activities in Zhangye City.

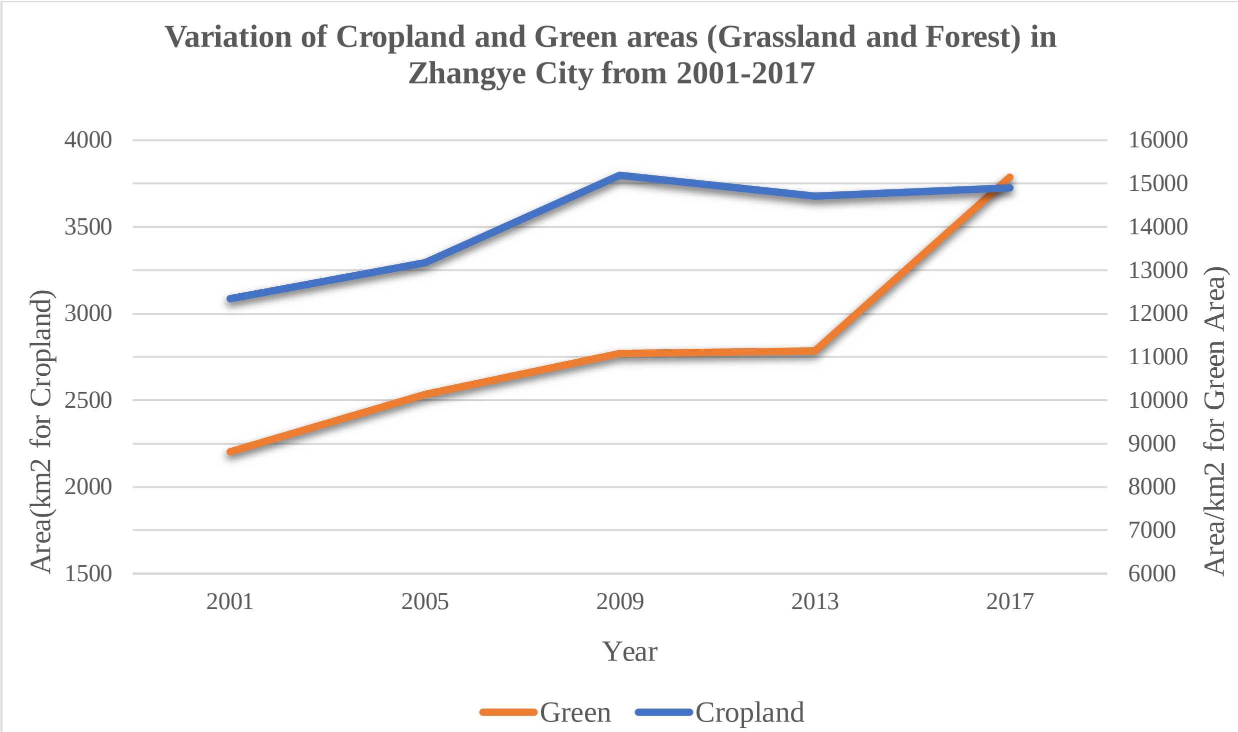

Figure 6. Variation of Cropland and Green areas (Grassland and Forest) in Zhangye City from 2001-2017

4.3 Urban expansion

According to the numbers listed in Table 6, the built-up area had the highest percentage change from 2001 to 2017 among all seven land cover types. The area of built-up increased to 101.9% of the total area in 2001. Based on visual interpretation of the obtained land cover maps (as shown in Figure 4), the heavier urban expansion happened in the Ganzhou district (major urban area) compared to the other five counties of Zhangye City. Figure 7 presents the primary land use and land cover map in Ganzhou District from 2001 to 2017. Comparing to 2001, the built-up in the Ganzhou district expanded to all directions in 2017, and the most significant change occurred at the northeast and west sides of the city.

There is a noticeable area of classified barren land on the west side of the Ganzhou district in

2017's classification result as Figure 7 shown below, while this area is planned as a new urban area that had been constructed since 2013. The new district on the west side of the Ganzhou District is named the Zhangye Riverfront District, which is designed as an ecologically friendly area, close to the newly created lake park and wetland park. Because of promoting the entire city as ecologically friendly and preserving the wetland, this district is regarded as a role model for the other five counties of Zhangye City (Zhangye City People's Congress,2016). Besides, the city administration wants to protect the city environment and make a more ecological-friendly lifestyle for all residents in Zhangye; in return, a greener environment could also help the tourism industries in Zhangye City be more profitable which leads to more money to invest on the environmental protection.

Zhangye's government departments also converted its airport for military purposes only to a dual-use airport. This, to some extent, promotes tourism. For example, with the help of this airport and new high-speed railway, travelers would find it easier to travel to Zhangye City and make Zhangye's tourism industries more attractive to both Chinese and foreigners.

In addition to these, significant urban expansion is also found on the northeast side of the Ganzhou District, Zhangye City (Figure 7), mainly because of the newly built high-speed train station. To a large extent, this development promoted the local urbanization around the station, including new shopping centers, apartments, schools, industries, and factories, based on the visual interpretation of high-resolution Google Earth images. Furthermore, the northwest area of the Ganzhou District is designed as an industrial area according to the Zhangye's masterplan, which is markedly consistent with the classification result in Figure 7.

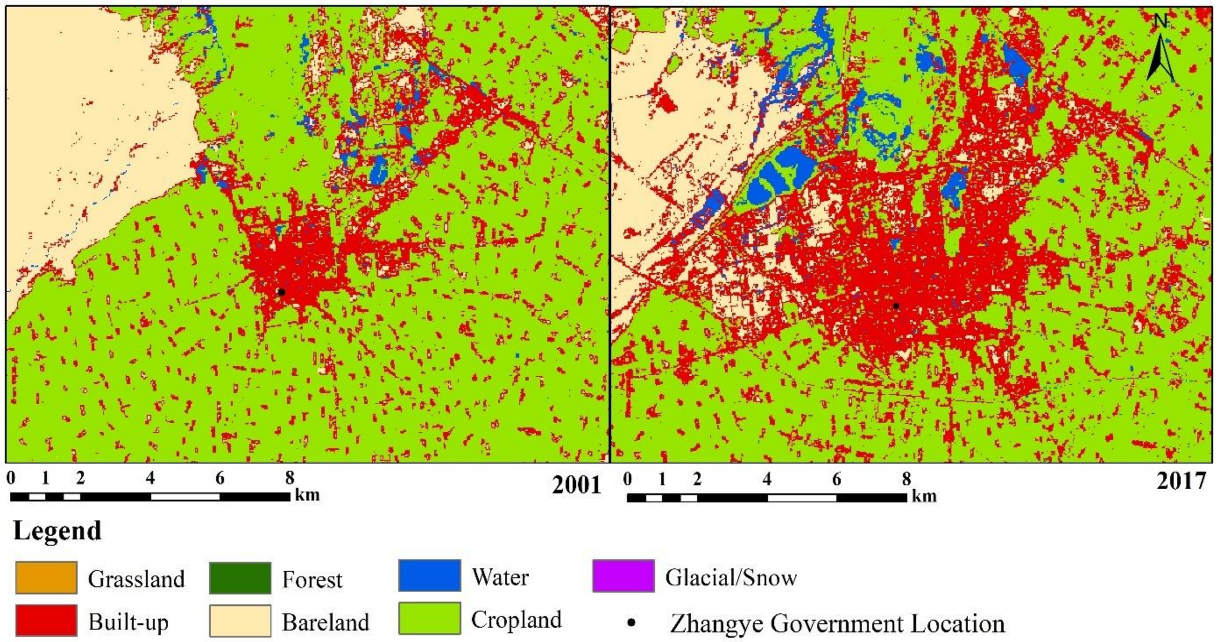

Figure 7. Land use and land cover change in Ganzhou District from 2001 to 2017

In addition to the remarkable urban expansion in Ganzhou district, the other five counties of Zhangye City also experienced urbanization to some degree, particularly in Gaotai and Shandan counties. For Gaotai County (Figure 8), a new reservoir and wetland park had been constructed near the county center, which mostly helped its environmental restoration and promoted tourism. Furthermore, Gaotai county seat's urban area is expanded near the Heihe River (Figure 8). In addition to natural parks, Gaotai also built several historical monuments and museums to promote tourism as well because Gaotai was a famous location in the Chinese civil war during the mid-1930s.

For Shandan County (Figure 8), its urban area expanded mostly towards the northeast side of the county, closer to the newly completed national G30 Highway and newly completed high-speed railway. For the two studied counties, the center of the urban area expanded not in the same direction, but their county seat both expanded in the direction of potential economic growth points.

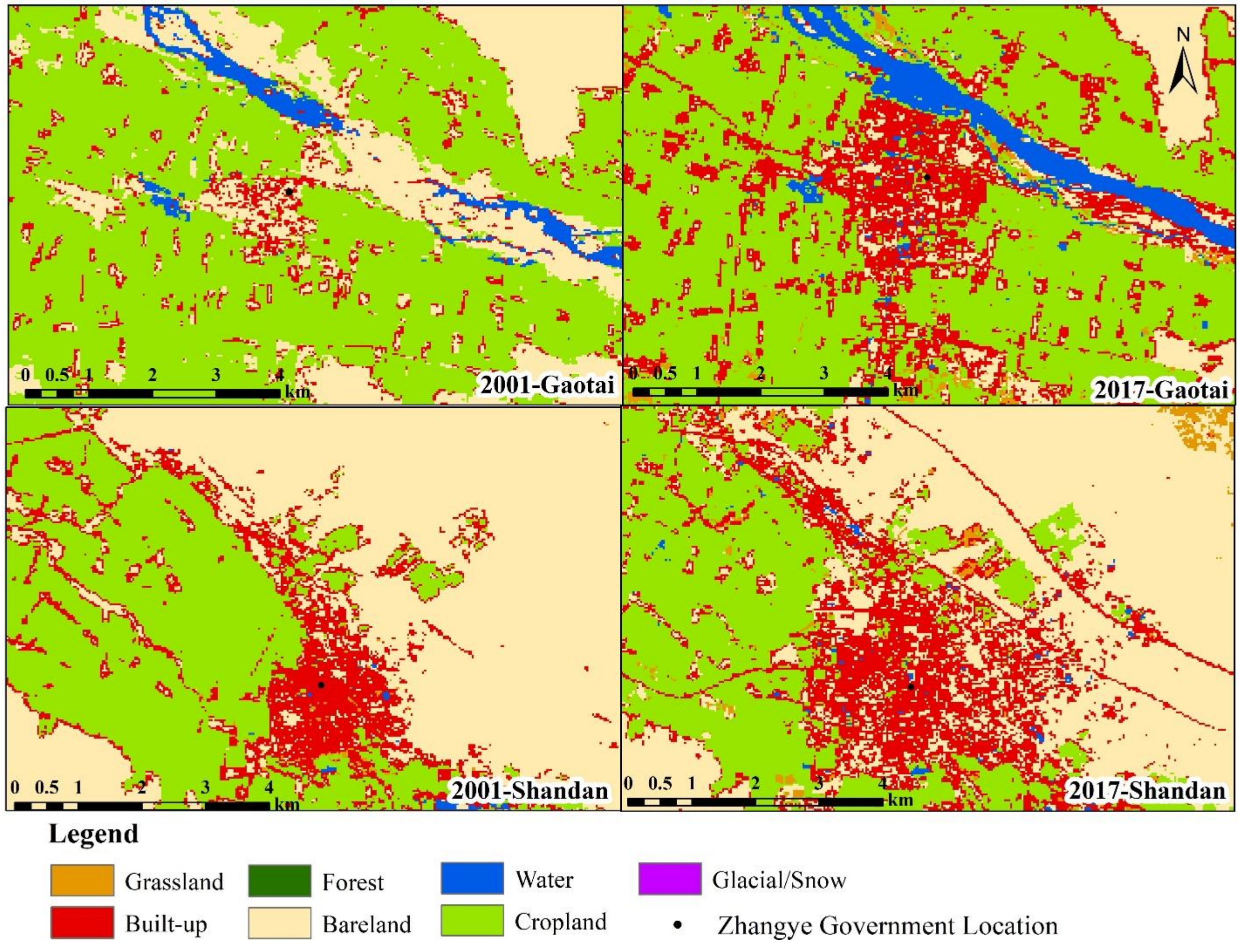

Figure 8. Land use and land cover map in Gaotai County and Shandan County from 2001 to 2017

4.4 Cropland expansion and surface water area increase

According to the land use change results, the cropland expanded by 639.94 km^2, which is about 20.7% of the total cropland area in 2001. Comparing the land use map, we can notice that the cropland expansion of Zhangye does not happen in one specific area in a sudden, but rather a general expansion towards the bare land, sometimes grassland in all Zhangye area.

Furthermore, the expansion is very often near the existing cropland; most of these newly converted croplands are from bare land. Figure 10 below shows how the cropland expanded in the central Zhangye oasis. It is worth mentioning that the cropland near the urban area had the tendency to be converted to urban areas due to urban expansion. Cropland near high altitude mountains or retired cropland had the tendency to be converted to grassland or forest, and it might be due to the Grain for Green policy. Some cropland was converted to other types of land use, such as grassland or forest. However, even some environmental protection policies are converting the existed cropland to grassland and forest, and the urbanization process is converting cropland to built-up land use. Zhangye government still managed to keep the cropland expanding from 2001 to 2017 to ensure food production.

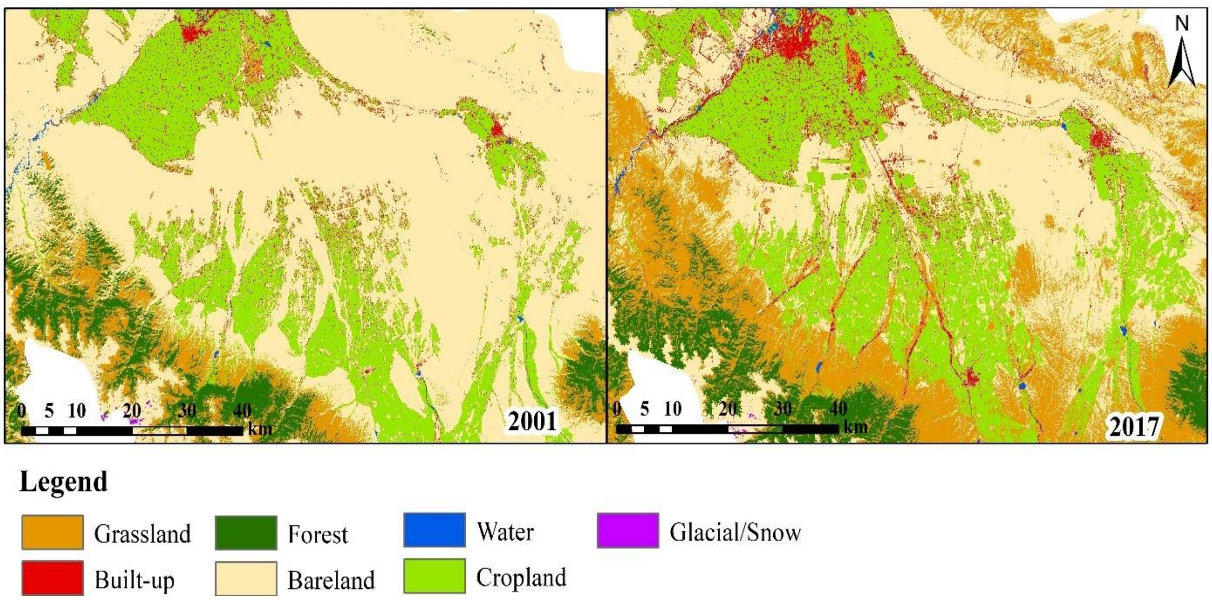

Figure 9. Cropland distribution in the central area of Zhangye Oasis from 2001 to 2017.

The dramatic expansion of surface water area is also an interesting discovery of Zhangye from 2001 to 2017. The total amount of the increased area is 104.74 km^2. The expansion of surface water area is mainly because of new reservoirs and newly preserved wetlands. During 2001-2017, 17 reservoirs and lakes were newly created or expanded in Zhangye using the latest technology and renovated canals that Zhangye government had built throughout the entire region. The city manages to save a large amount of water runoff during production activities and store this in its reservoirs. To save the water, Zhangye government is converting from surface irrigation to micro-irrigation, such as drip irrigation and sprinkler irrigation. They are also limiting industrial water usage and shutting down factories that use a large amount of water. The government is also doing water compensation to local farmers and industries.

Zhangye government is also promoting another policy that helped the wetland expansion in the city: wetland protection and construction project in Heihe River Basin. This project aims to restore and manage wetlands in Heihe River Basin; to construct national nature reserve of Heihe River Basin's wetland, wetland ecological compensation, and research projects on wetland in Heihe River Basin. Under this series of planned actions, Zhangye government had successfully restored several wetland parks and two national nature reserves of wetland in Zhangye. It also helped to increase the surface water area as well as local ecological diversity. Figure 11 below shows some newly established lakes, reservoirs, and wetlands in Gaotai county and Ganzhou district of Zhangye.

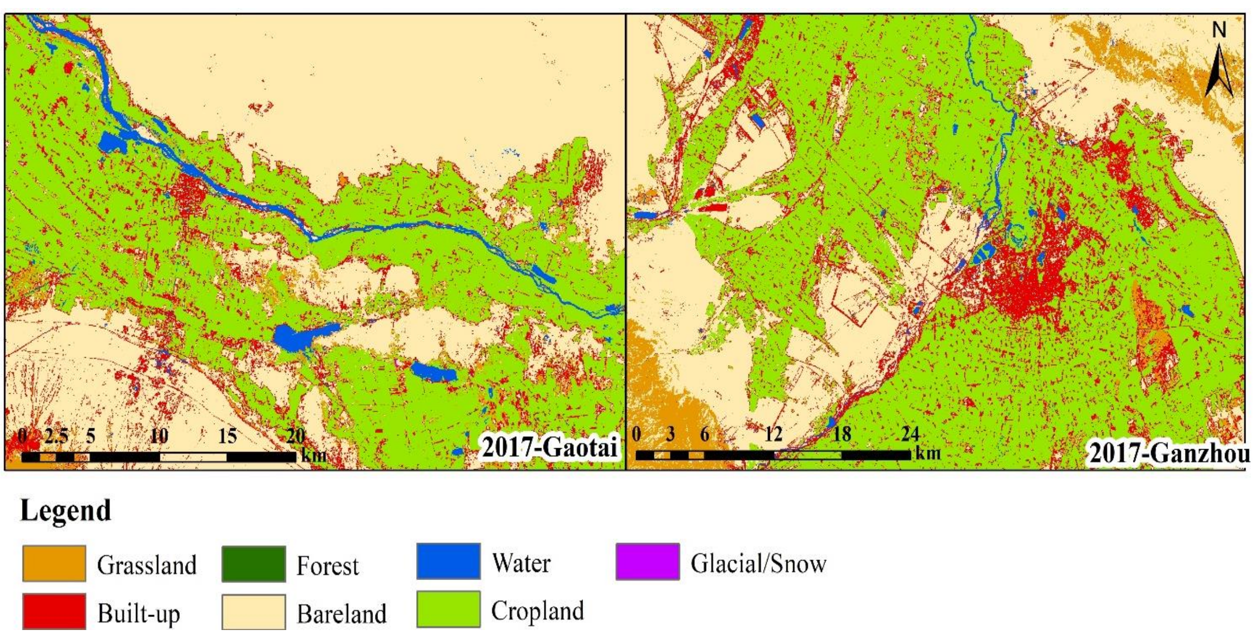

Figure 10. Waterbody of the lake, reservoir and wetland

4.5 Changes in GDP, population, and water resources associated with LULC changes

Water-saving techniques implemented in agricultural cropland had slightly affected the economic growth of Zhangye City and its urbanization process from 2001 to 2017. According to the Zhangye's statistical yearbook, GDP increased dramatically from 2001 to 2017; while the total amount of water usage changed slightly, as presented in Figure 11. According to the Zhangye's statistical yearbook from 2001 to 2017, the population in Zhangye City was 1.25 million in 2001 and 1.22 million in 2017 (Bureau of Statistics of Zhangye,2002,2018).

In order to maintain the economic growth without using a large number of water resources, Zhangye government put its focus on developing the economy by encouraging tourism, implementing water-saving agriculture activates and producing its agricultural products and exploiting renewable energy as well as technology innovations. To produce more agricultural products, specialty industries such as corn seed production and plateau summer vegetables were developed extensively with the support of Zhangye government. Moreover, the local agricultural production process has been planned to be more modernized, mechanized and energy saving.

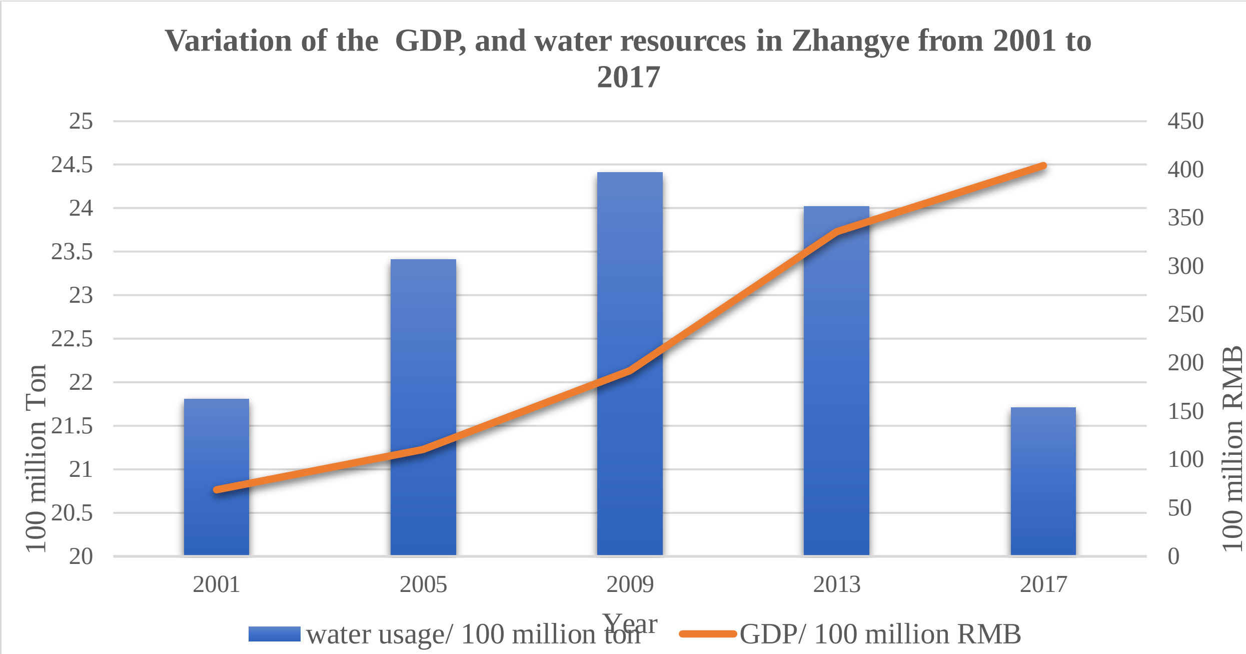

Figure 11. Variation of the GDP, and water resources in Zhangye City from 2001 to 2017(Source: Bureau of Statistics of Zhangye, 2002,2006,2010,2014,2018)

Figure 12 below shows the Zhangye's GDP and various sources of income from 2001 to 2017. One of the major sources of economic income is from tourism since 2017. According to the 12^{th} fifth-year plan, the administration decided to establish fixed eco-tourism routes, namely Qilian Mountain's forest ecological leisure tour, Shandan grassland landscape ecological tour, wetland ecological tour, Danxia landform tour, desert popular science eco-tourism, and Zhangye oasis agricultural eco-tourism (Zhangye City People's Congress,2016). These tour routes designated by local governments could boost the local economy. The boost of tourism also helped the local tertiary industry's development and urbanization. For example, the Danxia landform is one of the most famous tourist routes in Zhangye City because of its unique landscapes. To improve the tourist's pleasure and convenience, the administration had built a new small town for tourists to dining, lodging, and shopping, which would be beneficial to local residents and also increase local income

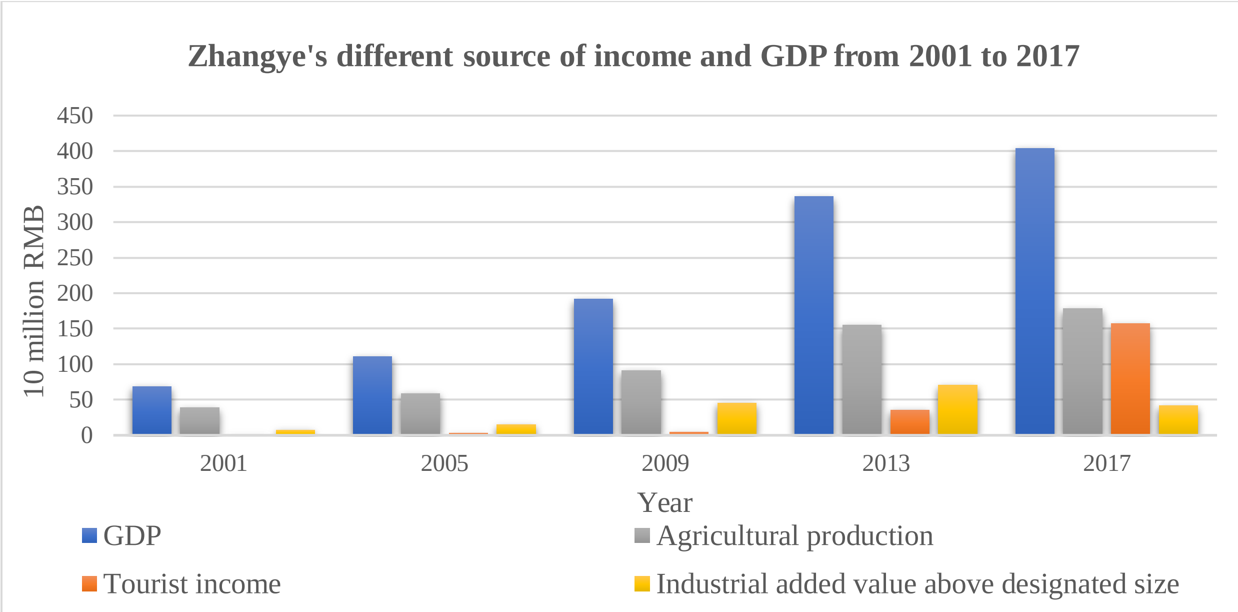

Figure 12. Zhangye's GDP and different source of income from 2001 to 2017(Source: Bureau of Statistics of Zhangye, 2002,2006,2010,2014,2018)

In addition, agricultural production was 39.02 million RMB in 2001, accounting for 56.7% of Zhangye's GDP and is 178.12 million RMB, about 44.07% in 2017 (Bureau of Statistics of Zhangye, 2002, 2018). The agricultural production increased gradually during the study period, which showed reasonable agreement with the expansion of cropland for years of 2001-2017 (Table 6).

The tourist income increased from 1.46% (2001) to 38.9% (2017). This finding indicated that tourism was largely promoted the Zhangye's economic development since 2013. As shown in Figure 12, the economic income from tourism goes over 157.3 ten million RMB in 2017 compared to 1.1 ten million RMB in 2001. According to the Zhangye's statistical yearbook in 2001, about 25720 travelers come to visit Zhangye as tourists, including an 18000-Taiwan traveler group; and in 2000, only 4800 come to visit Zhangye. In 2017, 25.9 million person-times had come to Zhangye as tourists and this number increased about 1000 times. The tourism income increased sharply from 2013, with values increased by about 142.87 million RMB compared to 2017 (Bureau of Statistics of Zhangye, 2002, 2018).

From 2013 through 2017, a vast urban expansion, surface water area, and green land increases were also found according to the numbers listed in Table 6. This finding could be another good indicator that the year of 2009 is a good breakpoint that Zhangye city's development had dramatically changed.

The industry added value in Zhangye City from 2001 to 2017 is also shown in Figure 12. The industry added value exhibited a significant value of 70.45 billion RMB (20.9% of GDP) in 2013 compared to other years, while in 2017, the industrial add value is 4.1 billion RMB, about 10.3% of GDP (Bureau of Statistics of Zhangye, 2014,2018). These results indicated that Zhangye's development focus in 2017 was on environmental protection and related industries. According to the statistical yearbook in 2017, Zhangye's secondary industries are less competitive compared to those of other regions all over China, and these sectors are over capacity.

The basic infrastructure development in Zhangye City, such as the construction of the high-speed railway station from 2001 to 2017, also helped to promote the development of the entire city. Until 2017, Zhangye had built two major train stations, one is the standard railway, and the other is specifically for high-speed railway, and a dual-use airport, one national highway goes through Zhangye and four provincial highways (Zhangye City People's Congress,2016). According to the statistical yearbook and the 12^{th}, 13^{th} five-year plan of Zhangye City, Zhangye had expanded its classified road mileage from 1836 km in 2001 to 11170 km in 2015. By 2020, Zhangye should have constructed another 5551 km, which will lead the classified road mileage to 16721 km and will expand its airport (Zhangye City People's Congress, 2016). The sequences of conducted and planned actions also promote the urbanization in Zhangye City.

Policies related to agricultural production and environmental protection also had a critical influence on land use and land cover change in Zhangye city during the years of 2001-2017. One of the major policies that shaped the land-use change is the Grain for Green Policy initiated in 1999 (known as "returning farmland to forest program"). According to Zinda et al. (2017), the core of this program is that the government would be compensating rural residents for planting trees on retired farmland and other uncultivated lands. Farmers are to retire farmland on steep slopes in order to prone areas for soil erosion,

In 2002, the Chinese State Council's Article 23 defined the reforested area as two types of forest, namely ecological forest and commercial forest. Ecological forests have the primary purpose of restoring environmental functions, particularly for controlling soil erosion and desertification. Commercial forests provide products that can be marketed, earning more income for participating residents and also providing environmental services to a less degree. Zhangye's Grain to Green Policy started from 2002 (Chen et al., 2006). From 2002 to 2015, Zhangye had reforested 783.7 square kilometers from those fallow croplands located in the Qilian Mountains, the edge of Dahuang natural forest, and the deserted farmland in the oasis by paying each farmer about six thousand RMB (China Forestry News Network, 2018).

Other policies, like the project of ecological protection and restoration of the Qilian Mountains, also make the Zhangye region much greener. In recent years, the phenomena of glacial subside and overload pasture (Wang et al., 2017). Human activities showed serious threats to biodiversity; thus, there is an urgent demand for the Qilian Mountains' ecological restoration. This ecological protection and restoration project started in 2014 to restore the ecological environment of Qilian Mountains and made some progress until 2017. Some recent research indicates that the ecological protection and restoration project still needs to be improved and enforced (Ma et al., 2019; Wang et al., 2017).

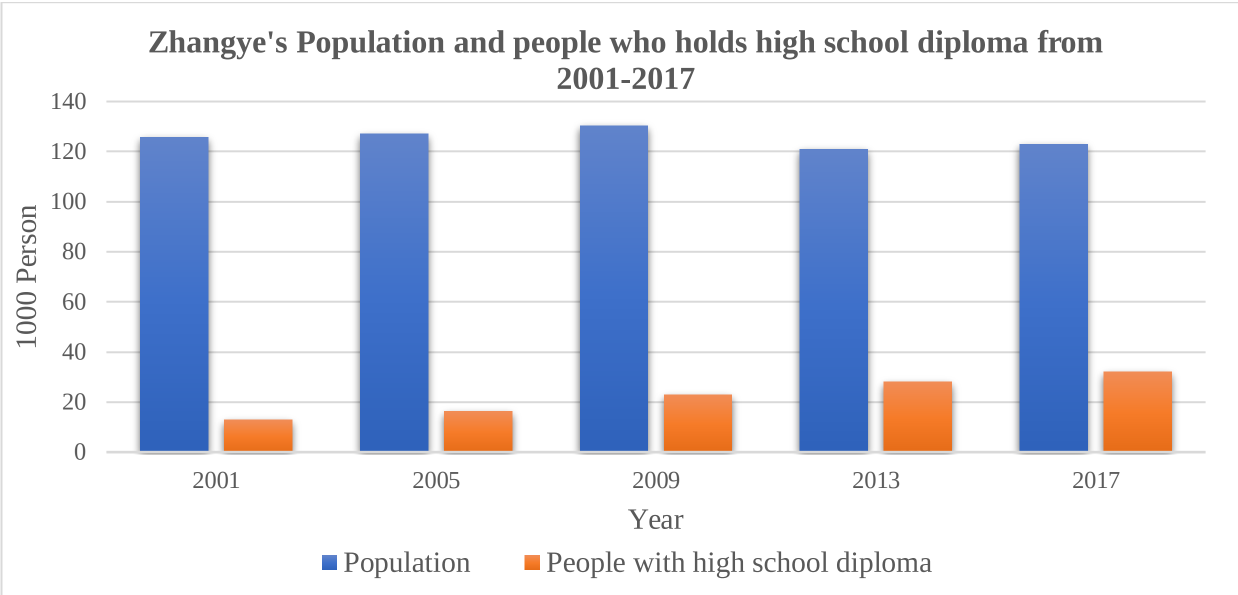

Figure 13. Zhangye’s population change and people who hold high school diploma from 2001-2017(Source: Bureau of Statistics of Zhangye, 2002, 2006,2010,2014,2018; Gansu’s provincial census office, 2002,2012)

Agricultural technology innovation and improved education level on local residents also have some relation to the land use land cover change in Zhangye City. According to the Zhangye’s statistical yearbook, people who received a high school diploma increased from 1.28 hundred thousand people in 2001 to 3.20 hundred thousand people in 2017 (Figure 13), about 10% of the total population in Zhangye City in 2001 and 26% in 2017 (Bureau of Statistics of Zhangye, 2002,2012; Bureau of Statistics of Zhangye, 2002, 2018). Though the number of agricultural technicians not changed dramatically, more mechanized farming made the farming pattern becoming more mechanized, while fewer people had to work on farming.

In 2001, the total number of working people in Zhangye City was 7.12 hundred thousand, and

4.14 hundred thousand of these people are working in primary industry, which is 58.18% of total working people. In 2017, the total number of working people was 7.31 hundred thousand, and 3.41 hundred thousand (about 46.7% of total working people) are working in primary industry (Bureau of Statistics of Zhangye, 2002, 2018). During the years from 2001 to 2017, people who work for the secondary industry had relatively increased from 0.92 hundred thousand to 1.17 hundred thousand people; and tertiary industry had relatively increased from 2.05 hundred thousand to 2.72 hundred thousand. A considerable increase in the population of working people with high school diplomas pushed the urbanization.

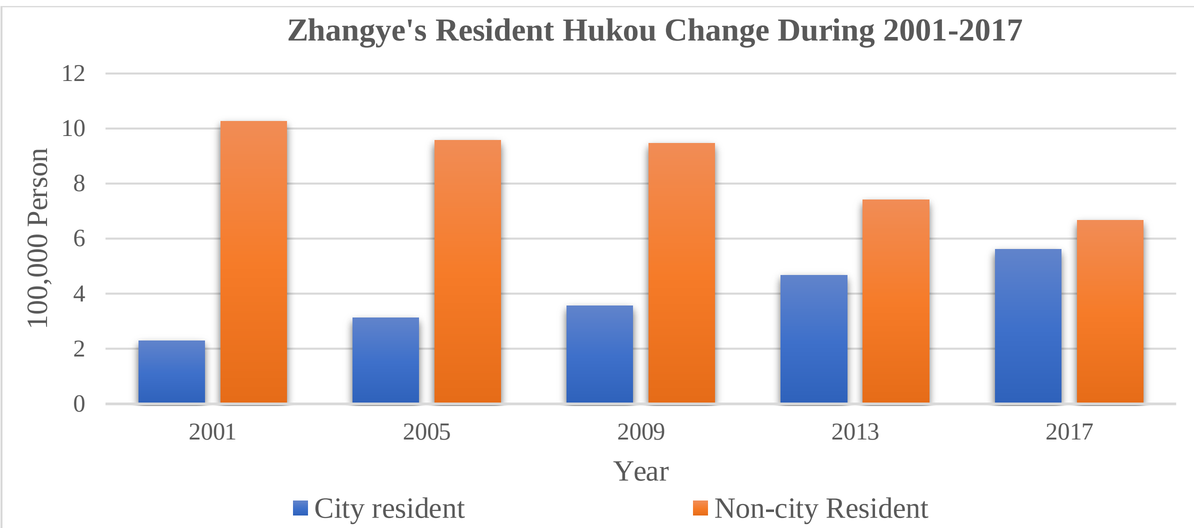

Figure 14. Zhangye's Hukou Change During 2001-2017(Source: Bureau of Statistics of Zhangye, 2002,2006,2010,2014,2018)

Industry adjustment has made the people changing their living style to be more centered in cities in Zhangye. Thus, it leads to non-urban residents to move to urban areas with urban Hukou. As shown in Figure 14, in 2001, about 10.27 hundred thousand people own a non-urban Hukou and 2.3 hundred thousand people own urban Hukou. However, in 2017, the number increased to 5.6 hundred thousand for urban Hukou and the non-urban Hukou owner dropped down to 6.7

hundred thousand, almost 45.5% of total residents with urban Hukou (Bureau of Statistics of Zhangye, 2002, 2010, 2018).

In addition, different counties in Zhangye City showed a different pattern in the city and rural residents (Figure 15). It is obvious that Ganzhou district had the largest population among them, followed by Minle County, and Yugur Autonomous County of Sunan owns the least amount of population. In 2017, Ganzhou district had about 0.25 million people on both urban and non-urban Hukou residents, while the Minle County-owned 0.084 million as urban and 1.41 hundred thousand as non-urban Hukou residents. For Gaotai County, the amount of urban Hukou is similar to the non-urban Hukou. This finding, to a large extent, explained the major urbanization process that occurred at Ganzhou district and Gaotai County.

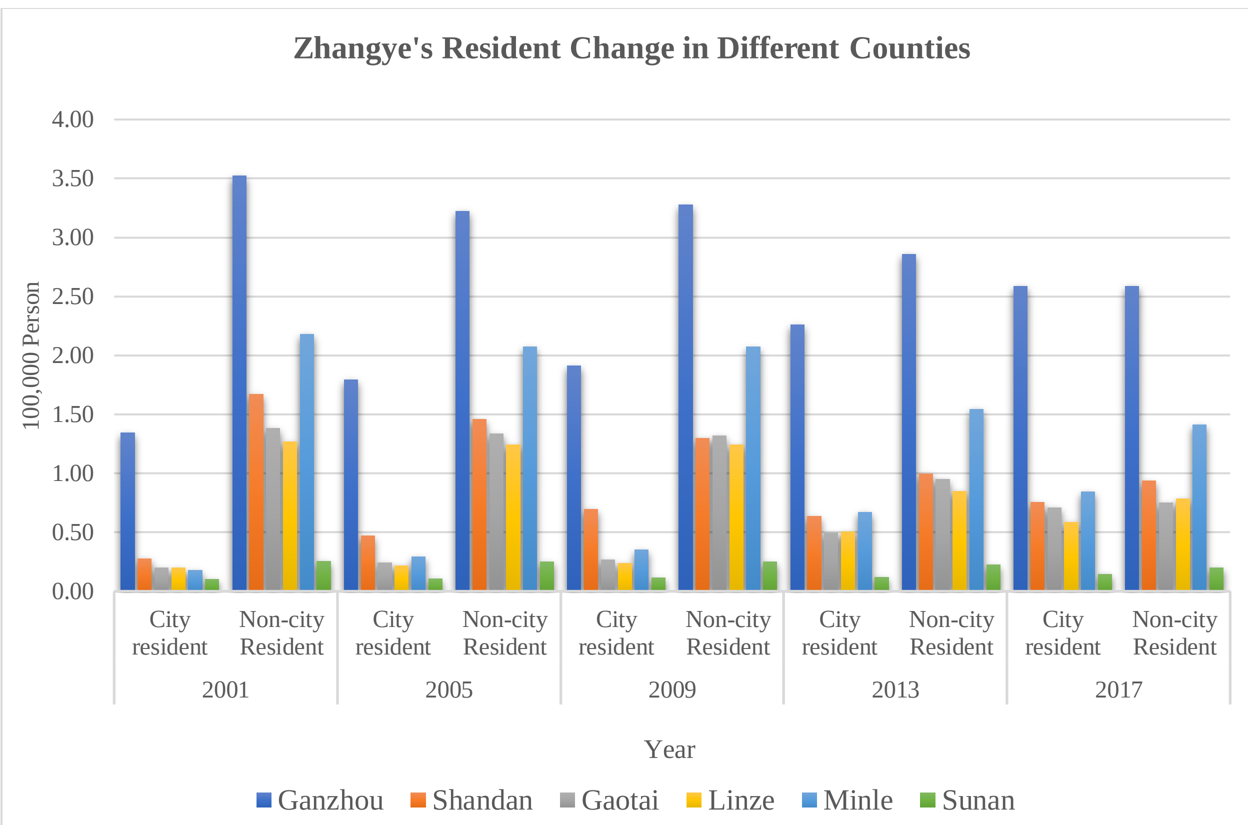

Figure 15. Change in Zhangye's Resident at Different Counties during 2001-2017(Source: Bureau of Statistics of Zhangye, 2002, 2006,2010,2014,2018)

Finally, urbanization and agricultural technology innovation leads to a steady increase in local resident's income for both urban and non-urban residents (Figure 16). The urban resident's per capita disposable income had increased from 5,239 Yuan per person in 2001 to 23,309 Yuan per person in 2017, whereas the non-urban resident's per capita disposable income had increased from 2,931.21 Yuan per person in 2001 to 12,612 Yuan per person in 2017 (Bureau of Statistics of Zhangye, 2002, 2018). Furthermore, it is surprising to notice that the non-urban resident's income is about 55% of the urban resident's income from 2001 to 2017.

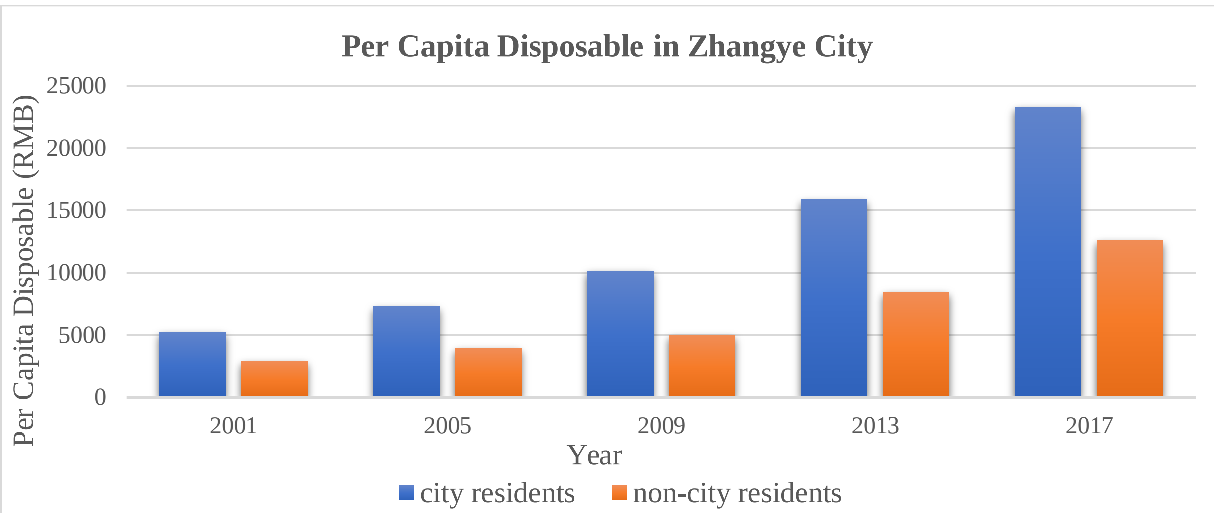

Figure 16. Per Capita Disposable in Zhangye City from 2001-2017(Source: Bureau of Statistics of Zhangye, 2002, 2006,2010,2014,2018)

4.6 The drivers of urban expansion

The logistic regression model generally assigned high probabilities to areas that were actually converted from non-urban to urban land. The goodness of fit of the logistic regression model is measured by the relative operating characteristic (ROC). The ROC values were all greater or equal than 0.8, indicating that urban land conversion can be reasonably explained by the independent variables (Table 8). The ROC value for 2001-2009 period is 0.823, the ROC value for 2009-2017 period is 0.821, and the ROC value for 2001-2017period is 0.800. A confusion matrix is created to test the model fitting, the accuracy of the 2001-2009 period's confusion matrix is 0.9372, the accuracy of the 2009-2017 period's confusion matrix is 0.9302, and the accuracy of 2001-2017 period's confusion matrix is 0.9275.

First, it is interesting to note that some variables were important determinants for urban land conversion for both periods; however, their effects decreased in the second period. These variables are: parkD, waterD, GoverD, roadD, railD, RailSD, BusSD. Between 2001 and 2009, the most significant positive driver towards urban land expansion is increased industry value, followed by the increased agricultural value and masterplan. From 2009 through 2017, the most significant positive driver towards urban expansion is the increased masterplan, followed by the increased GDP, while the negative driver toward urban expansion is increased agricultural production. From 2001 through 2017, the most significant positive driver of urban expansion in Zhangye City is the masterplan, and the negative driver is increased agricultural production.

Compared to the performance of explanatory variables from 2001-2009 to 2009-2017, it is interesting to notice that the masterplan keeps as a dominant positive driver for non-urban areas converting to urban land use. However, from 2001 to 2009, the masterplan is not the highest coefficient, while from 2009 through 2017, it is the highest coefficient. In addition, the explanatory variables about distances performed differently.

Generally speaking, the distance to park, the distance to water, the distance to local government and the distance to railway station had a positive effect on converting urban land use, which means if the non-urban pixel is closer to a park, water, government or railway station, it would have a higher possibility to converting an urban land both during the periods of 2001-2009 and 2009-2017. Besides, the distance to the road and the distance to the railway had a negative influence on converting non-urban land use. While the distance to the bus station had a low positive impact on converting urban areas between 2001 and 2009, it almost did not affect urban expansion during the 2009-2017 period. Interestingly, the increased GDP had a positive influence on urbanization during the period of 2001 to 2009, while it had a negative influence during the period of 2009 to 2017.

In comparison to the other two socio-economic variables, the increased agricultural production and GDP had a similar effect on non-urban convert to urban land use. In contrast, the increased industry total value had a positive influence on urbanization in Zhangye City during the periods of 2001-2009 and 2009-2017.

Table 8. Estimation of explanatory variables in the logistic regression model for urban development in Zhangye City over the study period.

Name	**2001-2017**				**2001-2009**				**2009-2017**			
	β_0	SD	z value	*p*-value	β_0	SD	z value	*p*-value	β_0	SD	z value	*p*-value
Constant	1.562	0.229	6.830	0	-4.663	0.360	-12.957	0	-0.645	0.179	-3.612	0
parkD	-0.045	0.002	-17.914	0	-0.008	0.004	-2.040	0.04	-0.046	0.002	-23.522	0
waterD	-0.102	0.006	-16.093	0	-0.082	0.007	-12.146	0	-0.095	0.007	-14.474	0
GoverD	-0.090	0.006	-15.110	0	-0.052	0.006	-8.250	0	-0.074	0.006	-12.438	0
roadD	0.161	0.011	14.506	0	0.253	0.010	25.227	0	0.161	0.011	14.544	0
railD	0.056	0.008	7.428	0	0.031	0.008	3.764	0	0.049	0.007	6.820	0
RailSD	-0.080	0.007	-11.385	0	-0.024	0.008	-2.946	0	-0.086	0.007	-12.157	0
BusSD	-0.027	0.001	-21.689	0	-0.003	0.001	-1.940	0.05	0.000	0.002	0.169	0.86
UrbanD	0.040	0.003	15.838	0	0.064	0.003	24.556	0	0.055	0.002	27.033	0
AvailD	-0.004	0.002	-1.616	0.10	0.000	0.002	-0.037	0.97	0.006	0.002	3.016	0
IGDP	0.116	0.038	3.078	0	-2.365	0.369	-6.414	0	0.759	0.058	13.172	0
IITV	0.117	0.020	5.801	0	2.978	0.413	7.205	0	0.086	0.018	4.738	0
IAG	-1.061	0.107	-9.893	0	1.720	0.396	4.344	0	-2.233	0.101	-22.011	0
Plan	1.636	0.053	31.132	0	1.100	0.060	18.195	0	1.461	0.056	26.300	0

Furthermore, the results of the logistic regression model showed that the city masterplan is the main driving force of urban expansion for the periods of 2001-2017 and 2009-2017. For the period of 2001 to 2009, the main driving force of urbanization is the increased industrial value. Under the consideration of the increased urban area (49.18 km^2) from 2001 to 2009, the urban area increased by 528.02 km^2 in 2017.

The total amount of the increased metropolitan area could have considerable influence on the model results in determining the main driving force of urban expansion. Therefore, it is difficult to find a strong positive relationship between masterplan and urban expansion using the logistic regression model. Besides, the local tenth five-year plan implemented in Zhangye City also promoted to build more industrial areas to improve the local economy (Zhangye City People's Congress,2001).

Some other interesting relationship associated with the non-urban land converted to urban land is increased agricultural production. Between 2001 and 2009, it favors the process, while between 2009 and 2017, it had a negative influence on the conversion process. It could be due to the second round of urban expansion, as a large area of agricultural land was converted to the urban area, particularly 10 km around the center of the city. The remained agricultural land area occupies less by comparing with the land use and land cover products between 2001 and 2009. This finding indicated that increased agricultural production did not favor urban expansion.

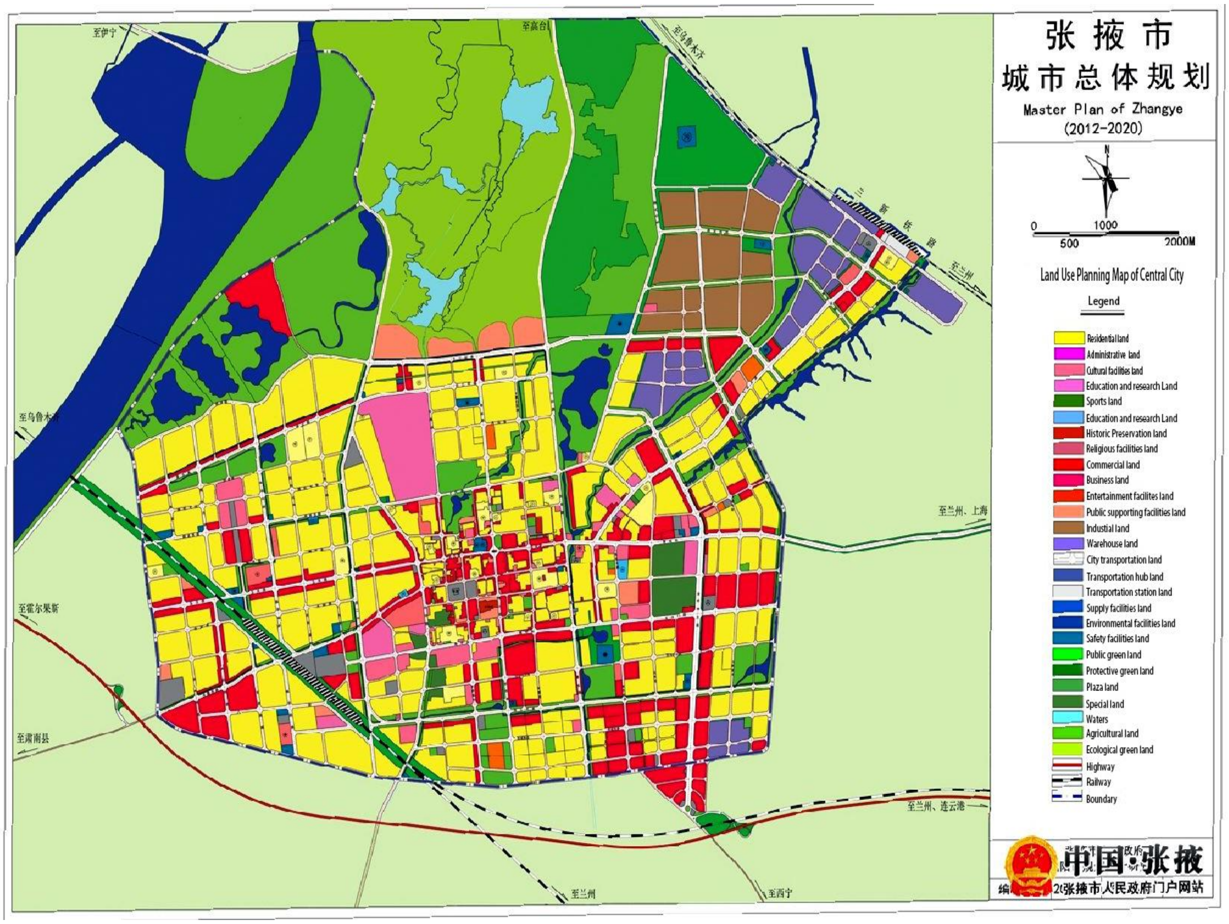

Figure 17. The masterplan of Zhangye city from 2012-2020 (source: Bureau of Natural Resources of Zhangye, 2014)

Figure 17 above is the masterplan of Zhangye, according to the model result, it indicates that the masterplan is the most influential variables among all explanatory variables. The masterplan of Zhangye labeled the city's different function areas and its expected size and shape of the city by the year 2020. According to the Zhangye's 13th five-year plan. The Ganzhou district should be a famous historical and cultural city, an ecological wetland city, a regional economic center, and tourist distribution center. They would like to construct the city by a “1+5” eco-friendly framework, which includes five new ecological functional zones and an urban center (Zhangye City People's Congress,2016). The urban center is the old urban area of Ganzhou; it is driving the economy industrial park on the northeast side of Ganzhou district, national wetland park, the new Zhangye Riverfront District, and an oasis modern agricultural experimental demonstration area.

Zhangye's government also introduced the "1+5" framework. The framework is to aim for a multi-function city that each sector is unique and well developed. Most importantly, as the government wanted, they want to the entire city to be both ecologically friendly and sustainable city. The model result and the land classification result show that from the driver of urban expansion of Zhangye is the policy, and the policy filled the purpose of the government to build a well-developed and ecological friendly city.

CHAPTER 5: CONCLUSIONS

In this study, the land use and land cover classification maps for the years of 2001, 2005, 2009, 2013, and 2017 in Zhangye were produced using the random forest classification method by integrating a new geospatial technology of GEE with Landsat data. The land use and land cover change in the past 17 years were analyzed with socio-economic data such as GDP, population, and water resources, particularly for urban area and cropland expansion. The spatial logistic regression model was applied in analyzing the driving forces to urban expansion in Zhangye city.

Based on our results from land classification, change detection and linear regression model result, we come up with the following conclusions:

Using Google Earth Engine to process imagery and perform land classification is very efficient and the results are highly accurate compared to other platforms or methods. Because the GEE is a cloud-based platform and the stored satellite images can be used without downloading them first, it could save researchers a lot of local storage and computation power. What is more, with the built-in machine-learning classification method, the classification result is very satisfying. This study achieved overall accuracies of 96.19% (2001), 94.99% (2005), 95.61% (2009), 95.55% (2013), and 89.57% (2017), respectively. We set up seven different land cover types for GEE to classify and the random forest classifier performed very well. A key finding is that GEE can be an effective tool for researchers who wish to produce a land classification product of their study area in a short period of time as well as high classification accuracy.

There is a dramatic land use land cover change from 2001 to 2017 in Zhangye. The urban built-up land use had been increased 540.79 km^2. The surface water area had been increased by 104.74 km^2. The cropland area increased by 639.94 km^2 and the total green area, including forest and grassland increased about 6336.30 km^2. Generally speaking, Zhangye is greener and more urbanized. The urban expansion mainly occurs at Ganzhou district, Gaotai county and Shandan county. The expansion of cropland is around the edge of old farmland in all regions of Zhangye except Sunan county, a dramatic increase in cropland area is mainly attributed to a decrease in bare land at the oasis edge and some part of grassland areas, the grassland were converted into cropland because of more than ten years of reclamation of new agriculture fields. The water surface area is increased mainly because newly instructed lakes, reservoirs and restored wetlands in Zhangye, while the total amount of water usage in Zhangye City changed slightly from 2001 to 2017 according to the Zhangye's statistical yearbook.; finally, the increase of green area is mainly along the Qilian mountains.

Although different land use type changes might be varied, all land use changes are directly linked with central to local government policies. The national returning farmland to forest program has a direct impact on reforestation in Zhangye area, as well as afforestation policy. In addition to that, policies related to the Heihe River Basin environment protection favors the local environment restoration process, as well as the Ecological Water Diversion Project, which aims to protect the water resource and regulate water usage in HRB. The project of ecological protection and restoration of the Qilian Mountains that coming up in recent years also intends to restore the ecological environment. Several policies connected with the urban expansion as well, such as the masterplan of Zhangye, as well as the five-year plan of Zhangye. It is worth mentioning that policies related to urban expansion also indicated that development should be ecofriendly, and the city itself should develop industries that could harm the environment. Instead, the city should develop tourism and water-saving agriculture and its products to improve the local economy. The government hopes that Zhangye could be a sustainable ecological city.

The city masterplan is the main driving force of urban expansion for the periods of 2001-2017 and 2009-2017. The distance to the park, to water, to local government, and railway station had a positive effect on converting urban land use; while the distance to road and the railway had a negative influence and the distance to bus station had a meager positive influence on urbanization during the period of 2001-2009. The increased agricultural production and GDP had a similar effect on urbanization in Zhangye City, while the increased industry total value had a positive influence.

There are some limitations in this study that should be further improved. First, the logistic regression model used some explanatory variables related to distances, such as distance to park, distance to the railway station, distance to the bus station, distance to railway, distance to road. Because the location of these sites is extracted from OpenStreetMap, the OSM server constantly updates these locations and add newly constructed site on the map, where these data points are the newest and most current. Therefore, some locations of these variables may not exist when conducting the model. Especially in the period 2001-2009. A better solution is to retrieve the existed locations of the park, railway, railway station, highway back to the start time of the model begins. Due to the lack of available data on the internet, the locations of different places of interest at the start time of each model are not available. It could be improved by collecting old existed maps or datasets published by the local government.

Another limitation of this study is that the classification process is limited by lacking ground truthing points. In this study, the controlled points for the classification were from the Google Earth or Google Earth Engine's high-resolution imagery. The classification results could be further accurate if a field trip to the actual site and create an actual ground truth pointset.

The third limitation is the classification accuracy was calculated at ArcGIS, not from Google Earth Engine, because the GEE has a computational limit set up for each task that because the study area is quite big and the total number of pixels are too many that the GEE cannot calculate the classification accuracy at the same time. Therefore, the accuracy has to be calculated at ArcGIS.

In summary, Zhangye's urbanization is closely related to increased GDP, tourism, industrial added value, population with high school diploma and urban resident Hukou, as well as the per capita disposable income. Most importantly, Zhangye's masterplan is a key feature that designed how Zhangye's expansion. It indicates that policy is the major reason for Zhangye's development, compared with other urban expansion studies on the eastern part of China, the government policy is less important while market and local business activities could also have a great impact on land use change (Liu, Yue, & Fan, 2011). It indicates that during the development of Zhangye, the local and central government should help the local business and market to invest more. Adopting market and capital forces into urban expansion might have a faster reaction to the newest demand by the public or the economy.

With the rapid urbanization in Zhangye, it is also important to point out that the total population of Zhangye is slightly decreasing from 2001 to 2017, yet the urban land use has been doubled in the same period. It is good that the housing area per capita in Zhangye is increasing, but it could be concerning that will Zhangye face a "ghost city" problem in the future? Especially when Zhangye's urban expansion is still an ongoing process while Zhangye is losing its total population. Another challenge that Zhangye government might have is how to balance the local ecology with the boosting tourism industries. Zhangye has successfully branded itself as a great eco-tourism visiting city in China, even around the globe. However, with more and more tourists coming to visit Zhangye, these tourists are inevitably using local resources such as water, food and energy. Zhangye, as a semi-arid city is already facing the water shortage issue, with about 26 million people coming to Zhangye in 2017, Zhangye's water resource is becoming more and more important, less water resource might have a negative impact in Zhangye’s future development. How to promote the local economy by tourism as well as not harm future development could also be an interesting topic for further study.

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