Rapid Urbanization, Changing Croplands and Increasing Population Health Vulnerabilities in the China-Central Asia-West Asia Economic Corridor

HOPE JUDKINS *

National Weather Center Research Experiences for Undergraduates Program
Norman, Oklahoma,
The University of Alabama in Huntsville
Huntsville, Alabama

DR. KIRSTEN DE BEURS
Department of Geography and Environmental Sustainability
The University of Oklahoma
100 East Boyd Street Norman, Oklahoma 73019

ABSTRACT

Inspired by the Silk Road, China's President, Xi Jinping, established the Belt and Road Initiative (BRI) in 2013. The BRI, consisting of six economic corridors, connects China with other countries to improve international trade, financial integration, and prosperity. The China-Central Asia-West Asia Economic Corridor (CCAWAEC) focuses on establishing numerous transportation and other infrastructure projects and provides a land bridge to enhance and increase trading to Europe. Many countries in Central Asia, such as Kazakhstan, have benefited from the initiative to view a rise in economic growth and infrastructure enhancements. Rapid urbanization and economic growth have deteriorated agricultural land and increased population health vulnerabilities. Based on satellite-derived data, the dynamics and changes of land cover over the past 25 years were outlined along with the causes. It was initially concluded that with the initiation of BRI, cropland decreased while barren land increased. After further investigation, the shift of urbanization from Central Almaty to Northwest Almaty, cropland has begun to increase while barren land fell. However, urbanization is still considered a threat to agricultural land and water availability.

1. Introduction

Worldwide urbanization has been vital to significant economic and social development. While this process has shown no sign of stagnation, the most potent and detectable human induced influence is land use degradation. Urbanization is progressing rapidly in less developed regions, and the urban population is anticipated to grow. By 2030, metropolitan regions will encompass less developed areas, which will be almost all of the world's total population. Rapid urban development can be a threat to health vulnerabilities. For example, rapid urbanization in Almaty is a persistent burden of citizens. Traffic has rapidly increased, therefore increasing traffic congestion, which raises pollution levels (Dave and Kobayashi 2018; Alexander et al. 2007), which can lead to asthma attacks, cardiovascular disease, and lung cancer. The Soviet Union controlled most of Central Asia from 1922-1991. The Soviets maintained authoritarian public health systems, resulting in public health regulations. Restrictions of trading and travel diminished the reintroduction of familiar infectious diseases and pathogens. After its fall, countries under Soviet rule were susceptible to political and economic changes, which reshaped urban and rural ecologies to increase disease risks. Some side effects of these changes included rapid urbanization, less regulation of international trading, and incomplete development of municipal services. Increasing international trading and travel networks increases the risks of unfamiliar pathogens in Central Asia. This increase of pathogens through trading was introduced to the region likely through developments such as the belt and road initiative (BRI). Launched by Xi Jinping of China in 2013, the BRI was presented as a trade and infrastructural development initiative that benefits all to deliver stability (Dave and Kobayashi 2018). The BRI merges existing economic investments and security-building measures while launching new projects to link the regions of Central Asia and West Asia more closely with China and develop them as a transport corridor that connects China to Europe. Kazakhstan, a Central Asian country, displays eco-

**Corresponding author address:* Hope Judkins The University of Alabama in Huntsville , 301 Sparkman Drive, Huntsville, Alabama 35805
E-mail: hopej16@gmail.com

nomic strength, and its largest city, Almaty, is a trading hub and a central transit location. The BRI enables it to better manage widespread expectations and relations with Europe, China, and Russia in the China-Central Asia-West Asia Economic Corridor. Rapid urbanization in Almaty, Kazakhstan in coupled with population growth, can lead to improper distribution of raw materials. The study explorers the progression of spatio-temporal attributes, land use and land cover changes regarding rapid urbanization in Almaty by integrating remote sensing technology. The overall objective is to understand the effects and consequences of rapid urbanization on land cover, croplands, and population health vulnerabilities and identify appropriate steps for sustainable urban development.

2. Study Region

Located in the Western Tienshan Mountains and Zailiysky Alatau region, Almaty sits at about 850 meters (m) above sea level at a longitude of 43.2 North and latitude of 76.9 East (Figure 1). It has a population of about 2 million spanning 340 kilometers squared (km^2). During the Soviet period, Almaty served as the capital of Kazakhstan. After the collapse of the Soviet Union, Almaty remained the capital until 1997 when the Kazakh government moved the capital to Akmola, which was later renamed Astana and since 2019 is called Nur-Sultan.

3. Data

3.1 Landsat Data

A satellite image collection of Landsat 5, 7, and 8 was selected from Google Earth Engine. These six images had a spectral resolution of 30 meters to view detailed images of the study region (Table 1). By using summer months (June-August), I investigated changes in vegetation, cropland, and urbanization. Images were selected, all with less than 20%cloud cover. Overall, these images were selected based on the criteria to provide explicit imagery of Almaty (Table 1).

TABLE 1. Landsat Image Path/Row and Acquisition Date of Almaty

Satellite	*Dates*	*Image Path/Row*
Landsat 5	*7/1/1994; 7/7/2000;8/17/2011*	*149/030*
Landsat 7	*7/26/2015*	*149/030*
Landsat 8	*7/15/2015; 6/27/2019*	*149/030*

In order to acquire data to view vegetation detection for Almaty, different band combinations with their respective wavelength were used for each landsat satellite image and year. The spectral resolution for the satellite images was 30 meters. This permitted me to differentiate between small details and intensively study Almaty (Table 2).

TABLE 2. Landsat Band Combinations and Wavelengths

Satellite	*Band Combinations*	*Wavelengths (μm)*
	7-SWIR	*2.09-2.35*
Landsat 5 & 7	*5-SWIR*	*1.55-1.75*
	3-Red	*0.63-0.69*
	7-SWIR2	*2.11-2.29*
Landsat 8	*6-SWIR1*	*1.57-1.65*
	4-Red	*0.64-0.67*

4. Methods

The goal of this research is to evaluate rapid urbanization, changes in cropland, and increasing population health vulnerabilities in the China-Central Asia- West Asia economic corridor. Remote sensing methods were used to detect rapid urbanization and changes in cropland. Validation methods were used for all datasets against validation points selected based on Google Earth Engine images. A mask was applied to omit noise originating from cloud and snow pixels to indicate clear conditions. The images produced allowed visualization of progression or digression of the region of study.

4.1 Classification

Classification and regression tree classification is a common tree growing algorithm. Image classification was used to classify the pixel into different land cover classes. For example, the classes used during this research include water, urban, forest, agriculture and grassland. The feature class polygons' training data were generated by homogeneous digitized polygons based on the continuity of 25 years of the study region For each land cover class, samples were assigned polygons which were merged into a single class. Once the samples were assigned, they were used to determine which class each pixel inherits in the overall image. The regression tree model is the primarily method of constructing a set of decision rules on predictor variables (Mastery 2019). Based on the feature class polygons, the regressions tree models examine and categorize positive and negative polygons. If deemed positive, the polygon is correctly categorized for the feature class. For instance, if I use urban areas as an independent variable, the regression tree model will indicate positive (true) or negative (false) digitized polygons. The regression model performs well to describe relationships between predictor variables and the categorical outcome variable (Peng et al. 2002). These variables may be discrete, continuous, or a combination of both classes, and a normal distribution of the data is not required (Lee 2005). A confusion matrix was calculated to evaluate the accuracy of the classification result. This allowed me to view the accuracy of classified images to the ground truth or referenced image.

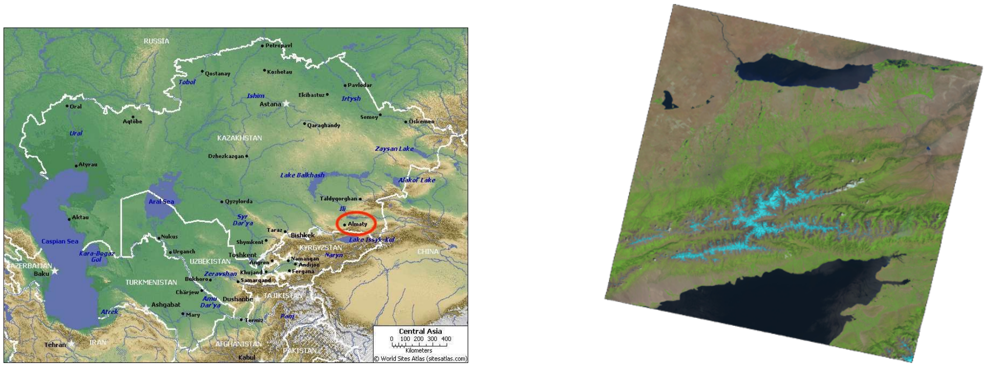

FIG. 1. (A) Study Region (B) Landsat 8 tile 140/032 (4,3,2 Natural Color)

4.2 Google Earth Engine and Validation

Using Google Earth Engine, I manually identified 300 validation and training (30 m by 30 m) grid cells for the study area. Since the specific interest is rapid urbanization and changing cropland, data was reserved by splitting the selected data into a training portion (70%) and a validation portion (30%). Different polygons for each sample feature class, such as water, urban areas, barren land, cropland, suburban, trees, and roads, contained 25-60 samples to receive sufficient information for the study region. The feature class polygon's training data were generated by homogeneous digitized polygons based on the continuity of 25 years of the study region. Once digitized, merging feature classes and defining bands, the training points were used to develop the classification of land cover, and then assess the validation of the training data in the form of a confusion matrix.

5. Results

5.1 Spatial Analysis

Using Landsat data, I was able to view and track land use and land change due to climate and urbanization (Figure 2). I used different band combinations to focus on the intended target. By using a false-color band combination (7,6,4) for Landsat 8 OLI and (7,5,3) for Landsat 5 TM and 7 ETM+ and stretching the image by 98%, I was able to view the changes in vegetation as well as urban areas. Vegetation vastly decreased from 1994-2000, likely caused by the collapse of the Soviet Union and lack of water availability hindering cropland growth. With each time, vegetation and cropland availability is decreasing and a shift and increase of urbanization.

5.2 Confusion Matrix

The confusion matrix described my classification model's performance by evaluating the final classification result (Figure 3). This allowed the visualization and performance of an algorithm. By calculating the producer's accuracy, given the confusion matrix, I was able to assess the quality of the classification training pixels with respect to the ground truth (Figure 4).

5.3 Classified Images

Based on the training dataset and the results of the confusion matrix, classified images were produced. The visualization of these images allowed me to view changes with each feature class (Figure 5). While intently studying both the confusion matrix images and the classified images, a further assessment of the study region was performed. While studying the classified images, I was able to denote changes in the feature classes. In 2015 based on the producer's accuracy, water availability and barren land increased while cropland availability decreased. This led me to believe the BRI was partly the cause of this. The BRI established a land bridge to induce increased trading with Europe, which increased demand for land compromises cropland availability and allows more land to be utilized for urbanization. In 2019, urbanization significantly increased along with suburban areas based on the producer's accuracy. Urbanization is expanding in different regions of the city instead of remaining compact in the centralized area (Figure 5 Panel A).

6. Discussion

Based on the results obtained by the confusion matrix and classified images, most findings were expected. With the producer's accuracy (Figure 4), all classes become more accurate. Water is the most accurate because it's simple to distinguish, unlike roads, since it is challenging to differentiate between other feature classes. Based on research, urbanization vastly increased partly due to the belt and road initiative. However, through each year of study, the water availability increased, yet only small amounts of

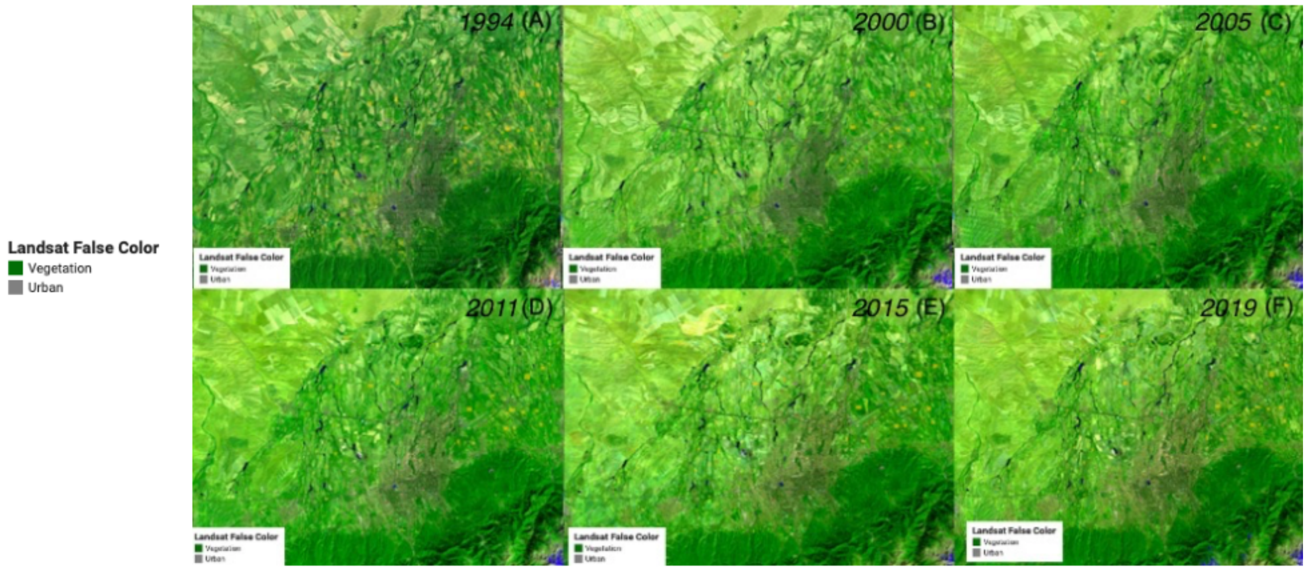

FIG. 2. False Color Landsat Images from 1994-2019

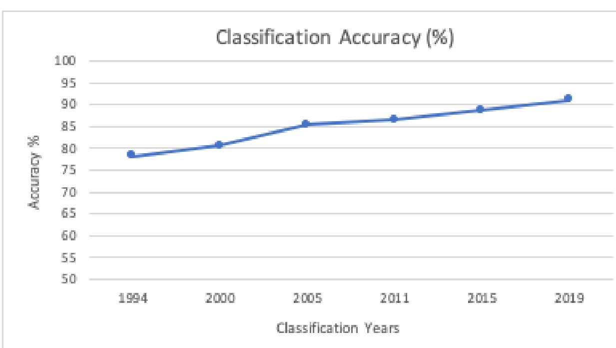

FIG. 3. Classification Accuracy

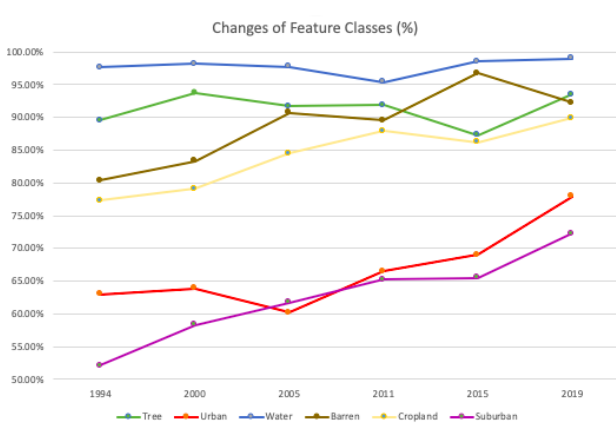

FIG. 4. Producer's Accuracy Feature Classes %

water were found. In Kazakhstan and surrounding countries, rapid urbanization has led to a decline in water quantity and water security Ergashev et al. (2013). While observing Landsat (Figure 2) and classified images (Figure 5), they showed signs of shifting cropland availability, yet an influx of suburban areas. I hypothesized that more urbanization areas are moving from central Almaty to other parts of Almaty, yet more suburban areas are increasing in central Almaty. In the past, Almaty experienced more emigration than immigration. However, recently, there has been an increase in population. These are likely due to the collapse of the Soviet Union in 1991, followed by the BRI in 2013, which created new jobs that led to an exponential growth in population.

7. Conclusion and Future Work

It is evident that rapid urbanization, changes in cropland and increasing population health vulnerabilities have a profound impact in Almaty, Kazakhstan. As urbanization increases, it is vital to assess the risks when comparing different variables. Between the three variables used in this study, urbanization, changes in cropland, and population health vulnerabilities, urbanization has the most substantial influence in the study region. By altering one variable, a positive feedback loop occurs concerning the other variables. Future work will include using the satellite-derived analysis to study urban development of large cities more intensively along with roads directly in the CCAWEAC. The study focuses on urban characteristics that might make cities more susceptible to emerging infectious diseases and how they will impact economic growth. The study further investigates different variables

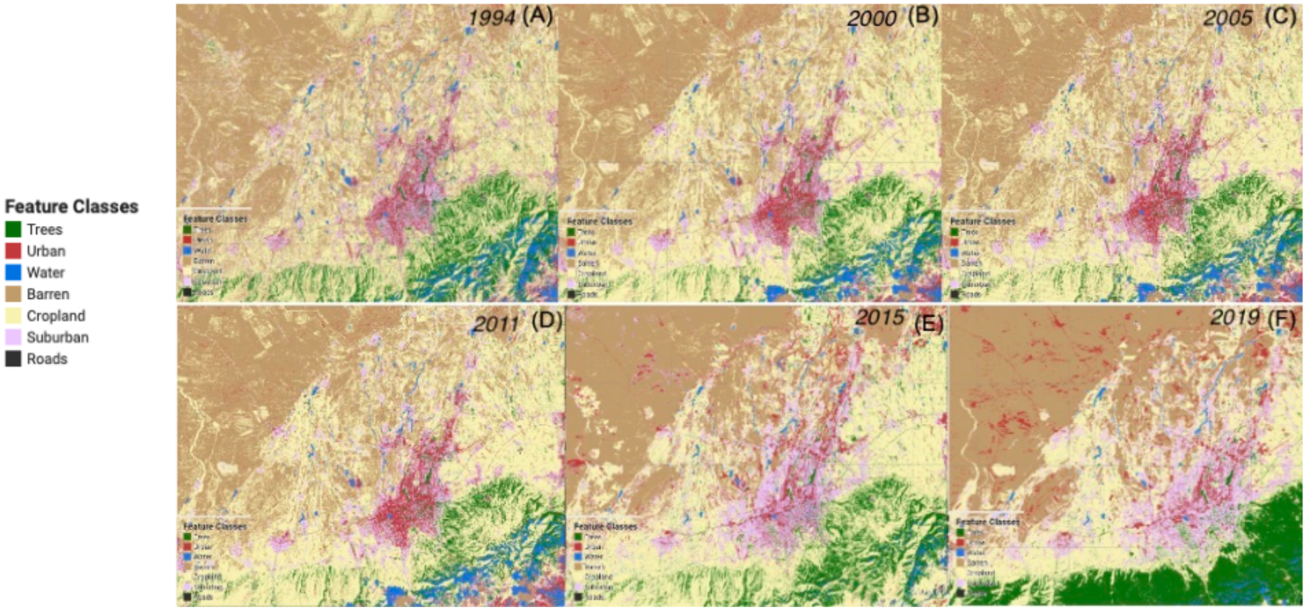

FIG. 5. 1994-2019 Classified Images

such as nighttime lights, land surface temperatures, and urban density measures within the CCAWEAC.

8. Acknowledgements

This study was supported by Grant No. AGS-1560419 from the National Science Foundation. The statements and findings are those of the authors and do not necessarily reflect the views of the National Science Foundation. A special thanks is due to the mentor for the project, Dr. Kirsten de Beurs from The University of Oklahoma Department of Geography and Environmental Sustainability (OU/DGES), for providing insight, guidance and understanding throughout this research process. The author would like to thank the REU Director, Dr. Daphne LaDue, the REU Asistant Director, Alexandra Marmo, and the National Weather Center Research Experience for Undergraduates (NWC REU) for hosting this program. The author would also like to thank Amanda Schilling, Christine Reed, Melanie Schroers and Mark Laufersweiler for offering encouragement and coding support during this REU program.

References

Ergashev, B., and Coauthors, 2013: Urbanization in central asia: Challenges, issues and prospects (analytical report no. 2013/03). *Center for Economic Research, Tashkent, Uzbekistan*.

Lee, S., 2005: Application of logistic regression model and its validation for landslide susceptibility mapping using gis and remote sensing data. *International Journal of Remote Sensing*, **26 (7)**, 1477–1491.

Mastery, M. L., 2019: Classification and regression trees for machine learning.

Peng, C.-Y. J., K. L. Lee, and G. M. Ingersoll, 2002: An introduction to logistic regression analysis and reporting. *The journal of educational research*, **96 (1)**, 3–14.