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Urbanization in Hanoi, Vietnam 2010-2015

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Introduction

The effects of globalization have caused varied consequences on different cities around the world. Today, 54% of the world's population lives in urban areas and this percentage is expected to rise to 66% by 2050 (United Nations, 2014). In Asia and Africa, much of the increase will occur in concentrated areas. An example is seen in the urbanization in and around Hanoi, Vietnam. Hanoi, which is the second largest city in Vietnam, is going through rapid urbanization due to large economic growth (Pham and Yamaguchi, 2011). Over twenty years, economic development and industrialization has stimulated urbanization in Hanoi (Van Suu, 2009). Most of the current migration to the city is made up of people from the immediately surrounding areas who are seeking employment in the urban center. From 1975 to 2015, the urban population of Hanoi has increased from 1.4 million to 7.6 million (General Statistics Office of Vietnam, 2014). To alleviate overcrowding and the increased pressure on land, Hanoi has been further transformed from large-scale agriculture to an urban center (Pham and Yamaguchi, 2011). This new industrialization has led Vietnam to invest in change from their traditional cropland, agriculture-based style of economy to metropolitan, modernized economy. This transformation has forced thousands of farming households to change their livelihoods, recognize, and adapt to the changing environment in which they now live (Pham and Yamaguchi, 2011).

This paper aims to detail the most recent changes in land cover in Hanoi using remotely sensed data. This urban growth mapping and change analysis is facilitated through interpretation of multidate aerial photography using imagery from the beginning and end of the study time. This paper will particularly focus on the land cover changes from agriculture land to urban area so to track the built-up expansion of the capital city. Data concerning locations, rates, and patterns of the new urban sprawl will be analyzed and the importance of urban remote sensing capabilities highlighted. Secondly, the study area will be identified and characterized. Next, details will be given on how the expansion was investigated using Landsat imagery and how the built-up areas were classified using data collected during two specific times (2011 and 2015). This paper's analysis will draw on previous classification work completed by

Schneider et al., 2011 who mapped Hanoi's urban sprawl from 1990-2010. Lastly, there will be a concluding discussion of the implications of Hanoi's urbanization and the future repercussions of this urban spatial expansion in the region.

Background

Remote sensing data have been used to characterize and classify urbanization and other land cover changes in cities and towns since field observations began mid-twentieth century. As Landsat and other medium resolution satellite data became more available in the 1970s, more applications for the data were introduced (Huang et al., 2002; Kontis et al., 2014). Through simple band ratios, image thresholding and differencing, early remote sensing users were able to discern urbanization and other land conversions at the urban-rural border (Huang et al., 2002; Kontis et al., 2014). However, despite the successes of the early approaches, many did not latch-on to this new technology. Recently, there has been a growing amount of research looking at urbanization and its effects on the global land cover change. This opened the door to considering the impacts of urban expansion on environmental systems, human health, and public policy (Hegazy and Kaloop, 2015). With these in mind, it is critical to continue to expand and develop more methods to research urbanization using remotely sensed data.

Over the years there have been many different methods used to generate maps of urbanization and built-up areas. One of the most used approaches is the Multidate Composite Image. This composite is created by combining two images from two different dates into one image to better see the differences between the two images (Huang et al., 2002; Kontis et al., 2014). This approach, first introduced in the 1990s, is used for change analysis and image classification. Using this composite, one can provide better class accuracies and can identify distinct spectral signatures from mixed pixels (Huang et al., 2002; Kontis et al. 2014). Though classifying these mixing pixels has continued to be a challenge even with the introduction of better computer programs, new program algorithms have helped increase the precision of classed maps.

When specifically looking at the history of the use of remote sensing imagery to track urbanization in Hanoi, Vietnam, there have been many previous reports and findings on urban change in Vietnam since the end of the Vietnam War. As Vietnam is currently 30% urban with 3.4% urban population growth per year, there has also been an increasing economic transition toward industrial manufacturing as a share of both employment and economic output (World Bank, 2011; Van Suu, 2009). Urban mapping of Hanoi has been well documented. The studies have focused on the urbanization growth of the city center and surrounding areas. Previous research has been on many topics including: comparisons between rapid urbanization areas in both Vietnam and China (Leaf, 2002), urbanization during post-war transitions of Vietnam (Thrift and Forbes, 2007; Turley, 1975), and changes in build-up areas after colonization (Chuc and Tomson, 1999). Some other studies focused on using remote sensing and spatial metrics to track urban growth and demonstrated how urban change can be seen by satellites, such as Landsat (Uy and Nakagoshi, 2008; Kontis et al., 2014; Hegazy and Kaloop, 2015). Overall urbanization research, which has improved greatly since 1990, has been helpful to international organizations such as the World Bank and local governments to help anticipate future urban expansion (World Bank, 2011).

Study Area

Since the end of the Vietnam War in 1975, new regime changes and subsequent reunification of the North and South regions of the country have shaped urbanization and development in Vietnam. In the 1980s, Hanoi had a population of less than half a million and was governed on a precinct level (Smith and Scarpaci, 2013). While Vietnam was not as anti-urbanization as China, the government did not see cities as the front line of economic growth at the time. Problems also arose from the differences between the North and South. After reunification in 1975, the government attempted to disperse surplus urban population but growth of cities did not decrease (Smith and Scarpaci, 2013). When socialist planning failed, there was a new plan put forward: *đổi mới (“renovation*”). Started in 1986, *đổi mới* kick-started Vietnam into a capitalist, market-driven economic system, a sharp departure from the previous socialist economy (Smith and Scarpaci, 2013; Quang and Kammeier, 2002). Economic performance since the 1990s has been concentrated particularly in the industrial and construction sectors (Smith and Scarpaci, 2013; Quang and Kammeier, 2002). Currently, Vietnam is in an urbanization transition with rapid growth in industrial manufacturing and trade.

Located in the northern part of the country, Hanoi is the capital of Vietnam. The city lies on the right bank of the Red River and has been developing and expanding for over 1000 years since its establishment in 1010 AD (Duong et al. 2007; Van Suu, 2009). Hanoi is an ancient city formed by nine urban districts and five rural districts. These provincial boundaries play an important role as administrative units when organizing local and regional development (Van Suu, 2009; Quang and Kammeier, 2002). Today, the urban population is growing rapidly fueling the competition between the supply and demand for land. Industrial production in the city has also risen since the urbanization boom in the 1990s. The urban sprawl has expanded to the opposite bank of the Red River and beyond. The economic structure has also undergone important shift, with tourism, finance and banking now playing an increasingly important role in the economy in Hanoi. This increase in trade and tourism in conjunction with the rapid urbanization of Hanoi has led to the decline in the farming industry within the capital city (Duong et al., 2007; Van Suu, 2009). Reclamation of agricultural lands for commercial land and housing has put a strain between urban and rural within Hanoi, especially in the face of greater urbanization.

Methods

In order to evaluate remotely sensed images with the intent of analyzing the urbanization patterns, images are first selected based on quality and scope. Once images with the least amount of cloud cover, haze, and other impediments have been selected, one can start work to find the best bands in which to view the data. In this project, images were collected from 2010 and 2015, the beginning and the end of the study timeline respectively. Though the images were not free from all clouds or haze, the images selected were as interruption-free as available.

The next step in creating the change map was to mask out the area of urban growth in 2010. The importance of creating this mask was to confine the image processing and classification to certain defined areas in the image. After finishing the urban 2010 masking layer, the water mask was created. Once both masks were complete, the new image was generated where the masked areas appear black, while the rest of the image has the same to-be-classified imagery. The masking part of the project was completed using a previous change map created by Schneider et al. in 2011. To start creating the masked image, a multidate composite image for 2015 was created. After finishing the multidate image, the mask was applied to create the final 2015 "mask-on" image.

After building and masking the clearest 2015 image, one can start classifying the picture. All classifications utilize training sites, determined and drawn by the user, to identify specific classes within the entire image. A respectable set of training data will be from points spread throughout the image and should also include the darkest and lightest hue within the specific classes so to make sure the algorithm can pick out not only the main area but also the mixed pixels as well. One should repeat the process to make sure the best training data are collected. To start the process of defining classes, an unsupervised classification was run first. In the Schneider et al., 2011 classed map there were six classes: crop, urban, forest, water, seasonal water, and agriculture to urban. Hence, these classes were retained for this study. Once the unsupervised classification was run, it was used as a map of reference for the supervised classifiers.

The supervised classifier was run many times with different but specific algorithms. First, the supervised parallelepiped classifier was run. However, even when changes were made, the classifier still did not reach a respectable accuracy. After running many different other supervised classifiers, the classifier that produced the best map was the Mahalanobis Distance classifier. The Mahalanobis Distance classifier is a direction-sensitive distance classifier that uses statistics to determine classification for each class. When this classifier was run and retested with new training sites, the final and best-classed image was reached. A confusion matrix and accuracy assessment was applied to this final classed image and it confirmed that the image had the highest accuracy overall. The assessments were both run twice to verify their calculations.

Results

The original images, Image 1 and Image 2 respectively, show the difference in the urbanization change in Hanoi, Vietnam. Both images are shown in one of the best 3-band combination for the data, namely 4 (shortwave infrared), 3 (red), 2 (green). Using the shortwave infrared band allowed for the image to become clearer and show the urban areas in bright cyan.

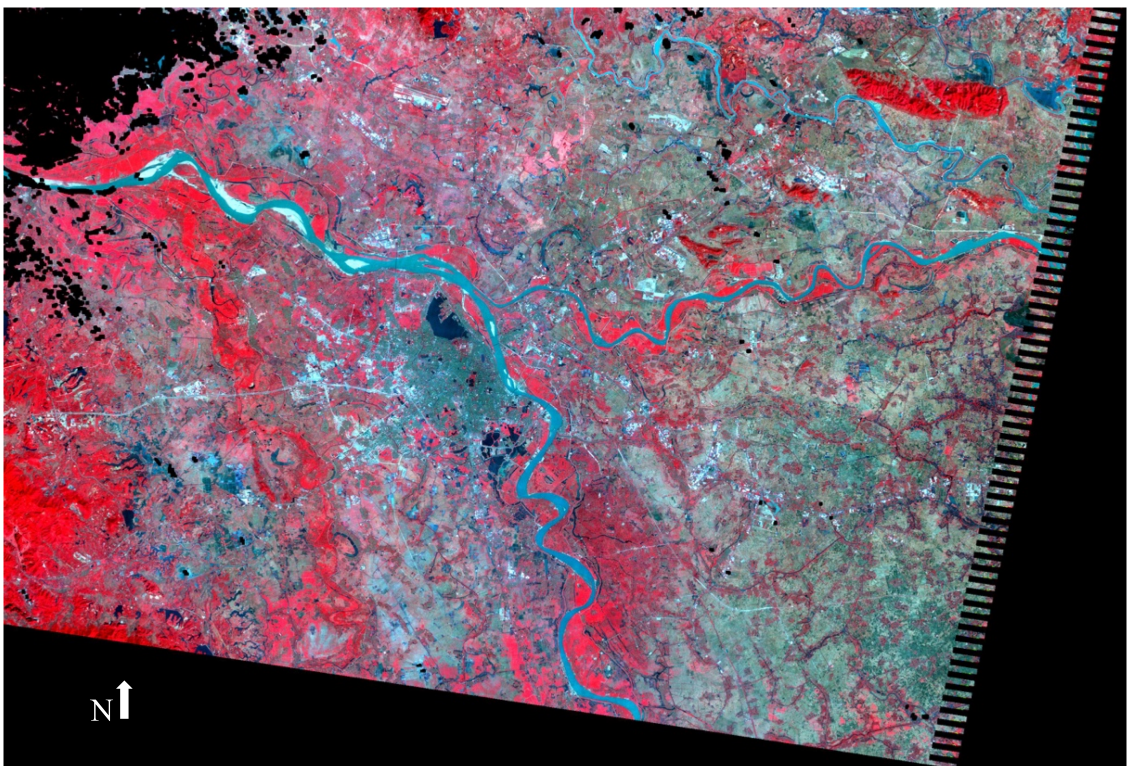

Image 1: Study Area in False Color. Image taken November 8th, 2010.

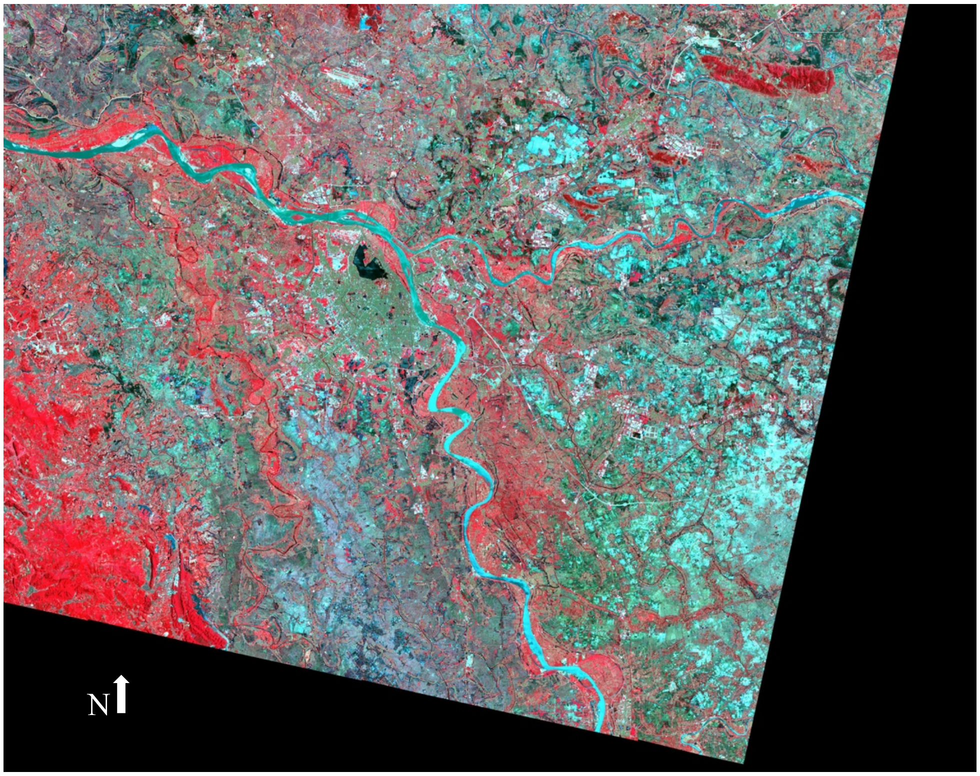

Image 2: Study Area in False Color. Taken July 1st, 2015.

The 2010 Hanoi classes map is seen in Image 3. The distinct mask, shown in gray, red and orange was easily picked out as the 2010 urban masking band. This finished 2010 urban mask, shown in Image 4 in binary (black/white color) system, was then used to create the urban 2010 “mask-on” image seen in Image 5.

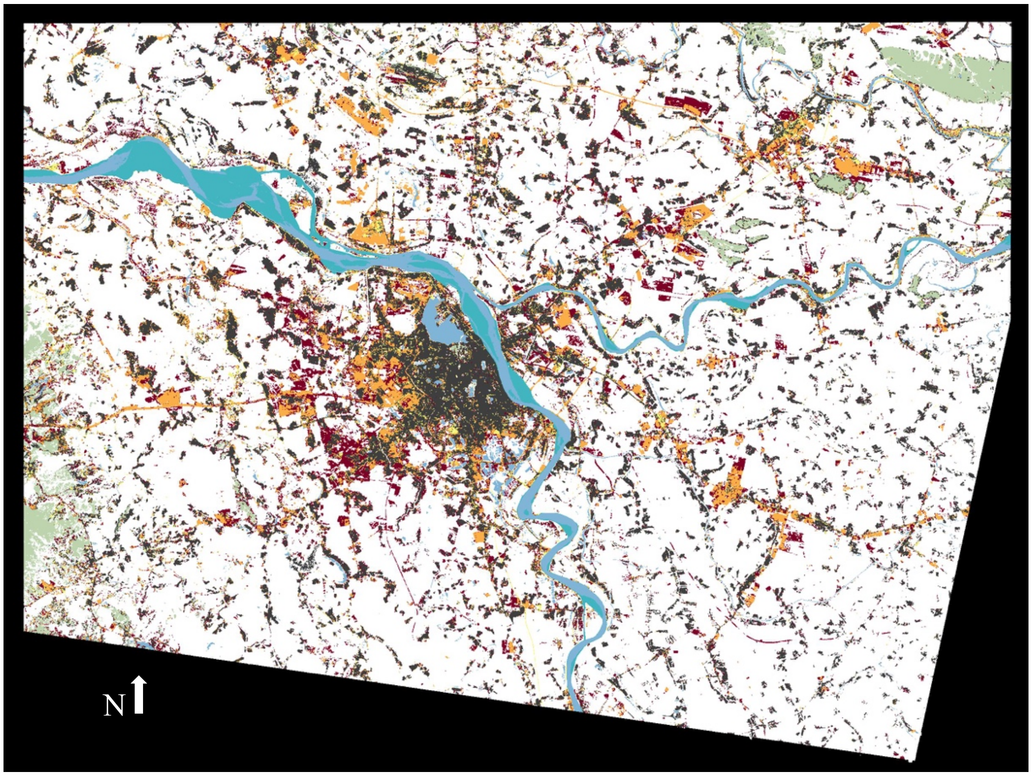

Image 3: Map of Urban expansion up from 1990- 2010. Water is shown in blue, expansion is shown in black, orange and red. Forest is shown in green.

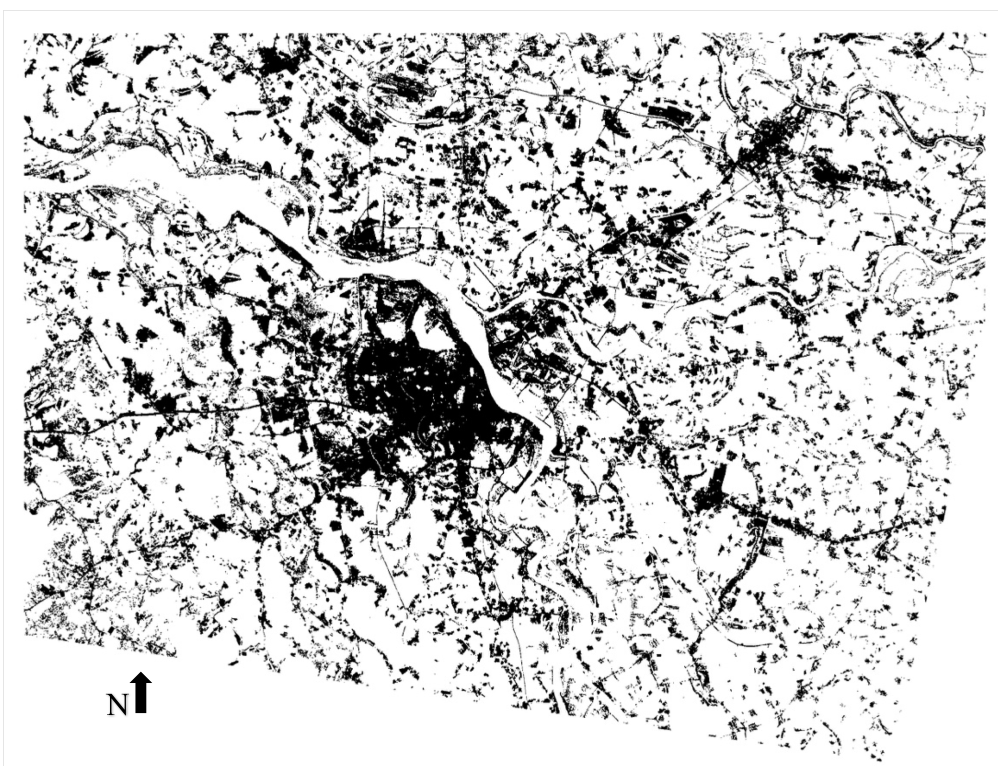

Image 4: Urban 2010 mask created from the map of urban expansion up from 1990- 2010. The masked out part is shown in Black.

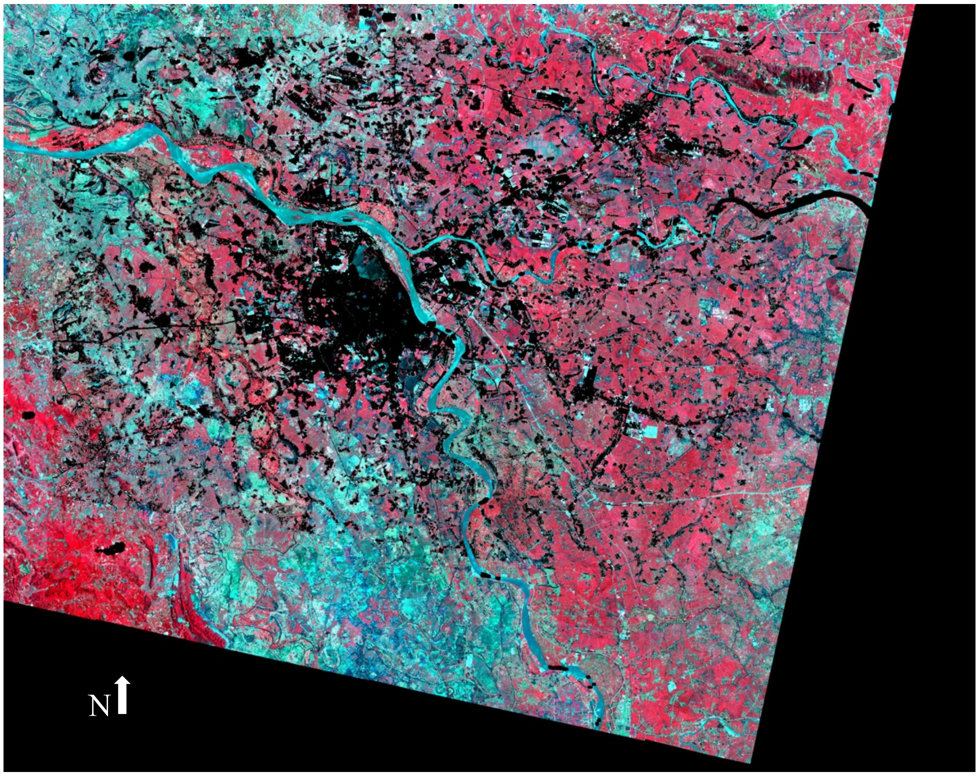

Image 5: Urban 2010 Mask applied to the 2015 study area image, shown in false color.

The masking process was then repeated for the water and seasonal water classes and then the water mask was added then to the urban 2010 mask. This finished water and seasonal water mask is seen in Image 6 and can be seen again as part of the “mask on” 2015 image in Image 7. One can notice that the water mask does not cover the entirety of the river. This is reason why the water and seasonal water classes remained as part of the training data in the supervised classification.

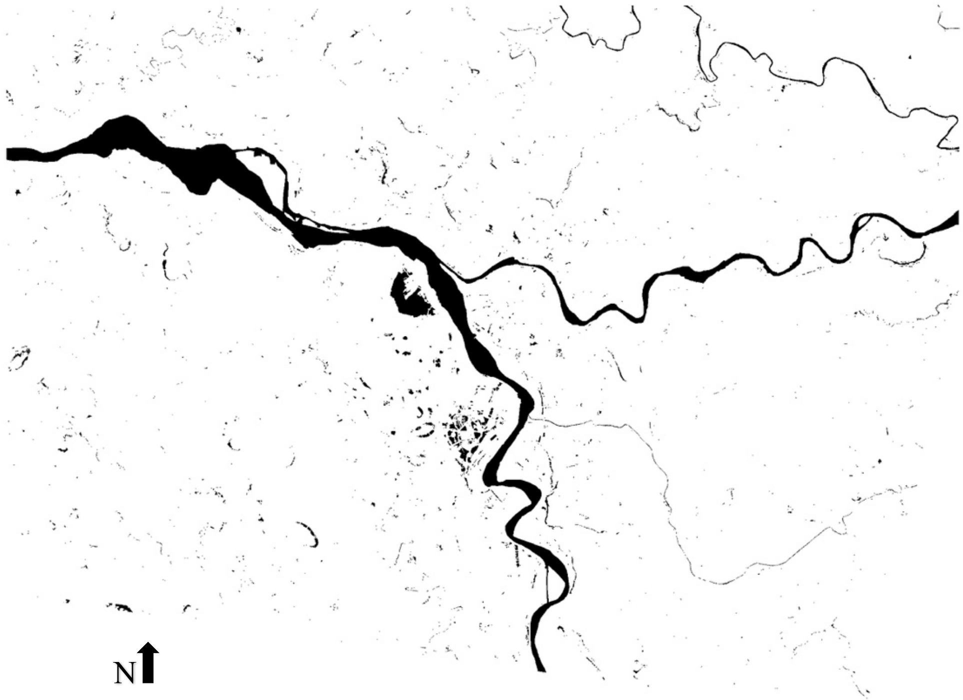

Image 6: The Water Mask created from the map of urban expansion from 1990 to 2010. The masked out part is shown in Black.

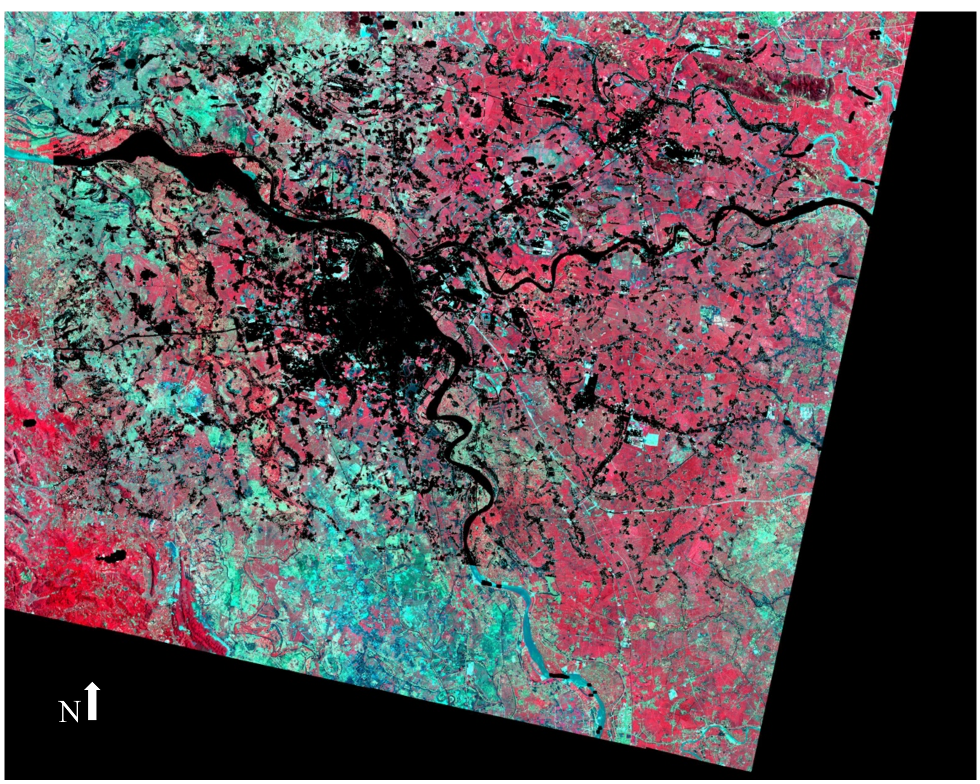

Image 7: Water Mask applied to the 2015 study area image, shown in false color.

The unsupervised classification image was rerun three times to find the exact threshold (3) and class number (25) that were best for analyzing the image. In Image 8, the urban area (seen in red) shows the exact region where the classifier believed the built-up area expansion has occurred. This unsupervised classification is important because it helped determine the training data for the supervised classification.

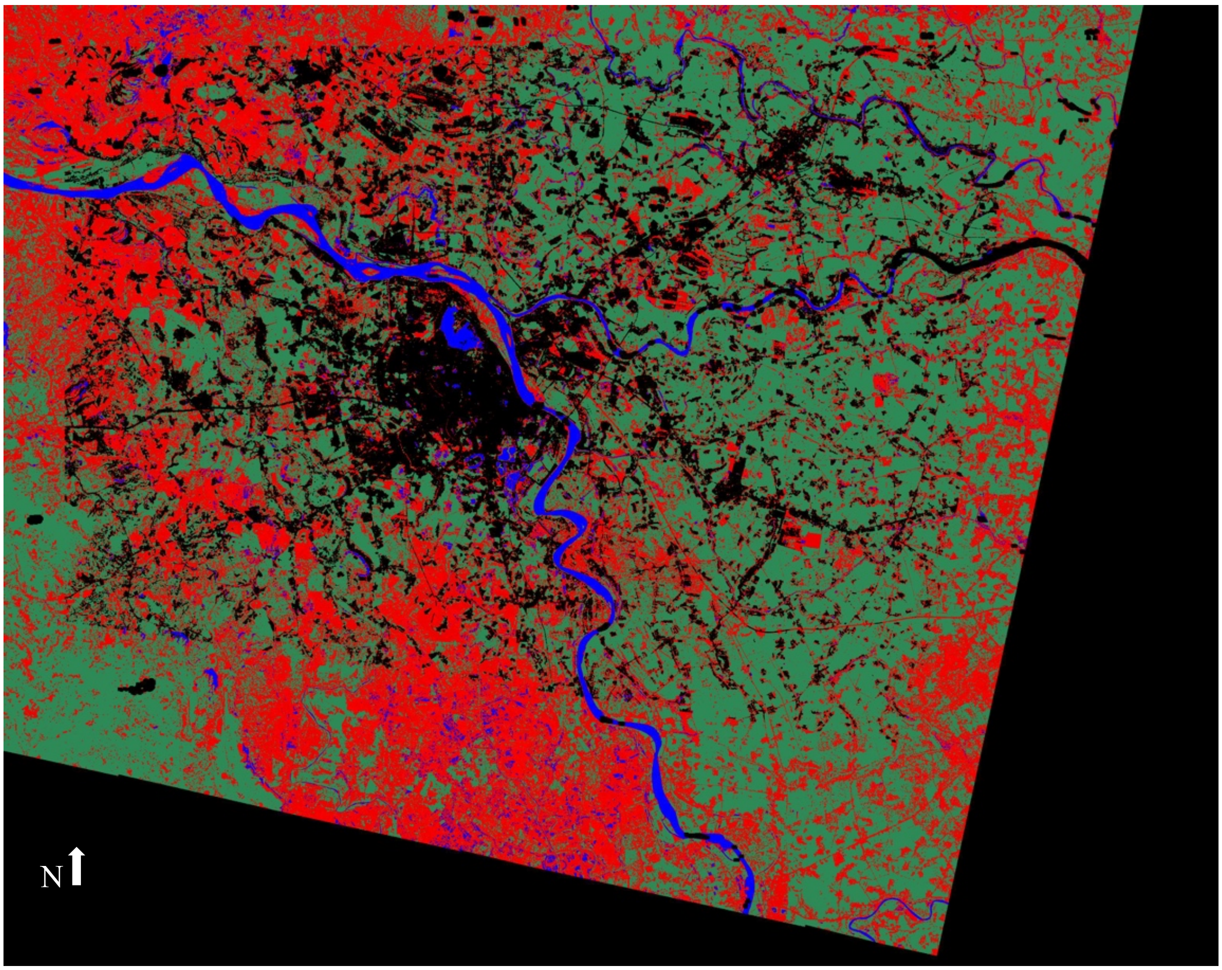

Image 8: The Unsupervised K-means Classification Image. Water is shown in blue, urban 2010 mask is shown in black, urban expansion is shown in red. Forest and crop is shown in green. No seasonal water class shown.

In the supervised Mahalanobis Distance classed image, Image 9, the masked urban, seasonal water and regular water areas are shown as well as all the classes. Though the same classes were used throughout, the training data were augmented in the first versions of the classifier and all new training data were later created when the classifier was run again for the final image. As seen in Image 9, the agriculture to urban land cover change, seen in red (and some cyan), is a significantly larger than the masked out 2010 urban areas, and the data also support this.

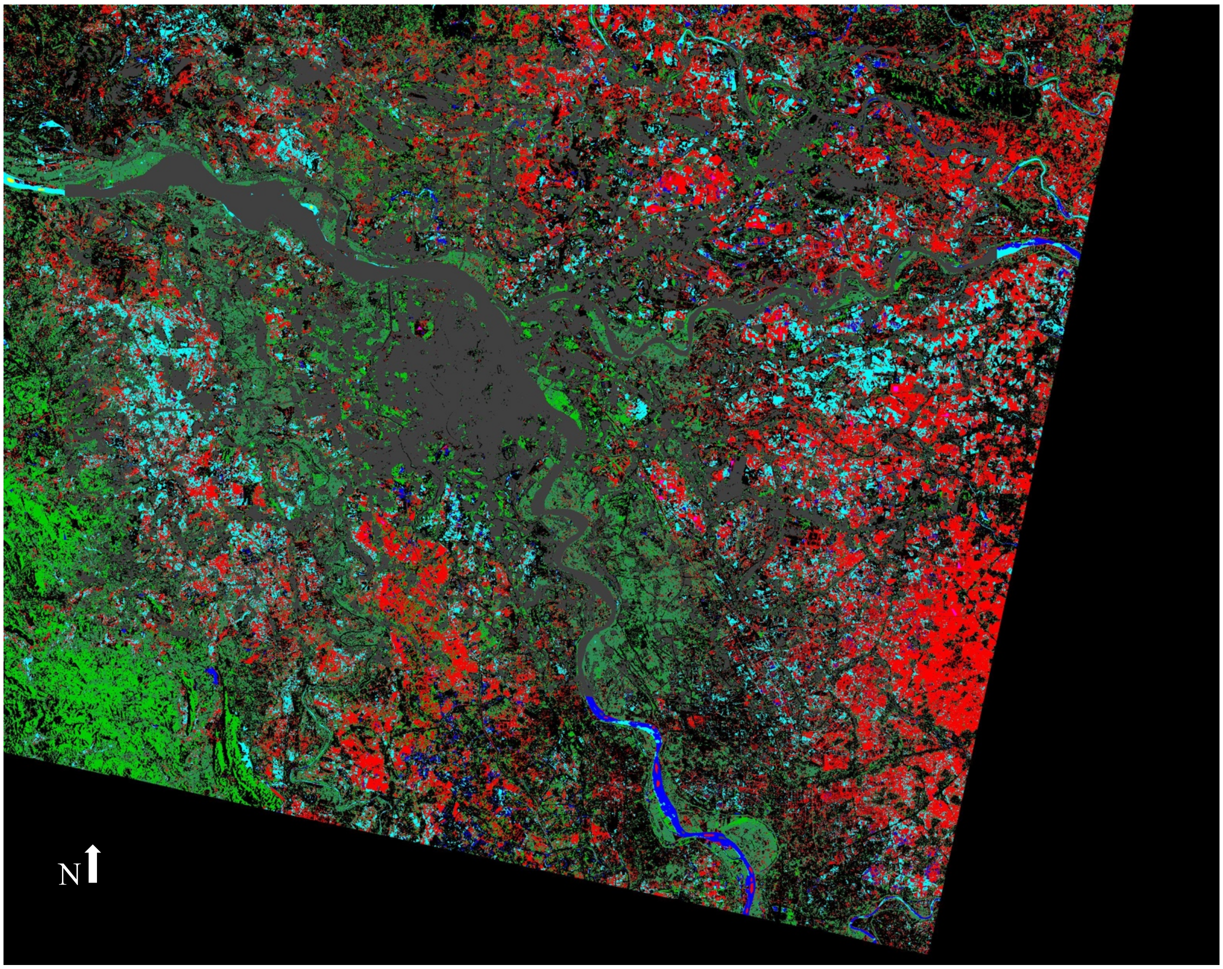

Image 9: Final Image created using the Mahalanobis Distance Classifier. Water is shown in blue, seasonal water shown in cyan, urban 2010 and water mask is shown in grey, urban expansion is shown in red. The forest is shown in bright green and the crop class is shown in (darker) sea-green.

Finally, as seen in Tables 1 and 2, a confusion matrix and an accuracy assessment were run on the supervised Mahalanobis Distance classification in order to assess how well the classifier preformed. In Table 1, the confusion matrix, one can see how well the classifier performed according to the entire image. In Table 2, the accuracy assessment, one can see how the 200 randomly generated sample points were assessed in relation to the classifier.

Table 1: The Confusion Matrix run on entire Mahalanobis Distance final classed map.

Overall Accuracy = (2518/2975) =84.6387%
Kappa Coefficient = 0.7810

	Ground Truth (Pixels)					
Class	crop	forest	seasonal water	water	ag to urban	Total
Unclassified	22	57	0	16	258	353
crop	128	17	0	0	0	145
forest	50	163	0	0	3	216
seasonal water	0	0	262	0	4	266
water	0	0	0	702	30	732
ag to urban	0	0	0	0	1263	1263
Total	200	237	262	718	1558	2975

	Ground Truth (Percent)					
Class	crop	forest	seasonal water	water	ag to urban	Total
Unclassified	11.00	24.05	0	2.23	16.56	11.87
crop	64.00	7.17	0	0	0	4.87
forest	25.00	68.78	0	0	0.19	7.26
seasonal water	0	0	100.00	0	0.26	8.94
water	0	0	0	97.77	1.93	24.61
ag to urban	0	0	0	0	81.07	42.45
Total	100.00	100.00	100.00	100.00	100.00	100.00

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
crop	11.72%	36.00%	17/145	72/200
forest	24.54%	31.22%	53/216	74/237
seasonal water	1.50%	0	4/266	0/262
water	4.10%	2.23%	30/732	16/718
ag to urban	0	18.93%	0/1263	295/1558

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
crop	64.00%	88.28%	128/200	128/145
forest	68.78%	75.46%	163/237	163/216
seasonal water	100.00%	98.50%	262/262	262/266
water	97.77%	95.90%	702/718	702/732
ag to urban	81.07%	100.00%	1263/1558	1263/1263

Table 2: The Accuracy Assessment run on the Mahalanobis Distance final classed map using 200 randomly selected points.

Overall Accuracy = (165/200)= 82.5000%
Kappa Coefficient = 0.7530

	Ground Truth (Pixels)					
Class	crop	forest	ag to urban	seasonal water	water	Total
Unclassified	0	0	4	1	0	5
crop	66	3	2	0	0	71
forest	9	21	0	0	0	30
ag to urban	0	0	64	0	0	64
seasonal water	0	0	14	6	2	22
water	0	0	0	0	8	8
Total	75	24	84	7	10	200

	Ground Truth (Percent)					
Class	crop	forest	ag to urban	seasonal water	water	Total
Unclassified	0	0	4.76	14.29	0	2.50
crop	88.00	12.50	2.38	0	0	35.50
forest	12.00	87.50	0	0	0	15.00
ag to urban	0	0	76.19	0	0	32.00
seasonal water	0	0	16.67	85.71	20	11.00
water	0	0	0	0	80	4.00
Total	100	100	100	100	100	100

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
crop	7.04%	12.00%	5/71	9/75
forest	30.00%	12.50%	9/30	3/24
ag to urban	0%	23.81%	0/64	20/84
seasonal water	72.73%	14.29%	16/22	1/7
water	0.00%	20.00%	0/8	2/10

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
crop	88.00%	92.96%	66/75	66/71
forest	87.50%	70.00%	21/24	21/30
ag to urban	76.19%	100.00%	64/84	64/64
seasonal water	85.71%	27.27%	6/7	6/22
water	80.00%	100.00%	8/10	8/8

For the supervised Mahalanobis Distance classification, the confusion matrix accuracy for the classification was 84.64%. The producer's accuracy was overall high (above 80%) for the classifications of seasonal water, water, and agriculture to urban. However, it only achieved an accuracy within the mid-60% for crop and forest land. The user's accuracy was also high (above 90%) for the areas of seasonal water, water and agriculture to urban. But again, the user's accuracy was lower, into the mid-70%, for forest and crop. For the accuracy assessment, 200 points were selected for the assessment and the overall accuracy result was 82.5%. The producer's accuracy was high (76.2%) for agriculture to urban, and in the 80s for rest of the classes. The user's accuracy also had a good overall accuracy with 100% for agriculture to urban and water and 93% for crop, even the lower classes, namely forest and seasonal water were lower but acceptable.

Discussion

Examining the result of these various maps and comparing the data from both 2010 and 2015, the first hypothesis of rapid growth in Hanoi was verified. The amount of agriculture-to-urban land cover change cannot be explained simply by normal and/or stable growth of a city. Instead the growth patterns show broad rapid urbanization in the capital city. When looking the confusion matrix and accuracy assessment that were run and also support this hypothesis, one can see that the accuracies in general ranged from acceptable to quite strong by using differing methods.

The selection of the Mahalanobis Distance classifier was a result of the underperformance of the other supervised algorithms classifier. The low accuracy of the other classifiers can be primarily attributed to the fact that many do not acknowledge or accept the masked class. Instead, many of the classifiers including the Maximum Likelihood classifier would not class any part of the map outside of the mask because according to the algorithm, nothing was similar enough to the mask to be classified. When using the parallelepiped, the classifier could not distinguish between seasonal water and urban areas or between forest and cropland. It also became confused when the masks were not added separately from the image. Last, the unsupervised classification was helpful, but it also could not separate the difference between the two water classes and so the classifier identified it as one large water class, mostly because of the identifiable shape of the rivers.

When focusing on the confusion matrix and how well each class performed, one can see that the Mahalanobis Distance classifier did very well. While water and seasonal water did best in both the producer's and user's accuracy, the agriculture-to-urban change was the class that was the most surprising in it particularly strong accuracy results. The accuracy for the agriculture-to-urban class was 81% for producer's accuracy and 100% for user's accuracy. While great numbers in general, the high accuracy was even more unexpected since it was the focus of the urbanization study. The one class that underperformed was crop. Though crop area should have been easier to classify because of its bright and distinctive red color (when viewed in the false color composite), it only had low user's and producer's accuracies. One possibility for this lower accuracy rate could be because the red color was also the color of the forest class, particularly in the mountainous region in the southwestern corner of the imagery. Despite some lower accuracy rates and some errors that occurred, especially with some urban areas being classed as seasonal water, the Mahalanobis Distance classifier overall performed very well.

The accuracy assessment strategy was to utilize 200 randomly selected points in order to quantify how well the classifier performed. The most significant problem of using this accuracy assessment came when differentiating the unclassified and masked out areas of the classed map. There were many areas in which the accuracy could have been higher but since there was a mask or an unidentified area in the places where the random points were placed, the accuracy assessment result was less accurate than it could have been. Overall, the accuracy result was acceptable, but it could have been improved on by the Mahalanobis Distance classifier classing more of the map and by removing the randomly selected points out of the unclassed or masked out areas. Specifically, the user's accuracy for the class of seasonal water could have been improved. Its low accuracy could be because of the water mask covering much of the seasonal water on the map but more likely it was from the difficulty the classifier had separating the agriculture to urban and seasonal water classes based on their similarity of bright cyan color.

To improve the accuracy of this classifier, one could find more cloud and haze-free imagery at different times of the year to accurately capture the difference in crops and seasonal water classes. This could help separate these classes better. Secondly, one could continue to perfect the training data. In this study, multiple attempts were made to achieve the best training data. After many tries with the first group of training data, new training sites were picked. But, when the sites were run through the parallelepiped and the Mahalanobis Distance classifier, the results were still unsatisfactory. Hence, new training data were selected for the third attempt. The final classed image was completed by utilizing this third batch of training data with the combined urban and water mask layer added to the 2015 false color image.

Conclusion

Asia's population will grow by an astounding 1.4 billion people by 2050, and in Southeast Asia, the percentage of the population living in urban areas will increase from 37% in 2000 to 53% by 2025 (United Nations, 2014). In 2030, the population of Vietnam will reach 10.5 million, an increase of 12.6% from 2015 and Hanoi is on track to increase in population by 30% from 2015 to 2030 (Vietnam Atomic Energy Commission, 2003). The goal of this research was to confirm and expand upon previous findings which indicated this rapid growth in and around Hanoi and to provide mapping of these findings. While urbanization has been well documented in China, Indonesia and other Asian countries, this research is of particular importance since there have been few investigations to monitor the urbanization trend in Vietnam. This rapid urban expansion in Hanoi will likely result in vast swaths of cropland being taken out of production and therefore it is crucial to monitor the agriculture-to-urban changes and anticipate ways to mitigate any detrimental impacts of this conversion. Monitoring this agriculture-to-urban land cover change will provide much-needed information to the local and federal governments so to help future development and management of expanding urban areas. Additionally, this information will help inform local urban planners and international organization such as the World Bank's Vietnam Urbanization Review when determining how best to allocate and invest resources into Hanoi's new urban expansion in an efficient, sustainable, and inclusive manner (World Bank, 2011).

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