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Modeling urban expansion in Yangon, Myanmar using Landsat time-series and stereo GeoEye Images

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Abstract. This research proposed a methodology to model the urban expansion based dynamic statistical model using Landsat and GeoEve Images. Landsat Time-Series from 1978 to 2010 have been applied to extract land covers from the past to the present. Stereo GeoEye Images have been employed to obtain the height of the building. The class translation was obtained by observing land cover from the past to the present. The height of the building can be used to detect the center of the urban area (mainly commercial area). It was assumed that the class translation and the distance of multi-centers of the urban area also the distance of the roads affect the urban growth. The urban expansion model based on the dynamic statistical model was defined to refer to three factors; (1) the class translation, (2) the distance of the multicenters of the urban areas, and (3) the distance from the roads. Estimation and prediction of urban expansion by using our model were formulated and expressed in this research. The experimental area was set up in Yangon, Myanmar. Since it is the major of country's economic with more than five million population and the urban areas have rapidly increased. The experimental results indicated that our model of urban expansion estimated urban growth in both estimation and prediction steps in efficiency.

1. Introduction

Urban growth is rather a complex process. Since urban expansion causes from many factors such as human behaviors, population rates, the economic states, the policies of the government and so on. Remote sensing technology provides the physical information that can directly observe the urban areas from the past to the present, and can detect the center of the urban areas. Hence, it can lead us to understand the mechanism of urban expanding and create the model. Urban expansion model can be taken an employment to understand how urban expands and predict urban areas in the future. This information can be used to support the urban development and management.

Urban expansion model has been widely introduced. Urban land-use model based on spatial interaction model was developed by Lowry [1]. The statistical model was used for introducing urban expansion model [2]. An Urban growth model based on automata cellular was proposed by Batty [3]. Moreover, by using multi-agent-based model, the residential distribution estimation was developed [4].

This work introduced a methodology to model the urban expansion based dynamic statistical model using Landsat and GeoEye Images in Yangon, Myanmar. Yangon is the major of country's economic with more than five million population, and the urban areas have rapidly increased [5].

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2. Methodology

2.1. Factors to indicate urban expansion

Firstly, we defined that urban expansion is related to (1) the class translation, (2) the distance from the multi-centers of the urban areas and (3) the distance from the roads. For the first factor, we assumed that the number of new urban areas can be identified following the statistical of the class translation. For the second and third factors, the locations of new urban areas can be calculated regarding the distance from the multi-centers of the urban area and the distance from the roads. We assumed that the center of the urban area is the group of the high-rise buildings such as department store, hotel, office, school and so on. We supposed that each area depends on the nearest center of the urban area. The flowchart of our methodology to model urban expansion is displayed in figure 1.



Figure 1. The flowchart of our methodology.

2.2. Preparing data for urban expansion model

In this research, four multi-spectral Landsat images with a 30 m.-resolution and 1,000x1,000 pixels from 1978 to 2009 were used to provide land cover change. Stereo GeoEye images with a 0.5 m.-resolution were employed to obtain the height of the building. The locations of the roads were provided by ICUS (International Center for Urban Safety Engineering, The University of Tokyo, Japan). The details of satellite dataset are shown in table 1 and the images are displayed in figure 2.

Table 1. T	he details	of Satellite	images.
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No.	Satellite and Sensor	Bands	Resolution	Acquired Date
1	Landsat -3 MMS	4	60m. x 60m.	1978-11-22
2	Landsat -4 TM	7	30m. x 30m.	1990-11-12
3	Landsat -7 ETM	8	30m. x 30m.	2000-11-7
4	Landsat -5 TM	7	30m. x 30m.	2009-11-08
5	GeoEye Stereo-mode	3	0.5m x 0.5m.	2013-11-08 2013-11-16



Figure 2. (a) Landsat image in 1978 (False color), (b) Landsat image in 1990, (c) Landsat image in 2000, (d) Landsat image in 2009, (e) GeoEye image.

For obtaining the land cover change, the Landsat images were classified into three classes of (1) urban, (2) vegetation, and (3) water by using Mahalanobis distance method (supervised classification). Unfortunately, there is still some noise in the classification results. To improve the classification results, the rule of urban expansion and removing cloud effect were applied. The classification results are shown in figure 3 (a) and 8 (a, c, e).

For detecting the multi-centers of the urban area, the stereo GeoEye images were extracted to obtain the height of the building (figure 3 (b)). Then, the heights of the buildings were separated into two classes of (1) low and (2) high buildings by manual thresholding. After that, the locations of the high buildings were grouped into seven classes by using K-means (Unsupervised classification). The center positions of seven classes were defined as the multi-centers of the urban area (figure 3 (c)). The region of the multi-center areas is displayed in figure 3 (d).



Figure 3. (a) the land cover result in 1978 (b) the heights of the buildings (c) the classification result of the multi-centers, and (d) the region of multi-centers.

2.3. Monitoring urban expansion

For the statistical of class translation, we received the number of class translation by observing the land cover areas from the past to the present. By combining with the multi-centers of the urban area,

the examples of the number of class translation in the region of the center #1 with time variation are illustrated in table 2 and figure 4.

	1978-1990	1990-2000	2000-2009
urban→urban	8,410	10,942	12,780
vegetation \rightarrow urban	2,123	1,774	2,208
water -> urban	409	64	69

Table 2. The number of class translation in the region of the center #1 from 1978 to 2009.



Figure 4. The number of class translation in the region of the center #1 from 1978 to 2009.

For the distance from the multi-centers of the urban area, we observed the urban growth to obtain the histogram of urban expansion affected by the distance from the multi-centers. The examples of the histograms of the urban expansions among the varied distance from the center of the region #1 with time variation are depicted in figure 5.



Figure 5. The histograms of the urban expansions among the varied distance from the center of the region #1 in the years of (a) 1978-1990, (b) 1990-2000, (c) 2000-2009.

Table 3. Means and variances of the distance from the center that was effect to urban expansion in
the region #1 from 1978 to 2009.

	1978-1990	1990-2000	2000-2009
Mean	87.12	90.23	87.51
Variance	4411	4260	4608

We investigated that the urban expanded by beginning from the close distance from the center of the urban area to the far distance. The distributions of the histograms seem as Gaussian distribution.

For the distance from the roads, the histogram of the urban expansion affected by the distance from the roads was provided by observing urban growth. The histogram of the distance from the roads is shown in figure 6. The mean and variance of the distance from the roads by urban expansion are 1.42 and 4.34, respectively.



Figure 6. The histogram of the urban expansion among the varied distance from the roads.

We found that the urban grew along the roads, and the distribution appears as Gaussian distribution.

2.4. Estimation of urban expansion

The probabilities of class translation with time variations were defined as Markov chain. The probabilities of the distance from the center and the roads were assumed as Gaussian distribution. By integrating the probabilities, the estimation of our model by using maximum likelihood estimator was expressed in equation 1.

Maximize *The Probability of Class translation* + *The probability of the distance from the multicenters* + *The probability of distance from the roads* (1)

Since the Probability of Class translation and the probability of the distance from the multi-centers and the distance from the roads are independent, we separated them into two parts with equation 2 and 3.

Maximize *The Probability of Class translation* (2)

Maximize The probability of the distance from the multi-centers + The probability of distance from the roads (3)

Maximize
$$\prod_{i=1,j=1}^{1000,1000} \begin{bmatrix} \beta_1 \frac{1}{\sigma_{center} \sqrt{2\pi}} \exp(-\frac{(disCenter(i,j) - \mu_{center})^2}{2\sigma_{center}^2}) \times \\ \beta_2 \frac{1}{\sigma_{road} \sqrt{2\pi}} \exp(-\frac{(disRoad(i,j) - \mu_{road})^2}{2\sigma_{road}^2}) \end{bmatrix}$$
(4)

Since some parts are insignificant, and some parameters are constants, we converted equation 4 into equation 5.

$$\operatorname{Minimize} \sum_{i=1, j=1}^{1000, 1000} \left[\lambda_{1} \frac{\left(\operatorname{disCenter}(\mathbf{i}, \mathbf{j}) - \mu_{\operatorname{center}} \right)^{2}}{\sigma_{\operatorname{center}}^{2}} + \lambda_{2} \frac{\left(\operatorname{disRoad}(\mathbf{i}, \mathbf{j}) - \mu_{\operatorname{road}} \right)^{2}}{\sigma_{\operatorname{road}}^{2}} \right]$$
(5)

i and j are the locations of the images in x-axis and y-axis. λ_1 and λ_2 are required to assign. In our experiment, we found that $\lambda_1 = 0.3$ and $\lambda_2 = 0.7$ that provided a high accuracy. By using equation 2, the number of urban expansion was obtained. By using equation 5, the locations of urban expansion were provided. Then, the classification result in 1978 was set as the initial land cover image. We used the initial land cover image with observed parameters as input for our model to estimate the land cover image in 1990. Next, we used the estimated land cover in 1990 with observed parameters as input for our model to estimate the land cover image in 2000. We repeated the same step to estimate land cover image in 2009.

2.5. Prediction of urban expansion

Since the probability of the class translation and mean and variance of the distance from the center of the urban area in the future could not be observed. They are required to estimate. We used the previous information with polynomial regression to calculate the parameters used for prediction in the future. In this research, we estimated the urban areas in 2020 as the future time. The example of estimated parameter of the number of class translation to predict the urban areas in 2020 is shown in figure 7.



Figure 7. The estimated number of class translation in the region of the center #1 from 1978 to 2020.

After that, we used the estimated land cover in 2009 with estimated parameters as input for our model to estimate the land cover image in 2020.

3. Results and discussion

3.1. Estimation of urban expansion

The classification results in the section of 2.2 preparing data for urban expansion were defined as original land cover images. We compared the estimated land cover images by using our model (figure 9 (b, d, f)) with the original land cover images (figure 9 (a, c, e)). For the accuracy, two classes with urban and non-urban (vegetation and water) were used to calculate the accurate result. The accuracy of original versus estimated land cover images in 1990, 2000, and 2009 are expressed in table 4.

Table 4. The accuracy of original versus estimated urban areas in 1990, 2000,	and 2009.
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Year	Accuracy (%)	True positive (%)	True negative (%)
1990	93.51	64.95	96.52
2000	88.35	61.37	93.26
2009	83.72	63.68	89.62

3.2. Prediction of urban expansion

The Landsat image on November 25, 2015 (figure 8) was selected and classified to be a land cover image as an unseen land cover image (figure 10 (a)). We compared the predicted land cover image in 2020 (figure 10 (b)) with the unseen land cover image in 2015. The accuracy is 81.24% with true positive of 70.86% and false positive of 85.64%.



Figure 8. Landsat image in 2015



Figure 9. (a) original land cover in 1990, (b) estimated land cover in 1990, (c) original land cover in 2000, (d) estimated land cover in 2000, (e) original land cover in 2009, and (f) estimated land cover in 2009



Figure 10. (a) original land cover in 2015, and (b) estimated land cover in 2020

In the experimental results, our model of urban expansion estimated the urban growth in the years of 1990, 2000, 2009 with an average accuracy of 88.53% and also predicted the urban expansion in the future (in the year of 2020) with an accuracy of 81.24%.

Our model relies on the distance from the multi-centers and estimated urban areas grow up from the closest distance from the multi-centers of the urban area. However, In particular, some urban areas grow up far from the centers. As a result, our method cannot estimate the urban areas that grow up far from the multi-centers.

4. Conclusion

This research introduced a methodology to model urban expansion using Landsat time-series and stereo GeoEye images in Yangon, Myanmar. Multi-spectral Landsat images from 1978-2009 were used to provide land cover change. Stereo GeoEye images were employed to extract the height of the building that can detect the center of the urban area. The model of urban expansion was defined to refer three factors of class translation, the distance from the multi-centers, and the distance from the roads. Based on the dynamic statistical model, Estimation and prediction of urban expansion were formulated. In the experimental results, our method estimated urban areas from 1990 to 2009 and predicted urban areas in 2020 with an accuracy.

For future work, the other factors such as the direction of urban expansion, an elevation should be included to obtain a higher accuracy. The significant structure such as transportation, the bridge would be related to our model to understand the practical mechanism of urban expansion. Since some parameters are required to specify, the optimization method could be employed.

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