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Analysis of Change about Reclaimed Land using Landsat Satellite Images of Time Series

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Abstract
Reclaimed land development project is very efficient way in case of Republic of Korea where is around three sides by the sea, high population density compared to the land and ongoing urbanization continues to develop. Accordingly, since 1991, our country also began to target the west coast reclaimed business one. However, if the artificially altered the natural terrain ongoing management is needed because it exerts a significant impact on the natural environment. In this study, we monitored the environment caused by changes in the tideland reclamation project by using time series Landsat satellite images and to present a quantitative change in value. As a result, we could recognize that the area among sea, tideland, and bare soil is closely connected.

Keywords: Reclaimed Land, Reclamation Project, Saemangeum, Environmental Change, Landsat Satellite Image

Background and Purpose
Remote sensing means a comprehensive study or techniques to extract information from the measured data without physical contact with target [1][2]. Currently, it has been utilized in many diverse fields such as global environmental monitoring, weather forecasting, forest management and resource exploration [3][4]. Also, It is often used in consideration of economic efficiency, and when analyzing a large object area.
Saemangeum project was began on November, 1991 through the process such as economic feasibility analysis, environmental effects evaluation, agreement of residents, discussion of ministry concerned, license of public waters reclamation. Also, Saemangeum seawall was listed in the Guinness Book of World Records as the longest (33. 9km) seawall in the world which was constructed on January, 2010. Currently, the site development is now in progress in accordance with master plan of Saemangeum which was announced on September, 2014 [5][6]. In the case of reclamation because environmental changes may occur, a change in the reclaimed land and the surrounding area should be continuously monitored and managed [7][8].
Thus, in this study, we tried to detect the environmental change of time series by calculating the existing land use changed due to reclaimed land development project [9]. We used Landsat 5 TM and Landsat 8 OLI TIRS images to detect the land cover change about the large scale area corresponding to 409km^2 [10][11].

Classification of Time Serial Images
In this study, we utilized Landsat satellite images to monitor change of time series about tideland in west coast. We used a variety of images before and after the dyke built to detect changes in coastal reclaimed tideland and the construction of the seawall [12][13]. We acquired images before completion of seawall when is on September, 1996, October, 2000 and September, 2005. And we used images after completion of seawall when is on April, 2007, October, 2008, October, 2009, September, 2013, October, 2014, and May, 2015. To improve the image classification accuracy when compared were unified and September to October, except for 2007 and 2015. Table 1 shows the satellite images used in this study.

Table 1: Satellite images used in this study

Satellite images	Date of image	Cloud cover (%)	Image quality
5 TM L1T	1996. 09. 01	0	9
7 ETM+ L1T	2000. 10. 06	4	9
5 TM L1T	2005. 09. 26	28	9
5 TM L1T	2006. 10. 31	0	9
5 TM L1T	2007. 04. 09	0	7
5 TM L1T	2008. 10. 20	22	7
5 TM L1T	2009. 10. 07	0	9
8 OLI TIRS L1T	2013. 09. 16	0	9
8 OLI TIRS L1T	2014. 10. 05	0	9
8 OLI TIRS L1T	2015. 05. 01	14	9

We masked the satellite images to size as target area using masking band where contain the Saemangeum project and aroundregion. Figure 1 shows the target area which is indicated with latitude and longitude. Figure 1 is the image when is October, 2014. And then we set the ROI (Region of interest)s and selected the representative area in accordance with the classification items. Figure 2 shows the ROI setting. As shown in Figure 2, we set the ROIs 7 sort of classification. These are sea (red), tideland (green), farm (blue), mountain (cyan), lake (magenta), construction (yellow), bare soil (maroon). ROI selection for the categories was selected focusing on the most common areas of all the images. Also, we chose the ROIs the border areas and central area focusing. After selection of ROIs, we classified these images using the minimum distance, maximum likelihood, SVM (support vector machine) since it is the high frequency of use [4][14].

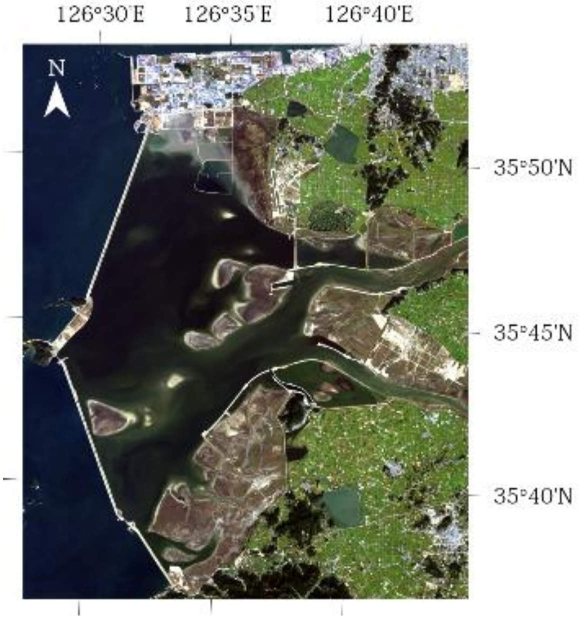
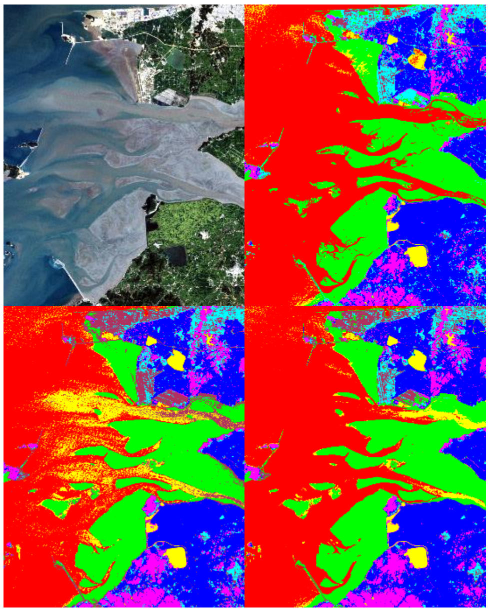


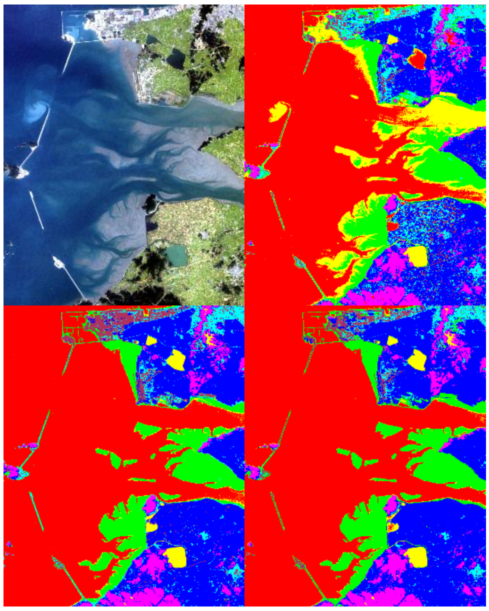
Figure 1: Target area

Figure 2: ROI setting

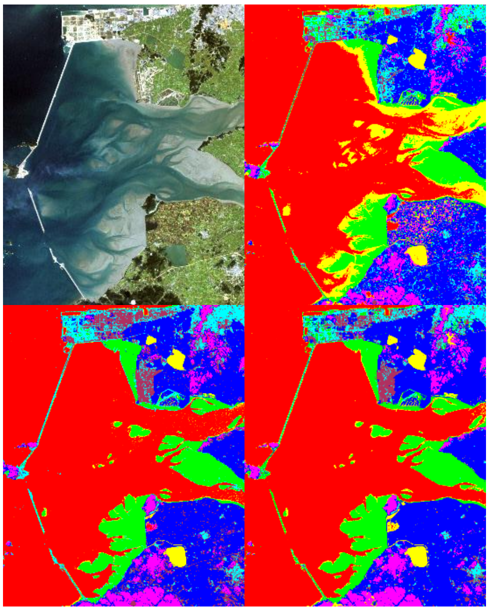
Minimum Distance is the method to allocate Euclid distance to the classification item of minimum distance. Maximum Likelihood is the method for computing the weighted distance or likelihood of unknown measurement vector belong to one of the known classes is based on the Bayesian equation. The unknown measurement vector is assigned to the class in which it has the highest probability of belonging. [15]. SVM is the algorithm to classify based on the notion of fitting an optimal separating hyperplane between classes by focusing on the training samples that lie at the edge of the class distributions, the support vectors [16]. We classifiedLandsat satellite images by these methods using image processing program. Figure 3 shows the time-serial satellite images and classification results. In this figure, bold lettering of classification method indicates the best result among three methods.



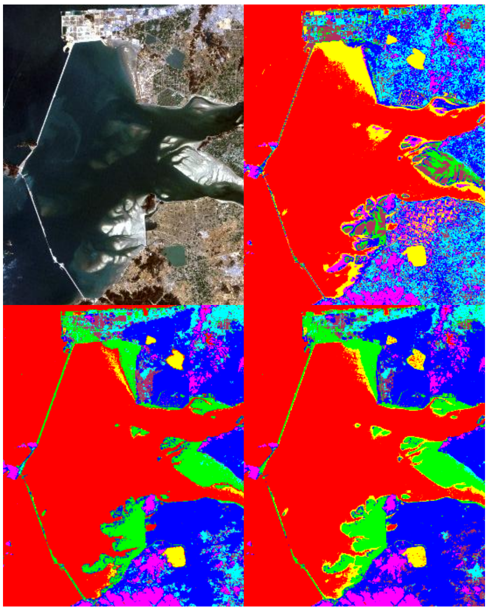
RGB imageMD result ML result SVM result 1996. 09. 01



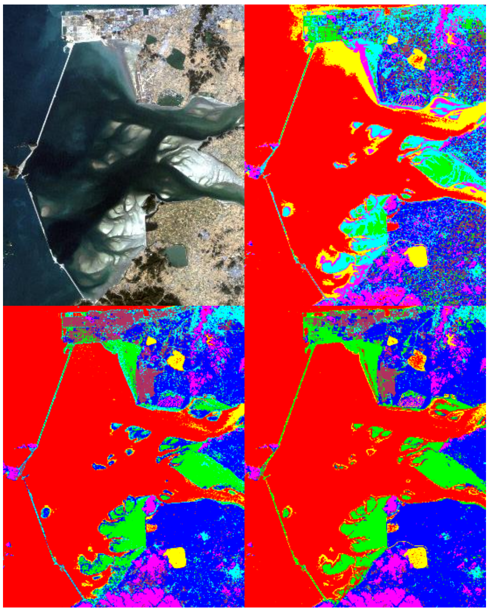
RGB image MD result ML result SVM result 2000. 10. 06



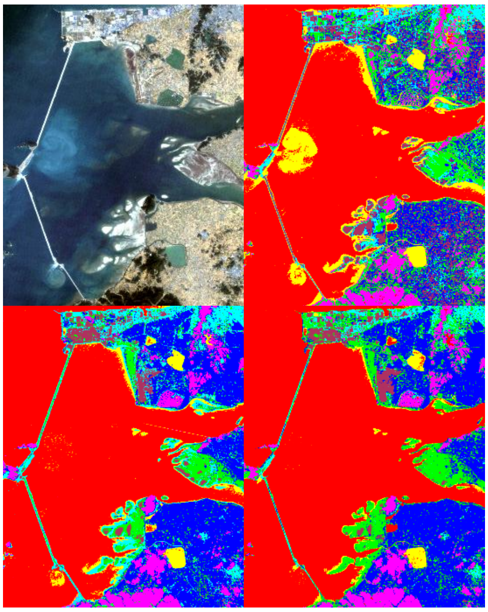
RGB image MD result ML result SVM result 2005. 09. 26



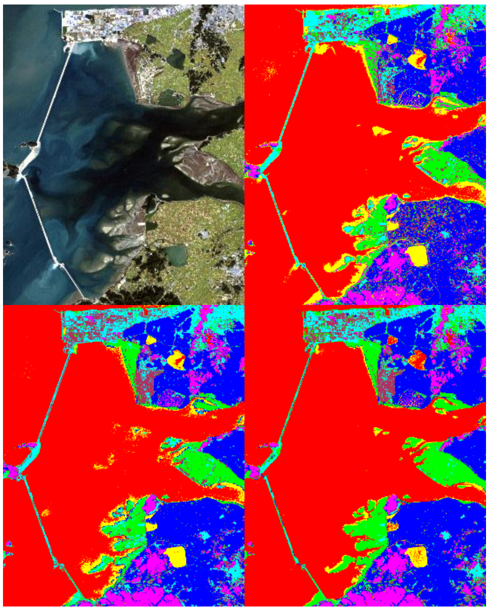
RGB image MD result ML result SVM result 2007. 04. 09



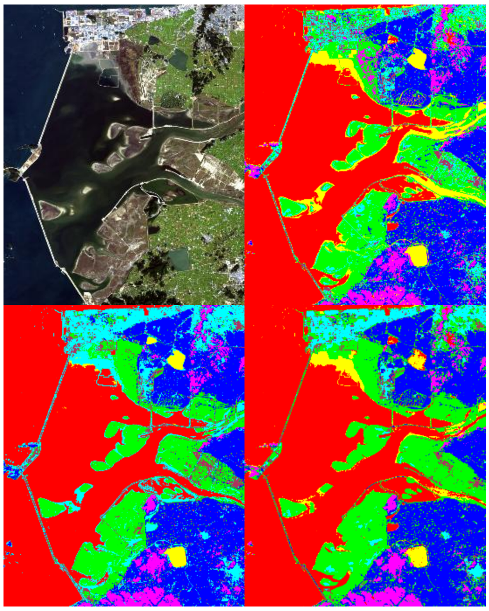
RGB image MD result ML result SVM result 2006. 10. 31



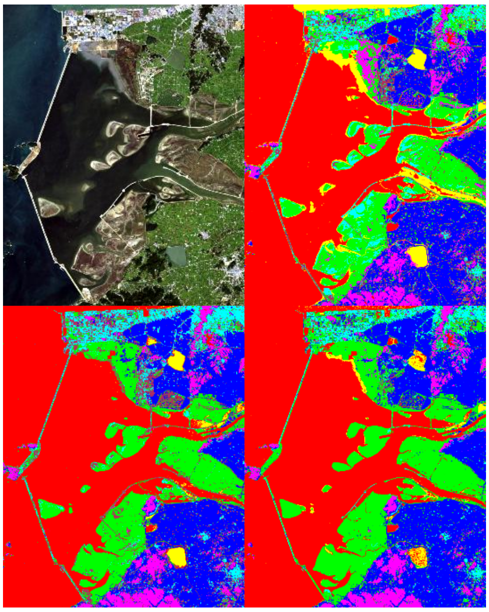
RGB image MD result ML result SVM result 2008. 10. 20



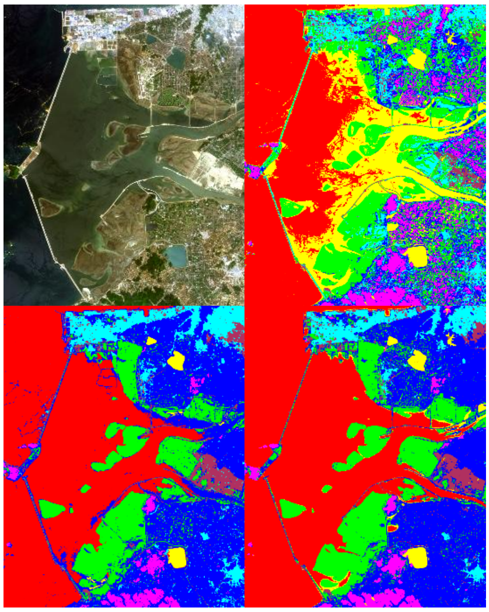
RGB image MD result ML result SVM result 2009. 10. 07



RGB image MD result ML resultSVM result 2014. 10. 05



RGB image MD result ML result SVM result 2013. 09. 16



RGB image MD result ML resultSVM result 2015. 05. 01

Figure3: Satellite images and classification results according to time series

As shown in Figure 3, In comparison with the original RGB composite image, the classification result of the overall time is found to be the most accurate SVM classification. The reason is that shows a high accuracy in the boundary area between the categories, presented the results of misclassification in the same area, it is also classified least it should support this. Especially, the apparent results were calculated to be at the boundary of the sea and tidal flats, boundary of the sea and reclaimed land, and boundary of reclaimed land and farm. These boundaries are included the most importance value in this study. In Figure 3, the results using SVM method showed the highest accuracy except for only 1996.

Analysis of Classification Results

In this study, we utilized Landsat satellite images to monitor change of time series about tideland in west coast. The three classification methods for the same destination in order to increase the accuracy of the classification was applied. And the change of area was analyzed using the high accuracy result of three classification method.

Table 2 and Figure 4 show the change of area according to the each items. In Table 2, it was calculated by multiplying the area of one pixel area of 9m^2 value based on the pixel resolution of 30m Landsat satellite images in number of pixels. In the case of Figure 4, each of the entries in the study area were creating a graph focusing on the high Sea, Tideland, Farm, bare soil is critical.

Table 2: Change of area according to the each items (unit : km^2)

	Sea	Tideland	Farm	Mountain	Lake	Construction	Bare soil
1996	366. 9	166. 5	168. 1	47. 8	19. 7	44. 4	11. 3
variation	73. 7	-71. 1	28. 5	-5. 8	-3. 9	-24. 3	2. 8
2000	440. 6	95. 4	196. 6	42. 0	15. 8	20. 1	14. 1
variation	-10	-5. 5	-6. 8	-3. 2	8. 5	7. 6	9. 4
2005	430. 6	89. 9	189. 8	38. 8	24. 3	27. 7	23. 5
variation	11. 7	-1. 8	4	-1. 7	-0. 7	-11. 3	-0. 3
2006	442. 3	88. 1	193. 8	37. 1	23. 6	16. 4	23. 2
variation	-9. 6	-4. 6	8. 1	-3. 7	5. 7	6. 6	-2. 5
2007	432. 7	83. 5	201. 9	33. 4	29. 3	23	20. 7
variation	23. 5	7. 9	-26. 1	7. 7	-11. 5	1. 6	-3. 1
2008	456. 2	91. 4	175. 8	41. 1	17. 8	24. 6	17. 6
variation	-1. 9	-15. 1	-6. 6	-0. 8	-1. 6	14. 5	11. 5
2009	454. 3	76. 3	169. 2	40. 3	16. 2	39. 1	29. 1
variation	-73	92	15. 5	-1. 1	-4. 4	-8. 7	-20. 3
2013	381. 3	168. 3	184. 7	39. 2	11. 8	30. 4	8. 8
variation	-20. 1	13. 2	-13	-9. 6	12. 6	7. 6	9. 3
2014	361. 2	181. 5	171. 7	29. 6	24. 4	38	18. 1
variation	4. 3	-54. 2	54. 8	-7. 5	-6. 3	-1. 5	9. 4
2015	365. 5	127. 3	226. 5	22. 1	18. 1	36. 5	27. 5

As seen in the area of the sea Table 3 and Figure 4 is an increased sharply in 1996-2000 showed little or no retained until 2009. From 2009 to 2014, while sharply reduced the area has increased between 2014 and 2015.

In the case of reclaimed land area with the most closely related to the sea, 71. 1km^2 value as an area similar to the increase in the area of sea between 1996and 2000. In addition, we were able to see that even though the area of the tideland area of the ocean decreases and decreases as the size increases between 2009 and 2013. Between 2009 and 2013 it was found to have decreased and rice fields, the field has been increased sound. Between 2013 and 2014, we could recognize that the area of the sea reduced due to a full-fledged comprehensive development plan and this is an area of reclaimed land with bare soil increases. In addition, the performance due to a full-fledged comprehensive development plan was found to appear through the fact that the reduced area (54. 2km^2) of reclaimed land as farmland increased 54. 8km^2 between 2014 and 2015.

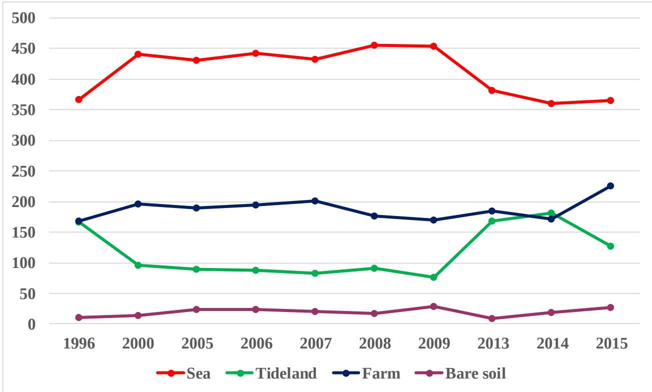


Figure 4: Change of area according to the each classification item

Conclusions

In this study, we classified and analyzed the images using Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI TIRS satellite images to figure out the time serial land use changed due to large-scale reclamation project quantitatively. As this result, we could recognize the followings.

First of all, we could recognize that area of the reclaimed land and the sea area were close relationship to each other with the progress of the reclamation. We could recognize the change of area through graph that area of reclaimed land increased as much as area of the sea of reclaimed land decreased and on the contrary, if the area of the sea increase was found to increase as the area of the reclaimed land.

Second, the performance due to a full-fledged comprehensive development plan was found to appear through the fact that reduced area of reclaimed land as farmland increased between 2014 and 2015. We could know that the area of the reclaimed land turned into farmland after a full-fledged comprehensive development plan through this result.

Henceforth, if the continuous monitoring is carried out using satellite images, it is expected to be a low-cost management about large-scale tideland.

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