Detecting Spatial Clusters of NDVI change in South Korea using AMOEBA-CH algorithm

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ABSTRACT: Recently, changes of land cover are occurred by human activities and natural phenomenon, such as construction of infrastructure, desertification, drought, flood and so on. Many researchers are studied land cover change for detection of change. In this Study, We will correct continuous values of land cover change and interaction of surrounding. Because land cover changes are ambiguity, and these change are not changed independent by surrounding area. So we identify hotspot of land cover change using probability density function and spatial autocorrelation. And we detect hotspot using hotspot algorithm. We use hotspot algorithm that is called AMOEBA. But we modified AMOEBA, because AMOEBA detected too many hotspot. Modified AMOEBA is called AMOEBA-CH(Core Hotspot). At first, we identify probability of land cover change. Next we calculate spatial autocorrelation from probability of land cover change. At last, we detect hotspot using AMOEBA-CH. Result of this study, Hwasung, dangjin, Seosan are detected hotspot area in South Korea. Urban and agriculture area's rate was increased 3.25%, 3.8%, respectively in the hotspot-Hwasung. On the other hand, water, forest, wetland area's rate was decreased 5.57%, 2.43%, 3.66%, respectively. Agriculture area's rate was increased 7.34%. On the other hand, forest area's rate was decreased 10.28 in the hotspot-Dangjin. Urban area is increased by construction of industrial complexes, residential facilities in the hotspot-Hwasung. And hotspot-Dangjin area tends to increase of agriculture area by construction of agriculture complexes. So land development of hotspot area is actively made. In significance of this study is detection of cohesive areas about land cover change with more objective data based probability and association of surrounding areas.

1.INTRODUCTION

Because of the effects of global warming, more attentions to climate change are paid all around the world. So many researchers are studying the cause and phenomenon of climate change. Besides as increasing human activity, various types of land cover change will occur such as urbanization, desertification, deforestation. Analysis of land cover change will give a guess about natural change and artificial change by human activity. Satellite images represent land cover change of these region quantitatively. As increase image resolution and obtained cycle due to develop technique of satellite image, we are analyze land cover change in the detail. Also, various technique of land cover change are developed, because proper and exactly detection of land cover changes give importance of resource management and utilization. Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different time(Singh, 1989). Also, change detection is utilized at various fields such as detection of land cover change, land use change, urban change, environmental change and so on.

There are many researches of change detection about land cover change using satellite image. For example, they studied about estimation of land cover change using techniques of image differencing and image ratioing(Bayarsaikhan, et al, 2009;Du, et al, 2010). Another research measured accuracy of land cover change depending on change of threshold using MODIS NDVI 16day data(250m ×250m) (Lunetta, et al, 2006). Also, there is research of urban change by correlation of population and land cover(Shahraki, et al, 2011). Most research is focus on composition rate of land cover and quantity of change by comparison of satellite image. These researches tend to comparison of pixel and use threshold independently. So results of land cover change were represent values of dichotomy such as "change" or "no change", 0 or 1. But these results don't appear continuous values of land cover change. Because If we enumerate values of change that appear continuity.

So we suggest that detecting areas of high probability change using probability density function. Usually, land cover changes can be in the form of cluster. So we consider spatial autocorrelation for interaction of surrounding areas for detecting cohesive areas of land cover change. Purpose of this study, we will detect cohesive area of land cover change by utilization of existing technique, and we will not be applied dichotomy value but continuous value of land cover change. Also, we correct association of surrounding area by spatial autocorrelation.

2.DATA AND METHODS

2.1. Study procedure

Target area for this study is South-Korea. Range of latitude is between 32.8 and 38.77, and range of longitude is between 124.48 and 130. In fig.1, study flow is as follows:

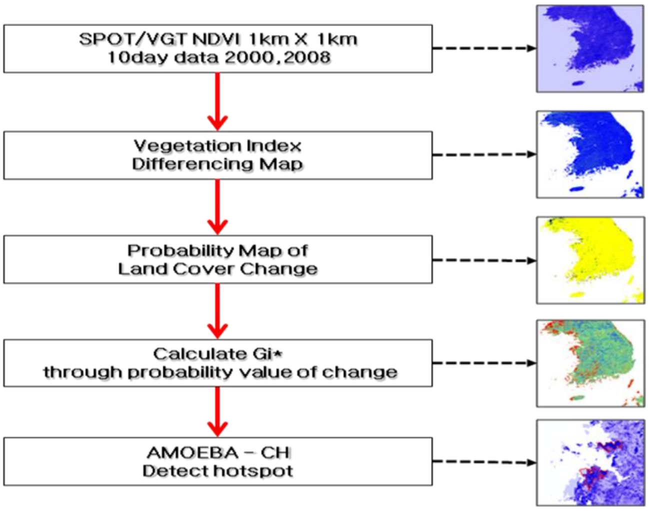


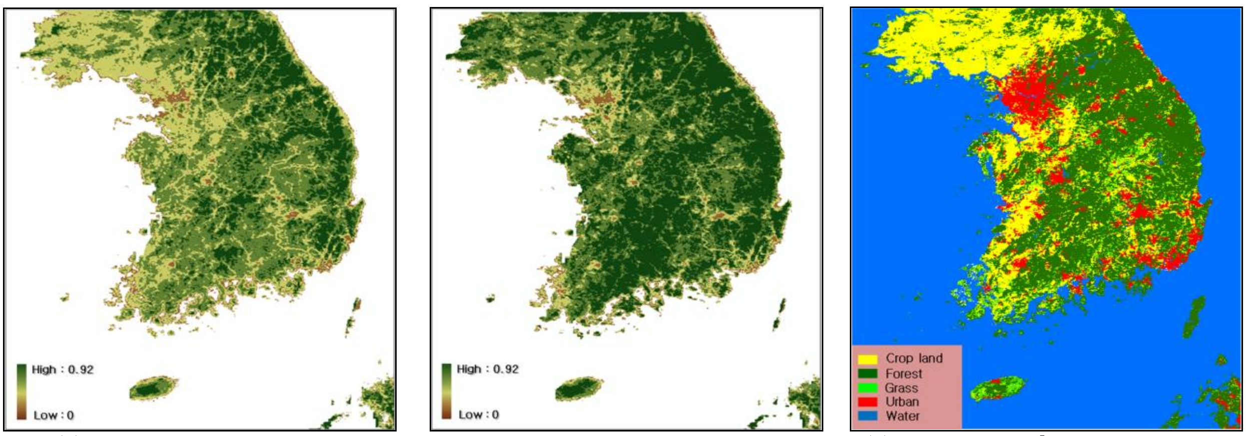
Fig.1. Study Flowchart

First, we calculated vegetation index differencing using SPOT/VGT NDVI data, 2000 and 2008. Next, we calculated probability values of change for degree of land cover change using probability density function, because land cover change has fuzzy values. Also, land cover change does not change independently. And we Consider not only the value of probability, but also spatial cohesion of the probability for detecting cohesive areas of hotspot. We corrected interaction of surrounding area. So we use spatial autocorrelation that is measure of association of surrounding area. Finally, we detected hotspot of land cover change using AMOEBA-CH(Core Hotspot). AMOEBA-CH modified from AMOEBA, because AMOEBA detected too many hotspot. So it modified for detect core hotspot.

2.2. Data preprocessing

This study, we used SPOT/VGT 10day NDVI products, 2000 and 2008(1km×1km). NDVI data was built using fourth-order polynomial multiple regression for removing Noises. How to apply multi polynomial regression is as follows. First, we calculated value of regression through time series NDVI data. And then, we selected high value after comparison of original NDVI values and calculated values. Finally, we repeat this process. And we get linear time-series NDVI data. In addition, NDVI values decreases due to the influence of the cloud and rain. So we extracted the highest values through comparing of same pixel using NDVI MVC(Maximum Value Composites).

In fig. 2, (a) and (b) are mapping images of NDVI max value 2000 and 2008, respectively. (c) is MODIS land cover image. Purpose of this study is detected land cover change, so we extracted land area using land area of MODIS land cover image.



(a) 2000 NDVI MVC image (b) 2008 NDVI MVC image (c) MODIS Land Cover image

Fig.2. Data of this study

2.3. Probability map of change

Land cover change is ambiguity. There are many ambiguous cases in distinguishing “change” or “no change”, depending on difference in attribute values. It is inherent uncertainty in spatial phenomena. So we detect land cover change based on probability. We will use probability variable. And Mapping change probability using Probability Density Function. Probability map can be calculated using NDVI difference between two periods.

The equation for probability of change is as follows(eq.1):

$$\frac{X_i - \mu}{\sigma} \quad .....(1)$$

We calculated NDVI difference of pixel(i) that NDVI of 2008 minus NDVI of 2000. In equation(1), numerator Xi is NDVI difference of Pixel(i), μ is mean of NDVI. Denominator σ is Standard deviation of NDVI change. We calculate z-score and get the probability for the z-score.

2.3. Spatial Autocorrelation

Land cover change does not occur independently. It occur cohesive area of land cover change, because of spatial interaction with the surrounding area. So we need measure of interaction with the surrounding area for land cover change. This is spatial autocorrelation. Spatial cohesion can be measured by spatial autocorrelation. Spatial autocorrelation is the correlation among values of a single variable strictly attributable to their relatively close locational position(Griffith, 2009). In other word, spatial autocorrelation is the degree of similarity between the near located values. This study use the statistic G_i^* , because it is excellent ability of detecting hotspots and coldspots. So, we calculated G_i^* of NDVI difference. For a given location i, the statistic G_i^* is defined as

$$G_i^* = \frac{\sum w_{ij} x_j - \bar{x} \sum w_{ij}}{s\sqrt{\frac{n \sum w_{ij}^2 - (\sum w_{ij})^2}{n-1}}} \quad .....(2)$$

In eq.2, n is the number of spatial units ,x_j is the value of land cover change at location j, $\bar{x}$ is the mean of all the values ,and w_{ij} is an indicator function that is one if unit j is in the same designated region as unit i and zero otherwise. If G_i^* value is plus, it has hotpot. On the other hand, if G_i^* value is minus, it has coldspot. And if G_i^* value equal zero, it has no autocorrelation. S is standard deviation.

2.4. AMOEBA-CH

Detection of land cover change area is important. Also, it is important that detect cohesion area of land cover change, too. So we detected cohesion area of land cover change through spatial autocorrelation and hotspot algorithm. AMOEBA detected hotspots and coldspots using spatial autocorrelation. AMOEBA measured spatial autocorrelation through calculated G_i^*.

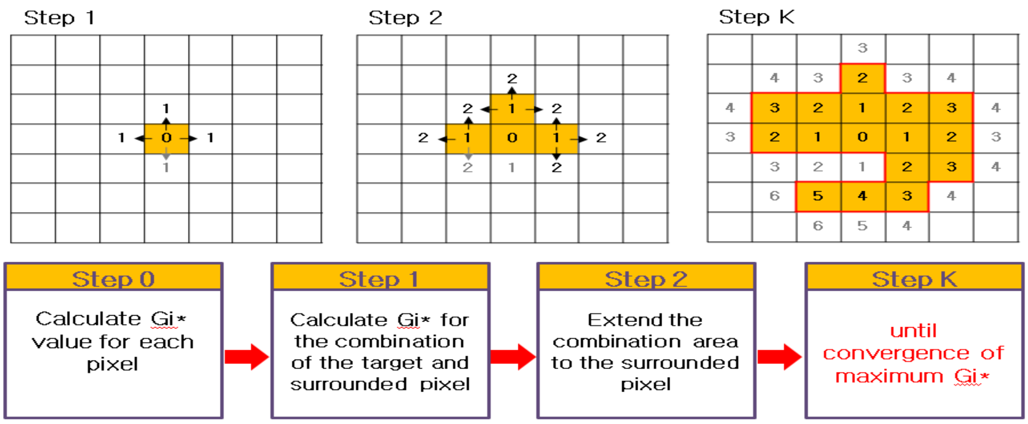


Fig.3. Process of AMOEBA’s detection

We use modified AMOEBA that is called AMOEBA-CH using calculated G_i^*. AMOEBA is developed by Aldstatd and Getis in 2006(Aldstatd, et al, 2006). AMOEBA is a design for the construction of a spatial weights matrix using empirical data. And it search for spatial association in all specified directions. In the sense that the scale is local and the analysis reveals all spatial association. Fig.3 is process of AMOEBA's detection. First, calculate G_i^* value for each pixel and find maximum G_i^*. Next, calculate G_i^* for the combination of the target and surrounded pixel. Next Extend the combination area to the surrounded pixel until convergence of maximum G_i^*. This process repeats for the whole pixel. But, In fig. 4, original AMOEBA and modified AMOEBA of other research detected too many hotspots(Lee, et al, 2010). So we modified Algorithm for detection of core hotspot using Contiguity-Dominance Model. Fig. 5 is work-flow of Contiguity-Dominance Model. We use JAVA for realization of AMOEBA-CH. Contiguity-Dominance Model search cell of max value, and merge cell of max value and surrounding cell. If value of merged cell is higher than existing max value, it is accepted. But if value of merged cell is lower than existing max value, it is excluded. Finally, AMOEBA-CH detected hotspot that is value of maximum merged cell.

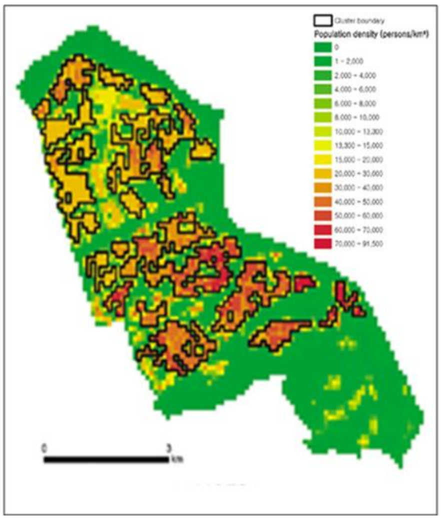


Fig.4. Detect hotspot using AMOEBA and modified AMOEBA in Lee' s research(2010)

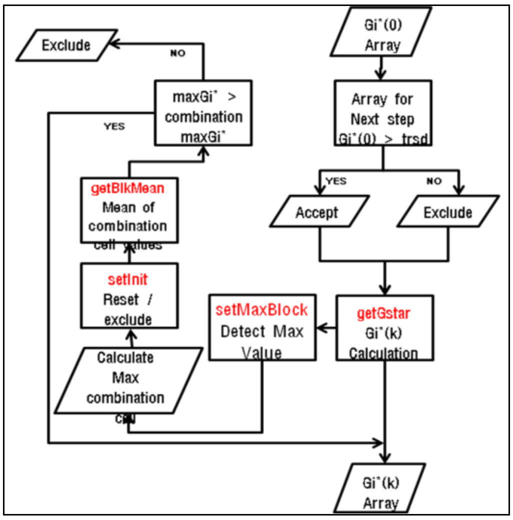
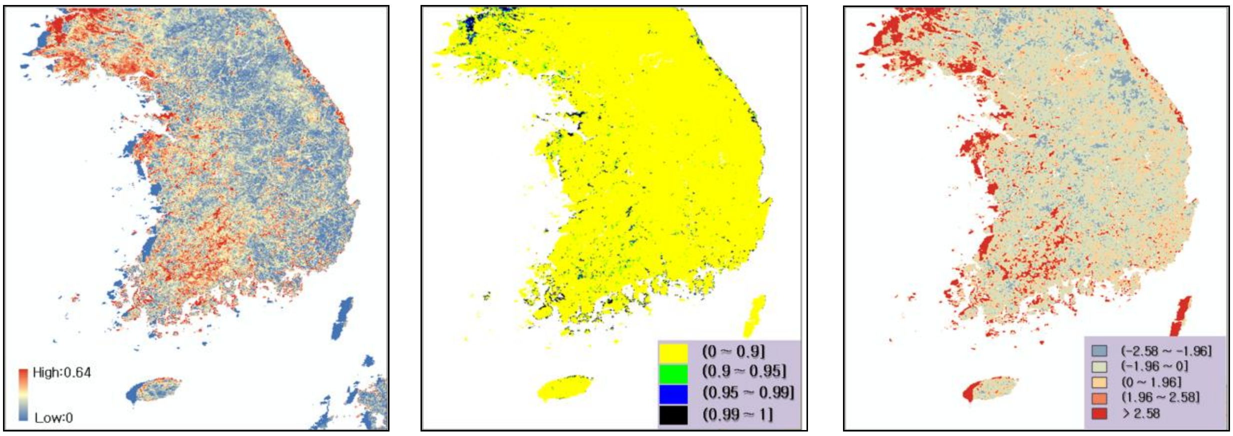


Fig.5. Contiguity-Dominance Model work-flow

3.RESULTS

Fig. 6 is result image of vegetation index differencing(a), mapping of probability of change(b), mapping of spatial autocorrelation index(c), respectively. We compare fig. 6. (b) and (c), if value of change probability is higher, then value of G_i^* is high, too. So we expect, if value of change probability is higher, surrounding areas have high value of change probability.

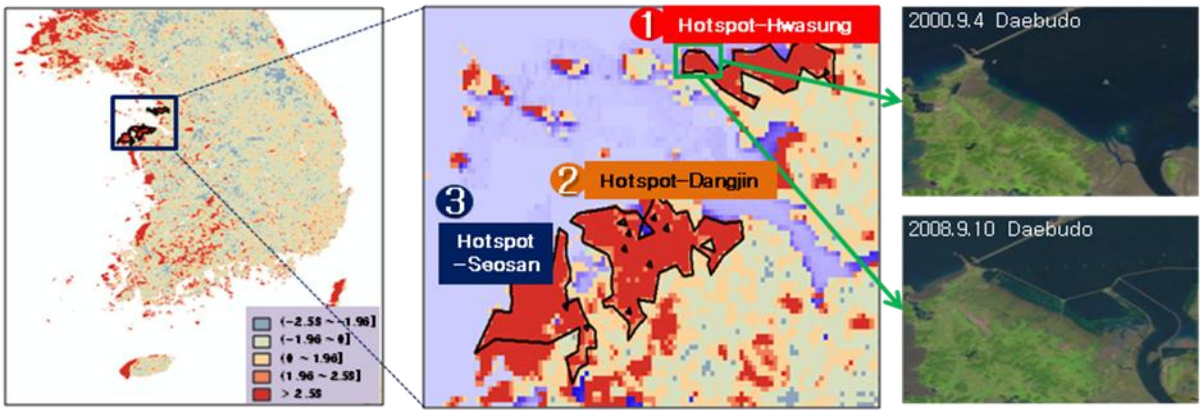


(a)Vegetation index differencing (b)Probability of change (c)Spatial autocorrelation index

Fig.6. Result image

In fig. 7(a),(b), Hwasung, Dangjin, Seosan are detected hotspot area in South Korea. Especially, Hwasung and Dangjin involve reclaimed land. It is putting up a large scale of industrial complex and residential facility in this reclaimed land. We analyze rate of land cover using land cover data from Korea Ministry of Environment. Urban and agriculture area's rate was increased 3.25%, 3.8%, respectively in the hotspot-hwasung. On the other hand, water, forest, wetland area's rate was decreased 5.57%, 2.43%, 3.66%, respectively. In this case, we expect change of land use that is occurred by construction of industrial and agriculture complexes, residential facilities. Fig. 7.(c) images are

Daebudo of Landsat image 2000 and 2009. When we compare two images, land cover change occurred due to the increase of reclaimed land. Actually, this area is constructed Daesong industrial complex now. Agriculture area's rate was increased 7.34%. On the other hand, forest area's rate was decreased 10.28 in the hotspot- Dangjin. We can expect change of land use that is occurred by construction of agriculture area.



(a) Hotspot in the study area (b) Magnified image of hotspot area (c) Landsat image of Daebudo(2000, 2008)

Fig.7. Hotspot area

4.CONCLUSIONS

In this study, we detect cohesion area of change using adaptation of probability density function, spatial autocorrelation for detection of land cover change. First, we make use of spatial statistics and improved algorithm for detecting hotspot of land cover change. Also, we obtain more disinterested result of land cover change, because existing research detected independently land cover change by comparison of pixel by pixel. But this study correct continuity of land cover change values and spatial association of surrounding area through application of probability density function and spatial autocorrelation. Second, we detect cohesion area of land cover change by modified hotspot algorithm using Contiguity-Dominance Model. Third, we analyze land cover change of hotspot area.

If it exist spatial data that is involved spatial information, AMOEBA_CH will expect many application of spatial data. We detected hotspot, but we don't analyzed details of land cover change, because we don't use high resolution image. We will analyze more detailed land cover change using high resolution satellite image. And we need analysis of another change by land cover change.

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