Thesis for the Degree of Master of Engineering

Hotspot Detection for Land Cover Changes Using Spatial Methods and Analysis of Environment Changes

by

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Pukyong National University

February 2012

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(공간통계기법을 이용한 토지피복변화의 응집구역 탐지 및 환경변화 분석)

Advisor: Prof. Yang-Won Lee

by

Jeong-Hun Lee

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이 정 훈

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요 약

최근 인구집중으로 인한 도시화, 택지개발 및 사회기반 시설의 확충 등의 토지개발과 지구온난화 및 가뭄, 홍수, 산불과 같은 자연적 현상으로 인해 광범위한 지역에 대해 토지피복 변화가 발생하고 있다. 토지피복 변화는 비점오염배출의 변화, 도시열섬현상 등 다양한 환경적 변화를 유발하기 때문에, 토지피복의 변화를 탐지하고, 그 변화원인을 분석하기 위한 다양한 연구가 진행되어 오고 있다. 이에 따라 본 연구에서는 애매한 토지피복 변화의 정도를 정량화하고, 주변지역과의 공간적 상호작용을 적용하기 위해 토지피복 변화의 확률과 공간자기상관을 이용하여 토지피복변화의 핫스팟 탐지를 수행하였다. 또한 핫스팟 탐지에 있어서 기존의 핫스팟 탐지 알고리즘인 **AMOEBA(A Multidirectional Optimal Ecotope-Based Algorithm)**에서 나타나는 과다탐지의 경향을 개선하여 핵심적인 토지피복 변화의 핫스팟을 탐지하는 **AMOEBA-CH(Core Hotspot)**를 개발하여 적용하였다. 본 연구는 애매한 토지피복의 변화를 표현함에 있어 절대적 기준

의 양분화된 결과가 아닌 상대적 기준에 의한 변화 확률 값으로 보완하고 공간자기상관에 의한 주변지역과의 상관관계를 고려하였으며, 인접-우세 모형을 이용한 AMOEBA-CH를 통해 토지피복변화의 핵심적인 핫스팟을 탐지할 수 있는 방법론을 제시한다. 또한 토지피복변화의 핫스팟이 탐지된 구역에 대하여 토지피복자료를 이용하여 그 변화요인을 분석하고, SWAT 모형 및 원단위 기법에 의한 비점오염 추정을 통해 토지피복변화로 인해 나타나는 비점오염 배출량의 변화를 확인하였다.

1. INTRODUCTION

Land cover changes are occurring for a variety of reasons such as construction of infrastructure, desertification, drought, flood, and so on. As Analysis land cover changes, we identified natural changes and social changes by human activities. Especially, resolution of satellite image is more higher, and cycle of image acquisition is more shorter. So it is possible to analysis detailed land cover changes. First of all, we detected area of land cover change for analyze of land cover changes. This is called 'change detection'. Change detection is identification process of another time and same area about land cover change using satellite images. applications of land cover change are land cover and land use changes, fire detection, environmental changes, urban changes, and so on(Singh, 1989). Various techniques of change detections are developed, because an accurate change detections of timely fashion provide importance of resource managements and resource use for human activities.

Looking at the existing studies of change detection, first, it performed change detection using classified based on land cover data or through the classification process from satellite image of two periods(Bayarsaikhan et al., 2009; Park, 2010; Du et al., 2010; Shahraki et al., 2011). Also, it adapt to detect land cover change using threshold of different pixel values and ratio(Ha et al., 2002). And another research studied measure accuracy of land cover change depending on change of threshold using MODIS NDVI 16day data(250m ×250m) (Lunetta et al, 2006).

Existing researches of land cover change tend to appear two characteristic.

First, these change detection are 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. These used absolute standard of land cover change such as threshold. But land cover changes have fuzzy standard. In this study, we will represent degree of land cover changes using relative standard. So we use probability for relative comparison. If we will extract the relatively high probability of land cover changes by probability of change, then we supplement result of land cover changes from absolute standard.

Second, existing researches represented land cover changes by comparison of pixel by pixel. But land cover change does not act independently, because land cover on a space do to interact with surrounding area. So these land cover changes have the form of cluster. Therefore it is a need of spatial association with surrounding area. spatial autocorrelation represent spatial association and it can be expressed numerical values.

Also, if we identified land cover change by probability of land cover change and spatial autocorrelation, we must acquire hotspot of land cover changes. So, we use modified AMOEBA(A Multidirectional Optimal Ecotope-Based Algorithm) for detection of hotspot. Original AMOEBA detected too many hotspot, So we modified AMOEBA through Contiguity - Dominance Model. this is AMOEBA-CH(Core Hotspot).

Particular, as non-point pollutions occurred in obscurity area, so calculation of non-point pollutions depend on land cover. We will identify emission of non-point pollutions for identification of environmental changes in land cover change areas. So method of identifying environmental changes use land cover data and emission of non-point pollution by SWAT(Soil and Water Assessment Tool), load rate.

In this study, we will detect core hotspot of land cover changes using probability, spatial autocorrelation, AMOEBA-CH. So, at first, we calculate probability of NDVI differencing index using probability density function. This is identified quantification of degree of land cover change for supplementation of absolute standard. And calculated probability values correct spatial correlation of surrounding area. Also, we detect core hotspot of land cover changes using AMOEBA-CH through calculated probability of land cover changes and spatial autocorrelation. In this chapter, we introduce background and objectivity of this study, in chapter 2, we will account for data of this study and method explanation. Next, we analyze cause of land cover change and estimation of non-point pollution through results of hotspot detection in chapter 3. Finally, we describe achievements and limitations of this study, future work in chapter 4.

2. DATA AND METHOD

2.1. Study procedure

Target area for this study is south korea(Fig.1). Range of latitude is between 32.8 and 38.77, and range of longitude is between 124.48 and 130.

Fig.1. Study area(www.naver.com)

All process of studies were performed about results of land cover change using JAVA. Fig.2 is work flow of this study.

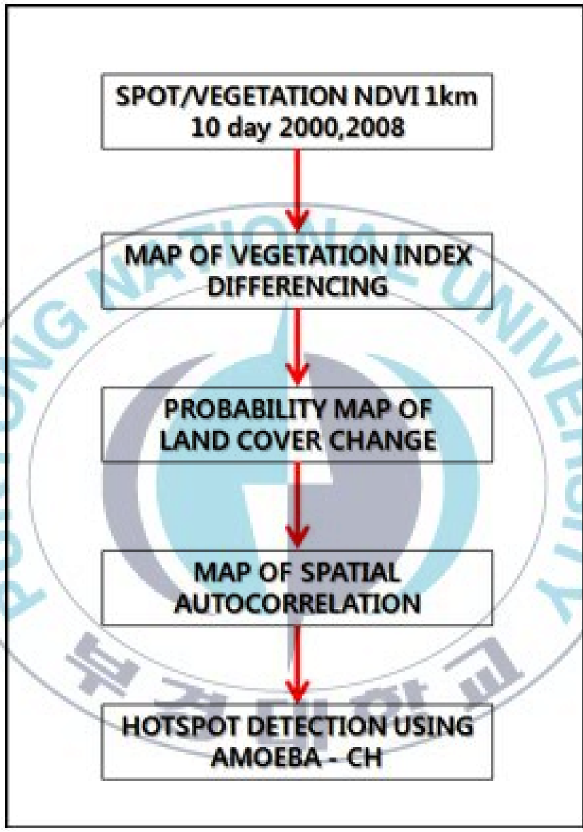


Fig.2. Work flow of hotspot detection

First, we build based data of analysis through preprocess of SPOT/VGT(Vegetation) NDVI 2000 and 2008. Next, we calculate vegetation differencing index 2000 and 2008. Then, we will calculate probability of land cover change. Reason of calculated probability of land cover change represent degree of land cover change. land cover change has fuzzy characteristic. So values of NDVI differencing don't represent land cover change. For this reason, we adapt probability. And we must do to calculate quantification of land cover change through probability of NDVI differencing values using probability density function. And next step, we calculate spatial autocorrelation index about probability of NDVI differencing values. Land cover changes were interacted surrounding area. So form of land cover change is shape of cluster by interaction of surrounding areas. If target pixel has high probability of land cover change, then surrounding pixels will have high probability of land cover change. Therefore we will perform to identify degree of land cover changes and calculate quantification of spatial association using spatial autocorrelation. At last, we detect hotspot of land cover change about result of probability process and spatial autocorrelation. We use modified AMOEBA for detection of land cover change. Original AMOEBA is useful for detection of hotspot. Also, AMOEBA is possible to adapt vector data and raster data. But original AMOEBA appear tendency that detect too many hotpot. So we modified original AMOEBA using Contiguity-Dominance model for detection of core hotspot. As a result, we adapt probability density function, spatial autocorrelation for comparison of relative land cover change. And we detect core hotspot of detected hotspot by AMOEBA using modified AMOEBA. So, we create AMOEBA-CH through Contiguity-Dominance model.

2.2. Data preprocessing

2.2.1. NDVI data

SPOT/VGT is a high resolution, optical imaging earth observation satellite system operating from pace. It observe almost area of earth once a day. Using NDVI data have resolution of 1km×1km from vegetation sensor.

We use NDVI 10-day MVC(Maximum Value Composite) data, 2000 and 2008. MVC method choose maximum value of 10 days. MVC method is one of the most general method for output of NDVI. This values are less affected by earth surface(Eidenshink and Faundeen, 1994). But this values are found low peak by influences of cloud, aerosol, rainfall, and so on although performed MVC method. So, many researchers are studied removal of low peak phenomenon. Typical methods are harmonic analysis(Roerink et al., 2000; Jakubauskas, 2001; Moody, A. and Johnson, D.M., 2001), used moving average(Chen et al., 2004), multiple polynomial regression analysis(yeom, 2006), and so on. As such the reason for presenting a variety of research methods, calculations of various variable provide wrong information by pixels of including error. So, closely to the true value is very important to approach using removal of error and statistical methods.

In this study, we use reproduction NDVI using multiple polynomial regression analysis for NDVI of improvement in quality. method of using multiple polynomial regression analysis is found high peak, and compare original NDVI regression equation and calculated NDVI regression equation. This method can provide a linear time-series NDVI data of removed low peak thorough empirical process of iterative. Therefore we use maximum values of each pixel using reproduction NDVI data 2000 and 2008 through multiple polynomial regression analysis. Also we use values of differencing NDVI, because we consider values of differencing NDVI as land cover change. So we use these data. Fig.3 is preprocessing NDVI data 2000 and 2008.

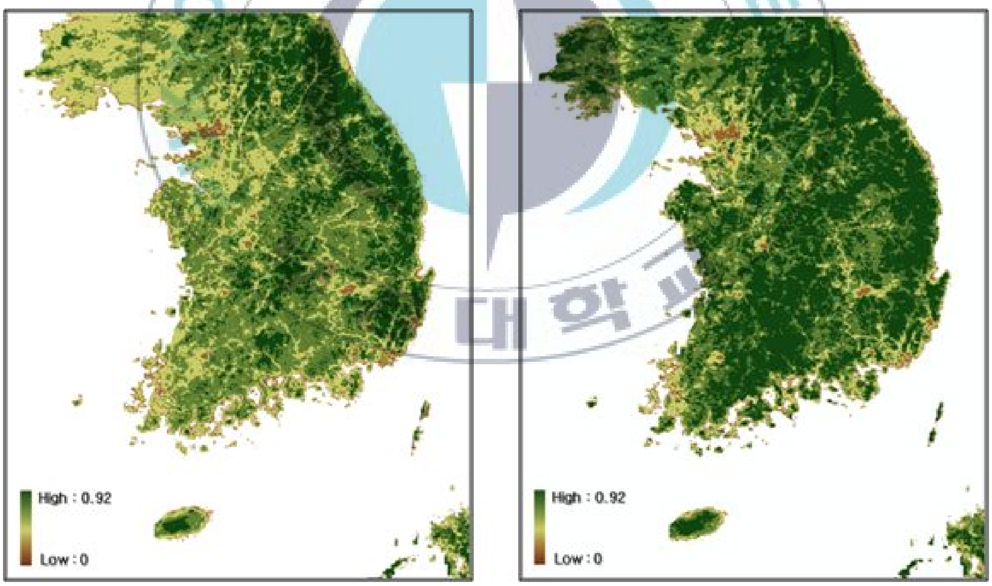


Fig.3. Preprocessing NDVI data 2000 and 2008

2.2.2. Land cover data

In this case of NDVI data, it is not distinguished land area and sea area. So we use MODIS land cover data for extraction of land area. 2006 MODIS land cover data is the newest data and adapt this data. resolution of MODIS land cover data is 1km×1km. Fig.4 is 2006 MODIS land cover image.

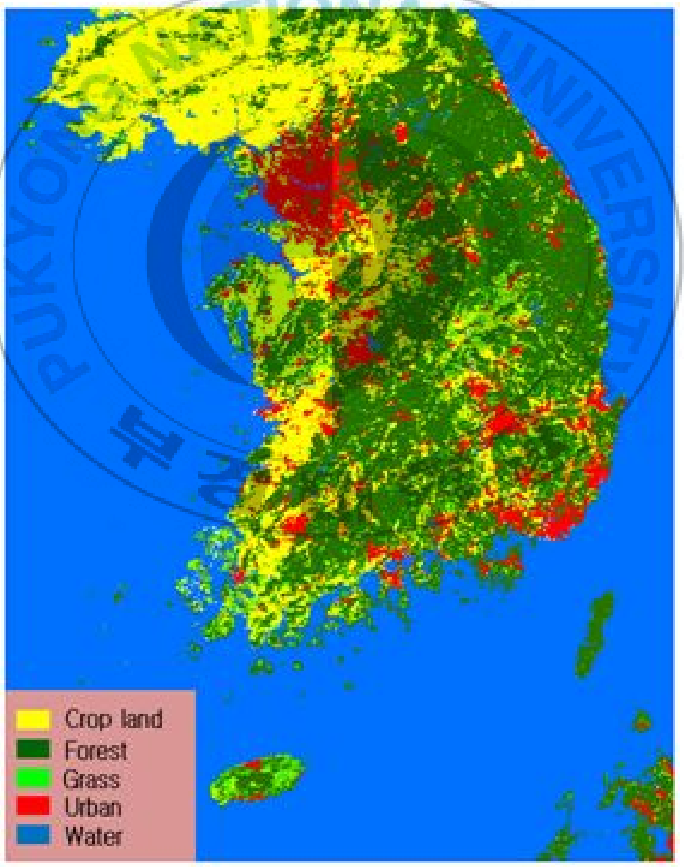


Fig.4. 2006 MODIS land cover image

2.2.3. Probability map of land cover change

Existing researches are used absolute standard such as threshold and change of land cover code. So results of existing researches are dichotomy, "change" or "no change". But Land cover change is ambiguity. So change standard of land cover don't have absolute standard. It is inherent uncertainty in spatial phenomena. So we detect land cover change based on probability. We will use probability variable. Because we need quantification of land cover change degree And Mapping change probability using Probability Density Function. Probability map can be calculated using NDVI difference between two periods.

We need standardization process of each variable for adaptation of probability density function. So, we calculate z-score of NDVI differencing values through eq.1.

$$z = \frac{X_i - \mu}{\sigma} \quad \text{.....eq.1.}$$

We calculated NDVI difference of pixel(i) that NDVI of 2008 minus NDVI of 2000. In equation(1), numerator X_i 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.

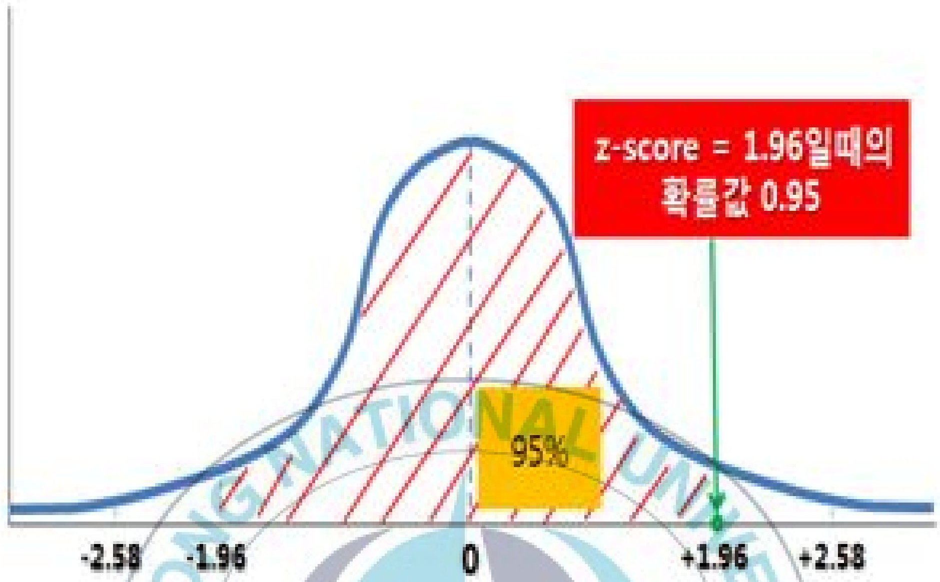


Fig.5. Example of probability density function

For example, In Fig.5, probability variable "1.96" is probability value "0.95". and probability variable "2.58" is probability value "0.99". Fig.6 is mapping image of vegetation index differencing 2000 and 2008. And Fig.7 is probability map of land cover change through vegetation index differencing. Range of probability values are 0 to 1. high values of probability appear blue area and black area.

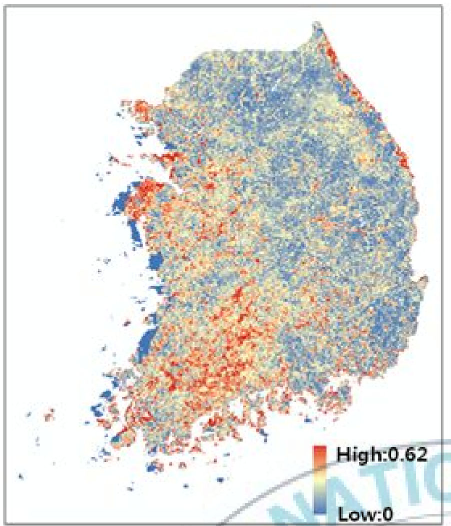


Fig.6. Vegetation index differencing map

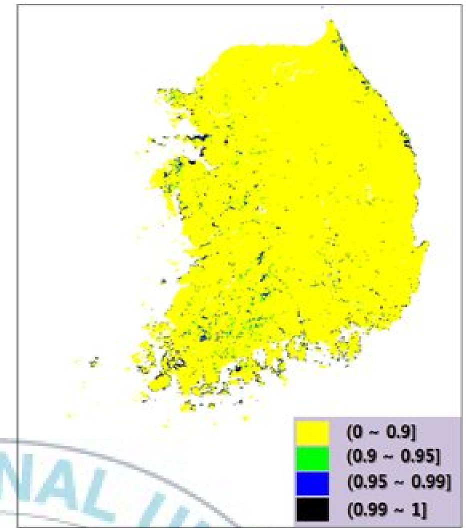


Fig.7. Probability map of land cover change

2.2.4. Spatial Autocorrelation

Probability values of land cover change using probability density function don't correct spatial association with surrounding area, because probability values are calculated independent pixels. So it is important to correct spatial association of surrounding areas, because land cover change appear forms of cluster by spatial association. Also each pixel's probability value of land cover change have spatial association. So we use spatial autocorrelation for quantification of spatial association with surrounding pixels.

Spatial autocorrelation is the correlation among values of a single variable strictly attributable to their relatively close locational positions(Griffith, 2009). Sptial autocorrelation index is quantification of spatial autocorrelation. Using suitable spatial autocorrelation of study objective is very important. So we use G_i^* in this study(Getis and Ord, 1992). G_i^* is identified whether hotspot and coldspot by calculated values(Lee, 2010), and for a given location i, the statistic G_i^* is defined as

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

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.

Fig.8 is mapping of calculated Gi* through probability of land cover change. Compared with result show in Fig.7, probability of land cover change and spatial autocorrelation of probability values have similar pattern of high value clusters and low value clusters. But we don't identify hotspot by G_i^*, values of spatial autocorrelation. So, we need algorithm that detect hotspot area.

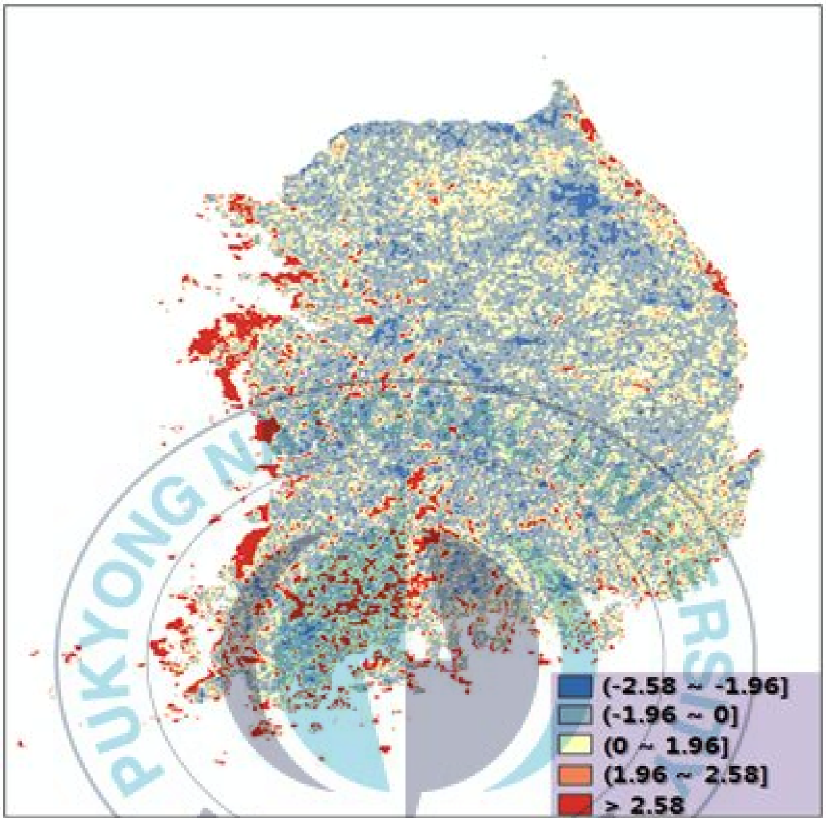


Fig.8. Spatial autocorrelation index of land cover change

2.2.5. AMOEBA

We calculate quantification of spatial association with surrounding area using G_i^* of spatial autocorrelation. However, it is not important to calculate quantification of spatial association, but also to set hotspot area of high value clusters and low value clusters in distribution of data(Lee, 2010). In Fig.8, it is difficult to detect hotspot using values of calculated G_i^*. So we will use AMOEBA. Because AMOEBA of developed by Aldstadt and Getis is demarcate hotspot area of land cover change using vector data and raster data. AMOEBA is a design for the construction of a spatial weights matrix using empirical data. And Searches for spatial association in all specified directions. Optimum in the sense that the scale is local (the finest scale) and the analysis reveals all spatial association. The algorithm for finding the ecotope is based on an analytical system that often finds highly irregular (amoeba-like) sub-regions of spatial association(Aldstadt and Getis, 2006).

We explain detection process of AMOEBA in Fig.9. Basically, we will detect hotspot of spatial distribution using original AMOEBA.

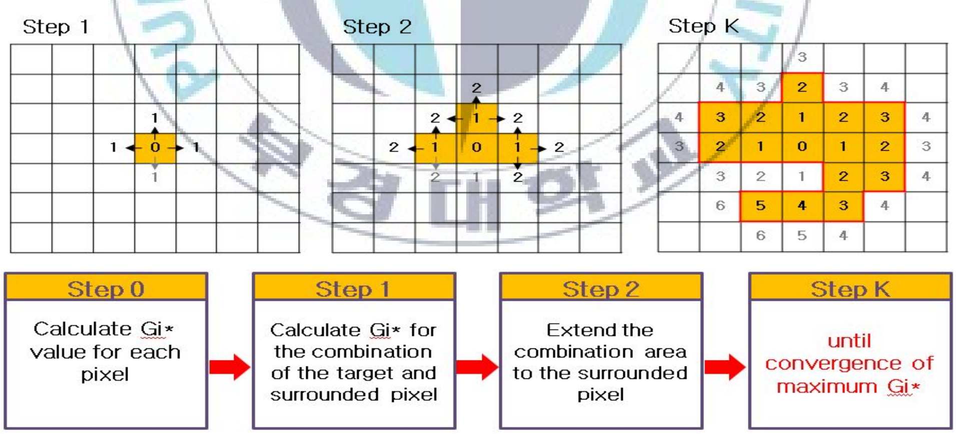


Fig.9. Detection process of AMOEBA

First, we calculate Gi* of whole pixel in study area, calculated Gi* are Gi*(0). This time, if calculated Gi* value of location i is higher than 0, then this is higher than mean of whole pixels. The other way, calculated Gi* value of location i is lower than 0, then this is lower than mean of whole pixels. In this case, we use Gi* higher than 0, and explain each step of detection cluster.

Second, we select target pixel from cell of maximum value through comparison of whole pixel. In general, 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 are at other surrounded pixel until convergence of maximum G_i^*. This process repeats for the whole pixel.

In 1 stage of Fig.9, we combine target pixel and upper, lower, left, right pixels for finding combination of maximum G_i^* value. In this process, 15 different number of cases will appear. Combination pixels are target pixel and 1 closed pixel(4), 2 closed pixel(6), 3 closed pixel(4), 4 closed pixel(1), total 15 case of combination pixel. Calculate Gi* of 15 case Combination pixel. we find maximum combination pixel. and maximum combination pixel to be $G_i^*(1)$.

But if $G_i^*(1)$ is higher than $G_i^*(0)$, we regard hotpsot, and it is end of cluster detection. On the other hand, if $G_i^*(1)$ is lower than $G_i^*(0)$, we performed next stage, pixel of including $G_i^*(1)$ is expended. But pixel of excluding $G_i^*(1)$ is not expended and it is excluded since this stage. In 2 stage of Fig.9, we select result combination pixel of 2 stage for target pixel of 3 stage. same as 2 stage, we find maximum Gi* through combination of closed pixel. And Expended clusters.

If combination pixel of each stage is higher than $G_i^*(0)$, process of hotspot detection is end. So, final stage of Fig.7 is shown(Aldstdat and Getis, 2006).

2.2.6. AMOEBA-CH

Original AMOEBA tend to detect too many hotspot in Fig.10. Therefore, we need to select core hotspot about results of original AMOEBA. So we modified AMOEBA and this session account for part of modified AMOEBA and calculation of modified AMOEBA.

AMOEBA-CH is modified AMOEBA using Contiguity - Dominance Model for detection of core hotspot from hotspot of original AMOEBA. work flow of AMOEBA-CH is shown by Fig.11. In this study, improvement is detection of core hotspot using Contiguity - Dominance Model. Finally we detect core hotspot of land cover change. This process contained detection of core hotspot and delimitation of hotspot areas.

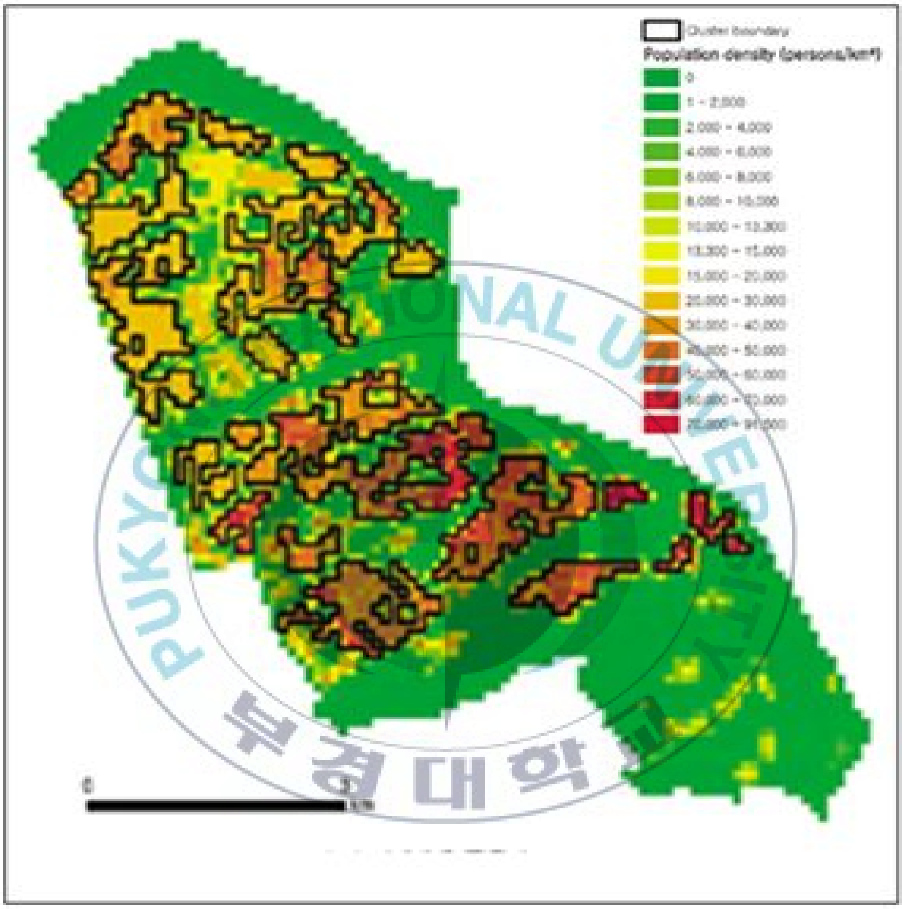


Fig.10. Hotspot detection of population density using AMOEBA(Lee et al., 2010)

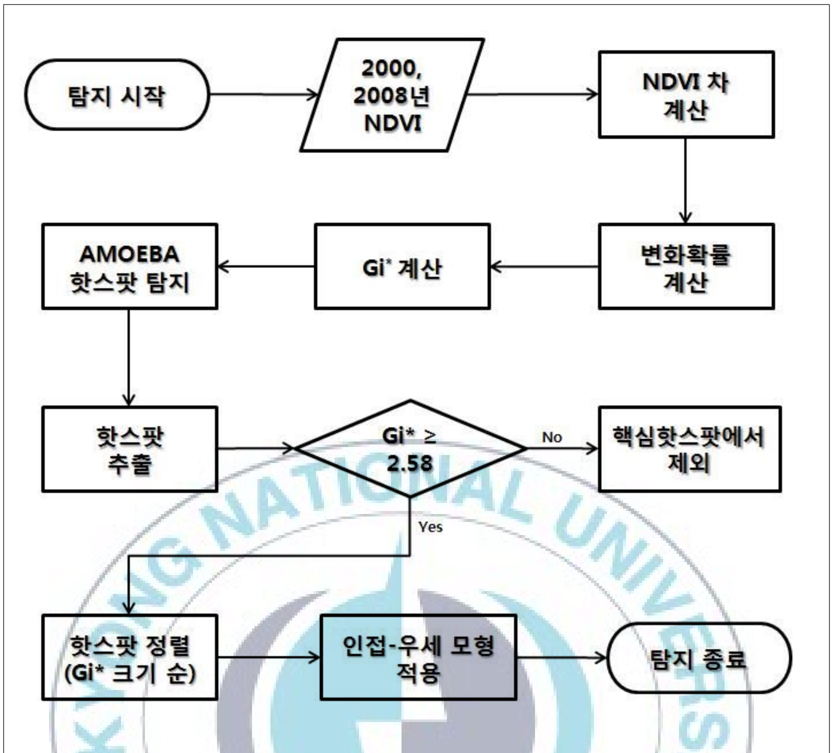


Fig.11. Work flow of AMOEBA-CH

Fig.12 is explain of Contiguity - Dominance Model. We use JAVA for realization of AMOEBA-CH. At first, we detect hotspot original AMOEBA. And we marked about hotspot of original AMOEBA. Next, we sort hotspot of original AMOEBA by values of G_i^*. And then, Merged pixel in sequence maximum value to minimum value. In merged process, if G_i* value is 1.96 or lower than 1.96, then we exclude pixel. And 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. And this process repeat. Finally, AMOEBA-CH detected hotspot that is value of maximum merged cell.

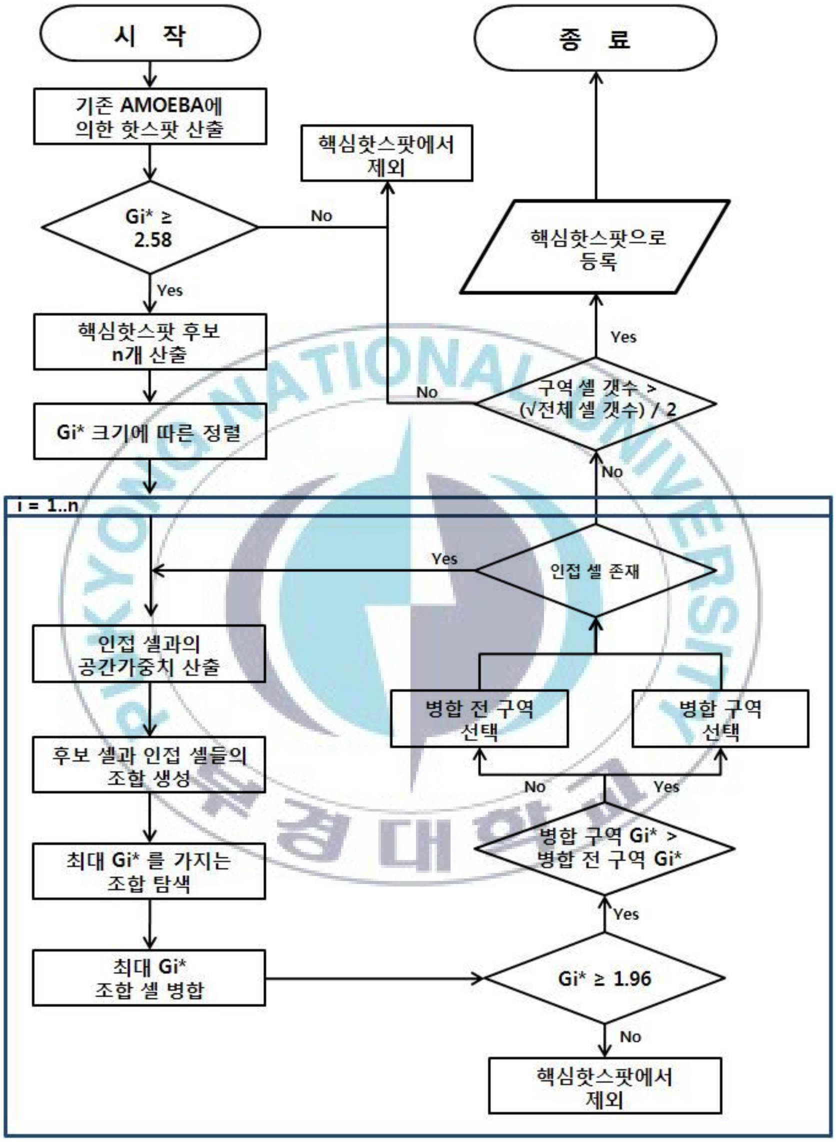


Fig.12. Work flow of Contiguity - Dominance Model

3. RESULT AND DISCUSSION

3.1. Analysis of land cover change

Fig.13 is result of hotspot detection in this study. we calculate probability of NDVI differencing values, and calculate Gi* through probability of NDVI differencing values, finally we detect core hotspot using AMOEBA-CH. As a results, Hwasung(①), Dangjin(②), Namwon (③), Seosan(④) are detected hotspot area in this study, as compare 2000 and 2008 NDVI data. Particularly, Hwasung, Dangjin, Seosan area in Korea of the west coast appear land cover change greater than other area by construction of complex since 2000. These area involved reclaimed land. Because government will increase land for construction of industrial and agriculture complex. It is putting up a large scale of industrial complex and residential facility in this reclaimed land. Reclamation project is being made even today.

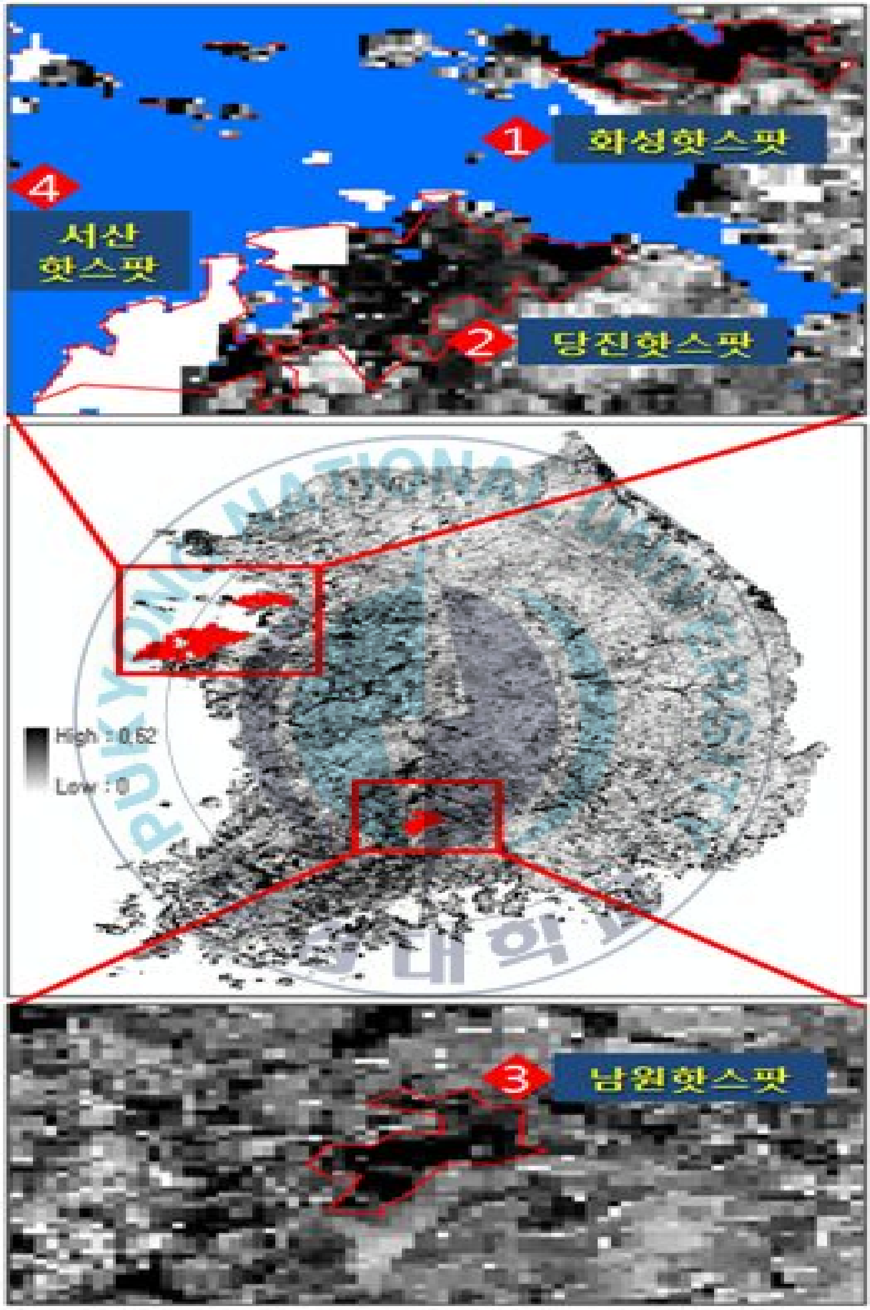


Fig.13. Results of hotspot detection for land cover changes

South reclaimed area of Sihwa lake is detected hotspot in Hwasung area. and Seokmoon reclaimed area and Iwon tide embankment area are detected hotspot Dangjin area and Seosan area respectively. West area is constructed agriculture complexes and East area is constructed industrial complexes in South reclaimed land of Sihwa lake. Also, increase of agriculture area is outstanding in Seokmoon reclaimed area by land use change and land cover change.

Reason of reclaimed land detection in this study area is changes bigger than other area in this study. Because probability values of each pixel is not only higher, but also probability values of surrounding area is higher, too. So, degree of land cover change is high value, and spatial association is high, too. Characteristic of These area occurred land cover change by reclamation project. So land area is getting larger, and increase construction of complexes. These area appear land use change and land cover change.

We analyze land cover change using 2000 land cover image from Water Management Information System and 2008 land cover image from ministry of environment in Korea for analysis of hotspot area. We identify rate of land cover through Table 2. Calculated results of land cover area, water area decrease $4km^2$, $13.15km^2$ to $9.06km^2$ in Hwasung hotspot area. Bare land area increase three times, $3.68km^2$ to $10.84km^2$. Forest, water, wetland areas decreased, on the other hand urban, agriculture, bare land area increased(Table 1). Particularly we expect reason of land cover change that increase of bare land is securing area of infrastructure construction.

Table 1. Changes in land cover fraction in Hwasung hotspot

Division	**2000(%)**	**2008(%)**	**change(%)**
Urban	6.21	9.9	+3.7
Agriculture	22.27	25.64	+3.37
Forest	20.92	15.74	-5.17
Grass	1.96	1.73	-0.22
Wetland	37.95	34.34	-3.61
Bareland	2.34	6.88	+4.54
Water	8.37	5.75	-2.61

Fig.15 is image of overlay 2000, 2008 land cover images and NDVI differencing image. decreased area of water replace wetland, and existing wetland area transport bare land. This result support land cover change for construction of agriculture and industrial complexes. Increase area of urban are placed on sihwa industrial complex and banwol industrial complex.

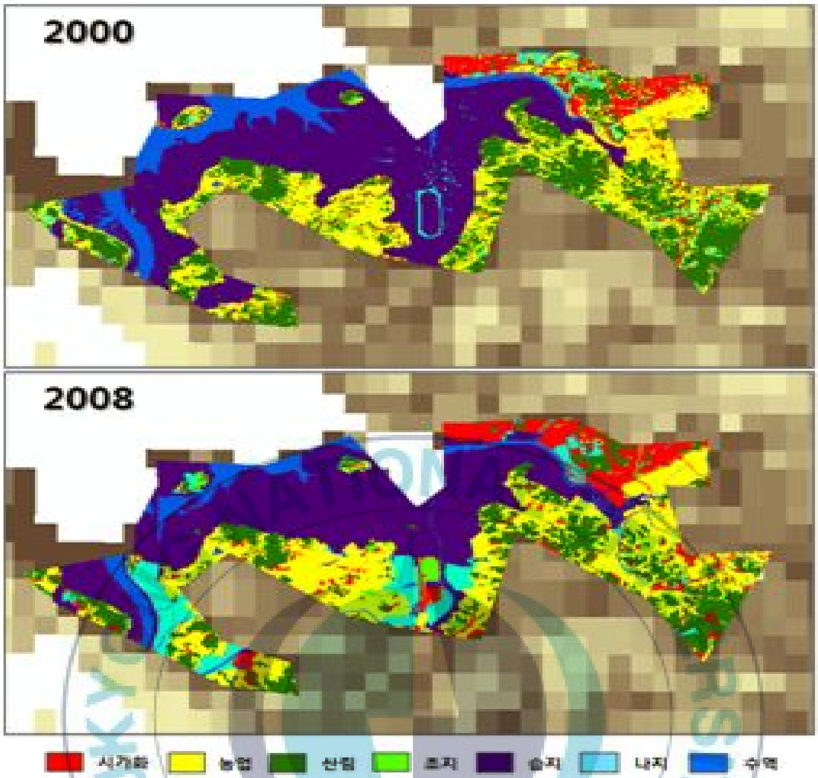


Fig.14. Land cover classification in Hwasung hotspot (2000 and 2008)

We use Landsat image of hotspot fraction area in Daebudo 2000 and 2008(Fig.14). Daebudo is involved south reclaimed land of sihwa lake, wetland area of 2008 is larger than wetland area of 2000. Actually, this area is placed on Deasong industrial complex. We identify to increase wetland through landsat image, but rate of wetland is decreased through rate of land cover change. Because urban and land developments in existing reclaimed area is made active.

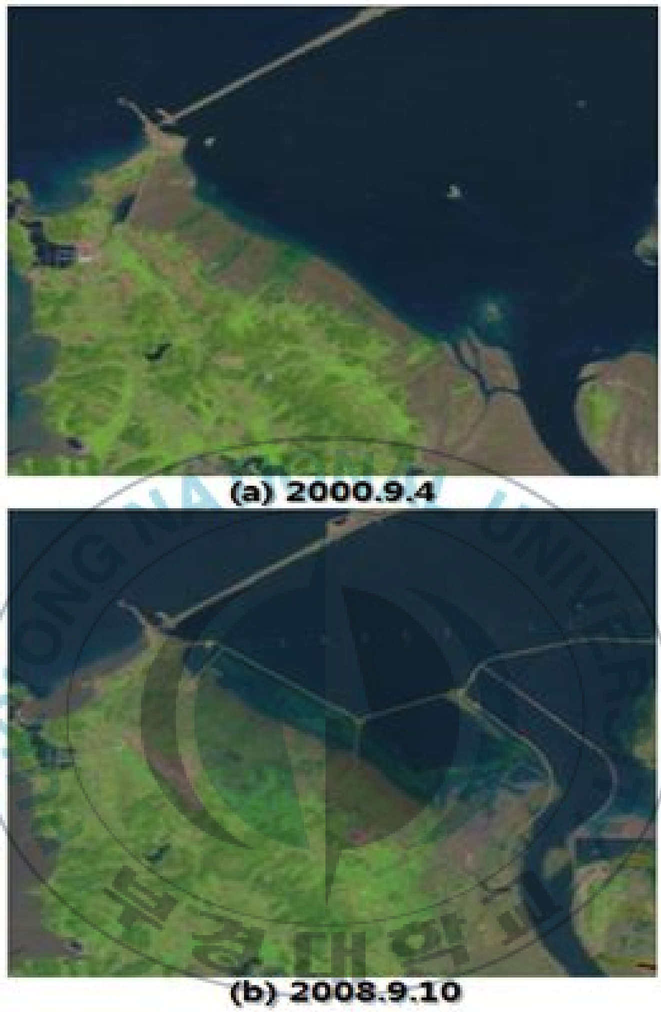


Fig.15. Landsat image in Hwasung hotspot 2000 and 2008

In Table 2, Forest areas decreased rate of 10%, on the other hand agriculture area increased rate of 9% in Dangjin hotspot. This is influence of agriculture complexes. Dangjin area occurred land cover change by construction of agriculture complexes in existing reclaimed area. Actually, detection area of hotspot is seokmoon reclaimed area. This area is being cultivated for rice paddy and farm.

Table 2. Changes in land cover fraction in Dangjin hotspot

Division	2000(%)	2008(%)	change(%)
Urban	4.4	5.6	+1.2
Agriculture	44.5	53.5	+9
Forest	43.2	33.2	-10
Grass	4.5	2.4	-2.1
Wetland	0.3	2.6	+1.3
Bareland	3.2	2.6	-0.6

Fig.16. Landsat image of Danjin hotspot

Seosan hotspot area is formed reclaimed land for construction of new renewable Energy complex in Tae-an region. Fig.15 are land cover image of Seosan hotspot, and Table 4 is rate of Seosan land cover. Significantly wider distribution of wetlands that can be found. Also, rate of wetland is increased 8.6% by land cover change.

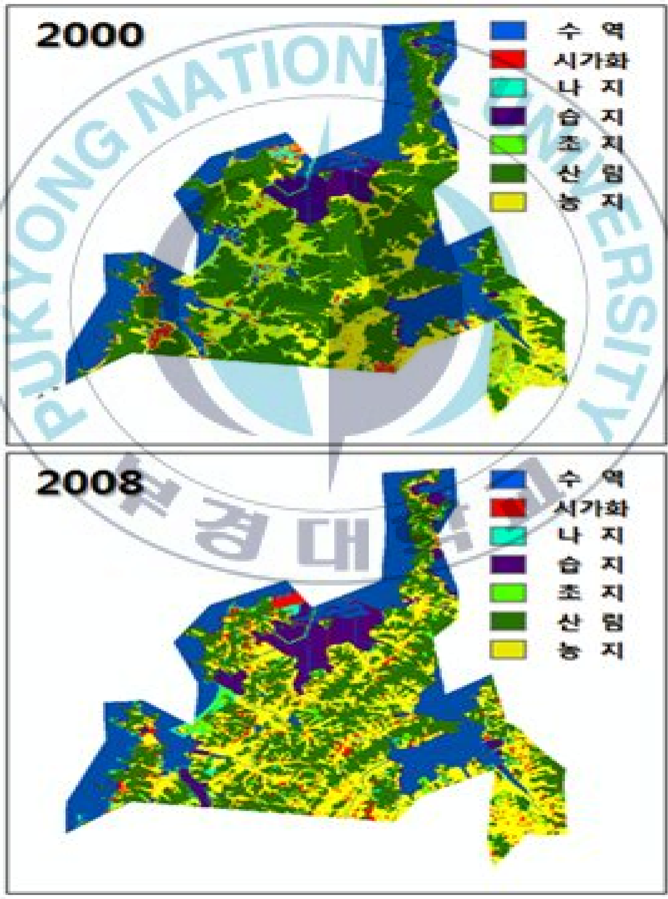


Fig.17. Land cover classifications in Seosan hotspot(2000 and 2008)

Table 3. Changes in land cover fraction in Seosan hotspot

Division	**2000(%)**	**2008(%)**	**change(%)**
Urban	3.4	5.4	+2
Agriculture	28.7	34.9	+6.2
Forest	62.8	44.5	-18.3
Grass	1.3	3.1	+1.8
Wetland	1.5	10.1	+8.6
Bareland	2.3	2	-0.3

Agriculture areas decreased rate of 8%, on the other hand urban and grass land area increased rate of 3.2%, 3.5, respectively in Namwon hotspot. Compare population data of Namwon, decreased 15621 person. So, agriculture population is not only decreased but also price of land is decreased. As result, appear expansion of urban area and grass land is increased by decrease of agriculture land demand.

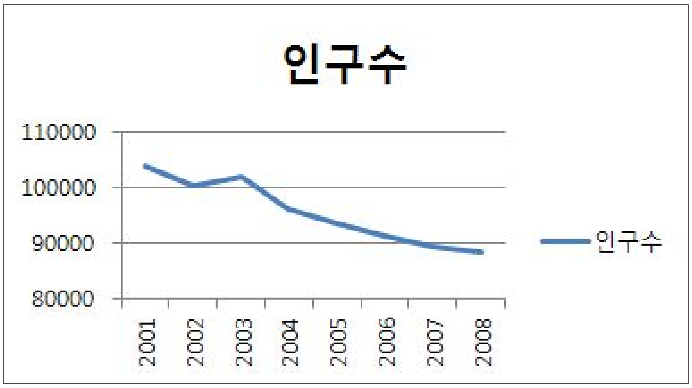


Fig.18. Population change of Namwon

Table 4. Changes in land cover fraction in Namwon hotspot

Division	**2000(%)**	**2008(%)**	**change(%)**
Water	0.4	1.6	+1.2
Urban	1	4.2	+3.2
Agriculture	45.9	37.8	-8.1
Forest	52.1	51.3	-0.8
Grass	0.7	4.2	+3.5
Wetland	0	0.4	+0.4
Bareland	0	0.6	+0.6

Hwasung, Dangjin, Seosan hotspot in Korea of the west coast are placed on tide embankment area and appear land cover change by reclamation project. And Namwon hotspot occurred land cover change by social factor such as decrease population and price of land.

3.2. Estimation of non-point source

We estimated non-point source load in hotspot area(Hwasung, Dangjin, Namwon hotspot). So we construct study data for analysis of swat model and load rate. And we performed estimation of TN, TP in hotspot area.

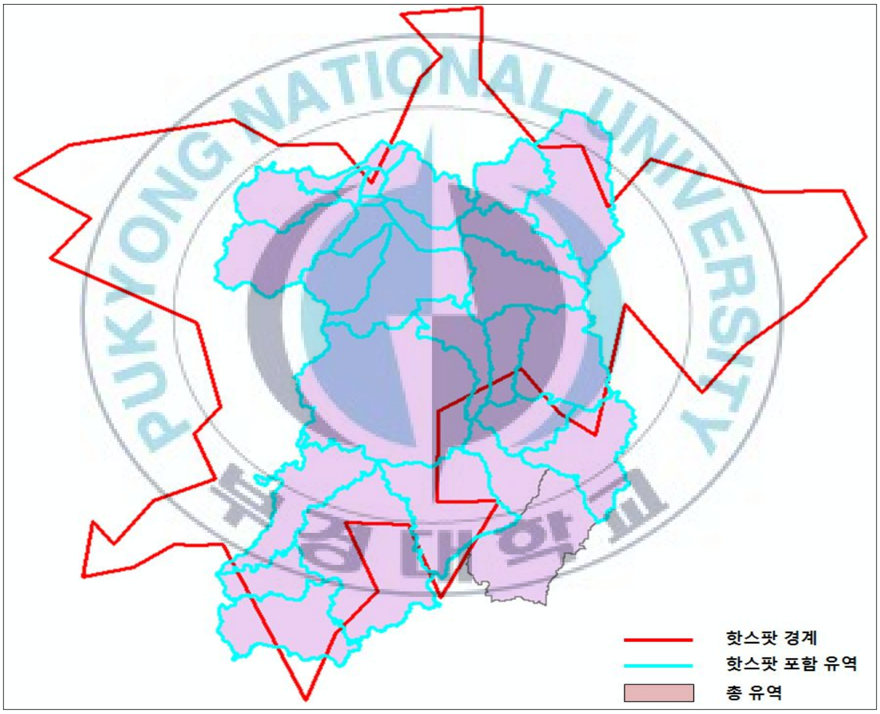


Fig.19. Extraction of sub-basins in hotspot area

At first, we construct using data in hotspot area, next we performed estimation of TN, TP using analysis of SWAT model and load rate at sub-basin. And we overlay hotspot area. Then we can extract sub-basin in hotspot area excluding more than 90% of water area. Because more than 90% of water area don't influence by land cover changes. Fig.8 is extracted sub-basins in dangjin hotspot area.

We Analyze of load rate based on sub-basins of SWAT model result. And we estimated TN, TP at each sub-basin. So we compare TN, TP emission result of SWAT and load rate with observation data by WAMIS(Water Management Information System) in Hwasung hotspot area. This process is intended to verify the accuracy of estimation. as a result of comparison, TN emission of SWAT model tend to be too little estimation in Hwasung hotspot area. But percentage changes have similar pattern TN, TP emission result of SWAT model and load rate. So we calculate percentage changes of Hwasung, Dangjin, Namwon hotspot area.

Table 5. Result of TN, TP emission in Hwasung hotspot area

measure : $kg/km^2/day$

Time	Division	TN	TP
2000	Observation	46.4	3.6
	Load rate	41.17	4.42
	SWAT	25.83	2.64

So we compare results of SWAT model and load rate. Next, we calculate daily percentage change of TN, TP emission in hotspot areas. Fig.9 and Fig.10 are daily percentage change of TN, TP estimation in hwasung hotspot, Dangjin hotspot, respectively.

TN, TP tend to increase in Hwasung, Dangjin hotspot. In case of Hwasung hotspot, percentage change of TN, TP estimation are 12.14%, 20.84%, respectively by SWAT model. And it also tend to increase 40.75%, 52.63%, respectively by load rate. In case of Dangjin hotspot, percentage change of TN, TP estimation are 15.83%, 19.52%, respectively by SWAT model. Percentage change of TN, TP emission are 15.59%, 14.2%, respectively by load rate. In case of Namwon hotspot, average percentage change of TN, TP estimation are -5.67%, -5.23%, respectively by SWAT model. average percentage change of TN, TP estimation are 0.89%, 0.11%, respectively by load rate(Table 6). Namwon hotspot appear different result by comparison of Hwasung, Dangjin hotspot.

Table 6. TN, TP percentage change in Namwon hotspot(%)

Division	SWAT		Load rate	
	N	P	N	P
Sub-basin 1	-4.49	-4.01	4.18	3.99
Sub-basin 2	-6.86	-6.45	-2.39	-3.76

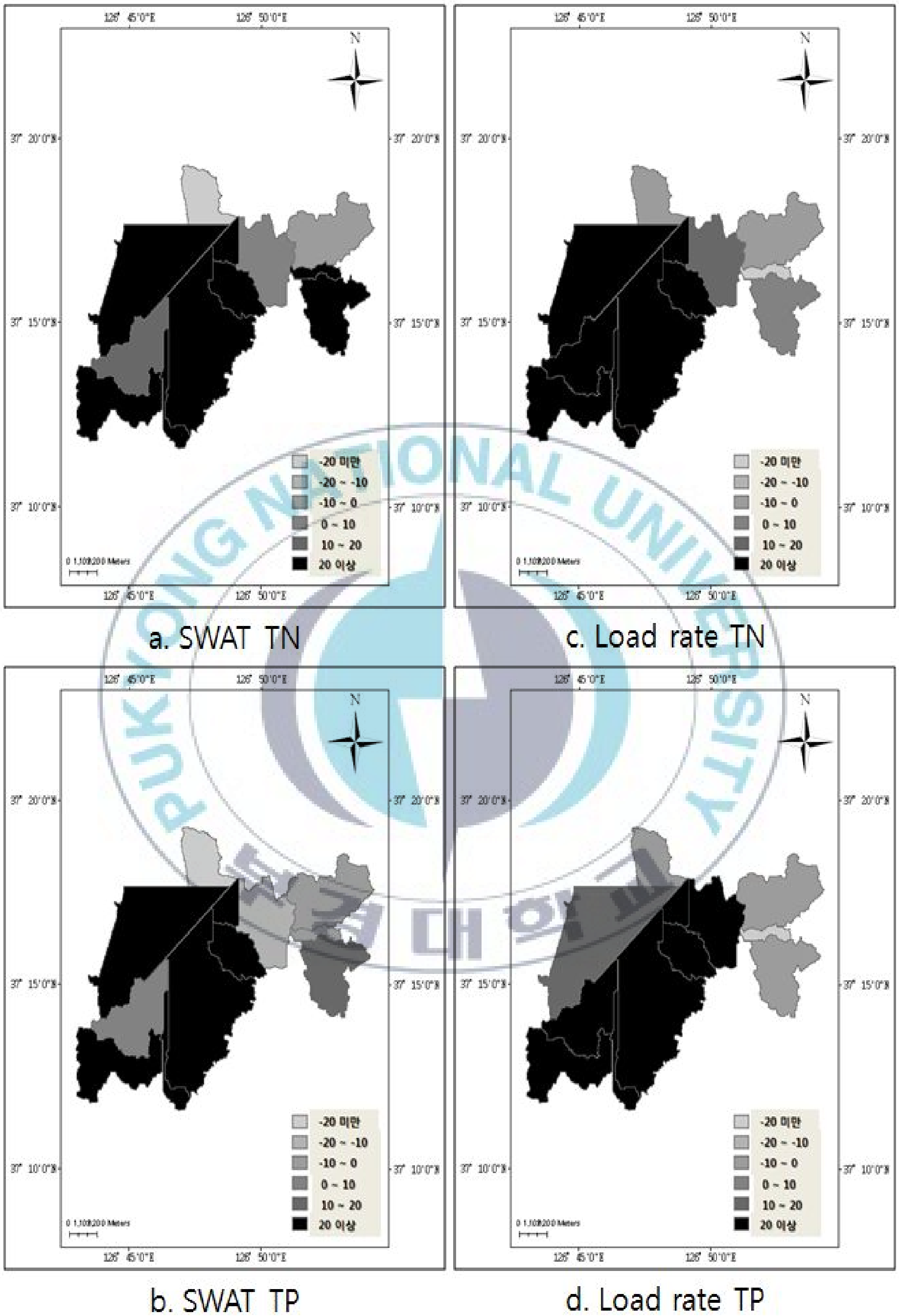
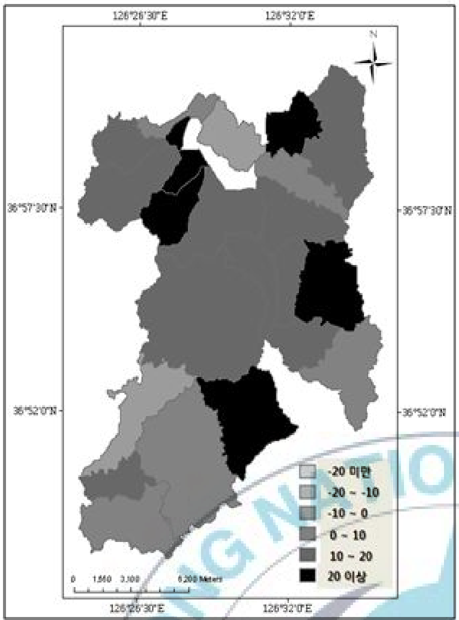
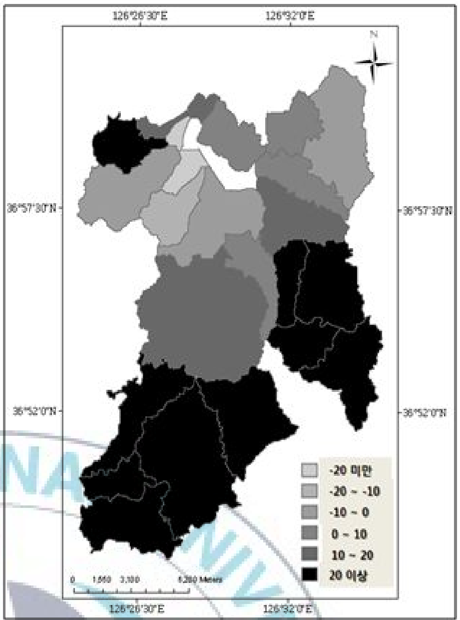


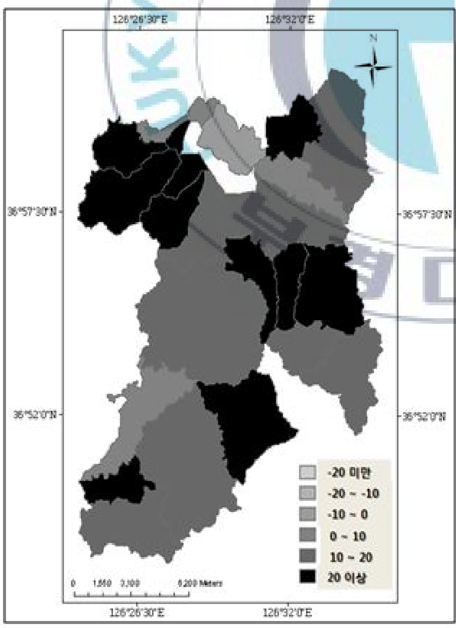
Fig.20. TN, TP percentage change of Hwasung hotspot(%)



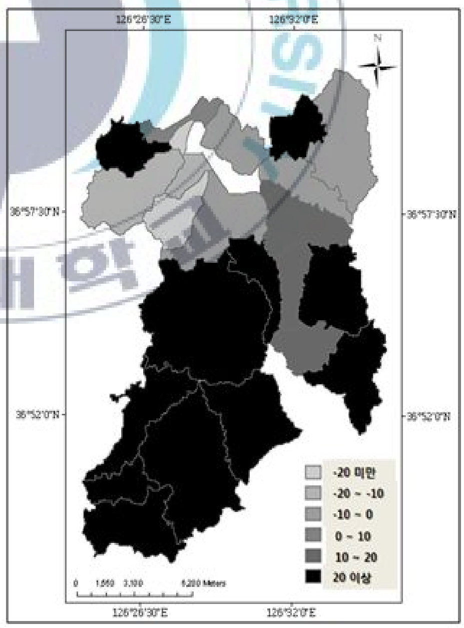
a. SWAT TN



c. Load rate TN



b. SWAT TP



d. Load rate TP

Fig.21. TN, TP percentage change of Dangjin hotspot(%)

Hwasung, Dangjin hotspot are the largest area of land cover change in study area. So these areas tend to increase TN, TP. This is occurred by land cover change. Because Hwasung, Dangjin area decrease rate of forest area 5.18%, 10%, respectively. But urban area, bareland, agricultural area increase 3.71%, 4.54%, 3.37%, respectively in Hwasung hotspot. And agricultural area, wetland increase 9%, 2.3%, respectively in Dangjin hotspot. These result seem to be increase influence factor of increasing non-point source in Hwasung, Dangjin hotspot. The other way, Namwon hotspot area tend to decrease TN, TP or have little change. Because agricultural area decrease as result of decreasing population and price of agricultural land. Agricultural area have an effect on change of non-point source.

So, we expect cause of increasing TN, TP by construction of industrial complexes and agricultural complexes in Hwasung and Dangjin hotspot area. Consequently, construction of industrial complexes and agricultural complexes have an effect on non-point source. Because, land cover of urban, agricultural area, wetland are occurred large quantities emission of non-point sources by land developments. But Namwon hotspot area does not seem to develop a large amount of complex development. So, percentage change of TN, TP emission doesn't have a lot of influence by decrease population and price of agricultural land. emission of non-point pollution have different result as tendency of land cover change.

Although result of SWAT and load rate are a little different, but we identify similar percent change of SWAT and load rate. Cause of different result by SWAT and load rate are calculated by different data. SWAT model includes weather, land cover, soil, DEM, etc., but load rate considers only land cover and the emission factor for non-point pollution based on observation data.

4. CONCLUSION

In this study, we detect cohesion area of change using adaptation of probability density function, spatial autocorrelation for detection of land cover change for hotspot detection of land cover change. So we calculate probability of land cover change using SPOT/VGT 10day data, next we compute Gi* of spatial autocorrelation through probability of land cover change. And we detect hotspot area of land cover change using AMOEBA-CH, modified AMOEBA.

First, we calculate probability of land cover change by relative standard. Because absolute standard of threshold and attribute change appear dichotomy results. So probability of land cover change can represent degree of land cover change by relative standard in study area for supplementation of absolute standard.

Second, we correct surrounding area of spatial association by spatial autocorrelation. Spatial autocorrelation calculate quantification of spatial association with surrounding areas. Because land cover change appear form of cluster by spatial association of surrounding areas.

Third, AMOEBA-CH can core hotspot of land cover change using Contiguity-Dominance Model. Because original AMOEBA detect too many hotspot. So it has need to detect core hotspot that is high value of result of original AMOEBA. Result of hotspot detection, hotspot pixel have higher values than surrounding areas.

Result of hotspot detection, hotspot areas are occurred land cover change by reclamation project in Hwasung, Dangjin, Seosan area, Korea of the west coast . These area appear conversion of land use by construction of industrial and agriculture complexes in existing reclaimed land. So we can identify cause of land cover change by satellite image and Comparison of land cover image 2000 and 2008. TN, TP tend to increase in Hwasung, Dangjin hotspot. In case of Hwasung hotspot, percentage change of TN, TP estimation are 12.14%, 20.84%, respectively by SWAT model. And it also tend to increase 40.75%, 52.63%, respectively by load rate. In case of Dangjin hotspot, percentage change of TN, TP estimation are 15.83%, 19.52%, respectively by SWAT model. Percentage change of TN, TP emission are 15.59%, 14.2%, respectively by load rate. So, results of estimation by SWAT, load rate tend to increasing emission of non-point pollution in hotspot area. But each hotspot area represent different result as cause of land cover change.

AMOEBA-CH is expected to be greater usability, because AMOEBA-CH is possible to detect hotspot using spatial data including vector data and raster data. In this study, reprocessing is important. Because this result is decided from accuracy of data. So if we use high accuracy data, we can detect detail hotspot area. Almost of all, we detect hotspot area near the coast area. Because using satellite image's resolution is not high resolution. Besides we will possible to suppose contained error in hotpost area. But Sihwa area in Hwasung hotspot affect more less tide movement by sea wall. Dangjin hotspot and Seosan hotspot are same cases. Hotspot area are placed on sea wall. In addition to, pixels of closed coast is not much. So, we are not going to affect result of hotspot detection. But Receiving areas heavily influenced by tide are need to calibrated. In future work, we use high resolution satellite images for detail analysis of land cover change. And we analyze correlation of land cover change and linked change by occurred land cover change in hotspot area.

5. REFERENCE

Aldstadt, J., and Getis, A., 2006, Using AMOEBA to Create a Spatial Weights Matrix and Identify Spatial Clusters, *Geographical Analysis*, Vol. 38, pp. 327–343.

Bayarsaikhan, U., Boldgiv, B., Kim, K. R., Park, K. A., and Lee. D., 2009, Change detection and classification of land cover at Hustai National Park in Mongolia, *International Journal of Applied Earth Observation and Geoinformation*, Vol. 11, pp. 273–280.

Chen, J., Jonsson, P., and Tamura, M., 2004. A simple method for reconstructing a highquality NDVI time-series data set based on the Savitzky-Golay filter, *Remote Sensing of Environment*, Vol. 91, pp. 332–344.

Du, P., Li, X., Cao, W, Luo, Y., and Zhang, H., 2010, Monitoring urban land cover and vegetation change by multi-temporal remote sensing information, *Mining Science and Technology*, Vol. 20, pp. 922–932.

Eidenshink, J. C. and Faundeen, J. L., 1994. The 1 km AVHRR global land data set: first stages in implementation, *International Journal of Remote Sensing*, Vol. 15, No. 17, pp. 3443–3462.

Getis, A., and Ord, J. K., 1992, The analysis of spatial association by use of distance statistics, *Geographical Analysis*, Vol. 24, pp. 186–206.

Griffith, D. A., 2009, Spatial Autocorrelation, *International Encyclopedia of Human Geography*, pp. 502–520.

Ha, S., B. Ahn, and S. Park, 2002. Change detection of land-cover from multi-temporal KOMPSAT-1 EOC imageries, *Korean Journal of Remote Sensing*, Vol. 18, No. 1 pp. 13-23.

Lunetta, R. S., Knight, J. F., Jayantha Ediriwickrema, Lyon, J. G., and Worthy, L .D., 2006, Land cover change detection using multi-temporal MODIS NDVI data, *Remote Sensing of Environment*, Vol. 105, pp. 142-154.

Roerink, G. J., Menenti, M., and Verhoef, W., 2000. Reconstructing cloudfree NDVI composites using Fourier analysis of time series, *International Journal of Remote Sensing*, Vol. 21, No. 9 pp. 1911-1917.

Shahraki, S. Z., Sauri, D., Serra, P., and Modugno. S., 2011, Urban sprawl pattурn and land-use change detection in Yazd, Iran, *Habitat International*, Vol. 35, pp. 521-528.

Singh, A., 1989, Digital change detection techniques using remotely sensed data, *International Journal of Remote Sensing*, Vol. 10, pp. 989-1003.

Park, J., 2010, Change Detection of Vegetation Using Landsat Image : Focused on Daejeon City, *Korean Journal of Geomatics*, Vol. 28, No. 2, pp. 239-246.

Lee, S., Cho, D., Sohn, H., and Chae, M., 2010, A GIS-Based Method for Delineating Spatial Clusters : A Modified AMOEBA Technique, *Journal of the Korean Geographical Society*, Vol. 45, NO. 4, pp. 502-520.

Yeom, J., Han, K., and Kim, Y., 2006, Identification of Contaminated pixels in 10-day NDVI Image, *Korean Journal of Remote Sensing*, Proceedings of KSRS Spring Conference 2006, Vol. 9, pp. 113-116.

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학교로 다시 와서 정말 많은 걸 느끼고, 학문이란 어떤 것인지에 대한 많은 생각을 하였고, 실제로도 정말 많은 걸 배워서 결코 헛된 시간이 아니었음을 느낍니다. 앞으로 사회에 나가서도 교수님들을 비롯한 저를 아는 모든 사람들에게 떳떳한 이정훈이 되기 위해서 앞으로도 끊임없는 노력을 통해 더욱더 성장하는 이정훈이 되고 싶습니다.