# The application of a prediction model on land surface temperature using Artificial Neural Network and Scenario

- Focused on Changwon in South Korea -

# 인공신경망 및 시나리오 분석을 활용한 지표온도 예측모델의 적용

- 창원시를 대상으로 -

이우성* · 정성관**
Lee, Woo-Sung· Jung, Sung-Gwan

**Abstract**

본 연구에서는 창원시를 대상으로 고해상도의 토지피복 및 토지이용 지도, 그리고 위성영상에서 추출한 데이터를 이용하여 지표온도 예측모델을 개발하였다. 또한, 최적 예측모델을 활용하여 도시개발의 시나리오에 따른 지표온도의 변화를 예측하였다. 신경망을 통한 지표온도의 예측결과에서는 영상으로부터 추출한 데이터(Case 1)나, 토지피복 데이터(Case 2)보다는 토지이용 데이터(Case 3)를 이용하여 분석하였을 경우 더 높은 정확도를 가지는 것으로 나타났다. 또한, Case 3 중에서도 은닉층이 3개일 때 가장 높은 정확도를 가는 것으로 분석되었다. 최적모델에 의해 예측된 결과의 RMSE는 0.455이며, $R^2$은 0.816으로 나타났다.

최적 모델을 활용하여 지표온도를 예측한 결과, 새로운 산업단지가 조성될 경우 건축물, 도로 등과 같은 인공지역의 증가로 인해 지표온도가 증가하였으며, 도시외곽지역에 대규모 주택단지가 건설될 경우 단위공간 당 차지하는 인공지역의 비율에 따라 지표온도가 증가할 것으로 분석되었다. 반면, 공업지역 내 녹지공간이 조성될 경우 지표온도가 확연한 차이를 보이며 감소할 것으로 분석되었다. 따라서 신규로 대규모 택지, 산업단지 등을 조성코자 할 경우에는 계획단계에서 적정한 규모 및 비율의 녹지를 적재적소에 배치하여 지표온도의 급격한 증가를 방지해야 할 것이다.

*키 워 드* ▪ 지표온도, 토지이용, 인공신경망, 시나리오 분석, 원격탐사
*Keywords* ▪ Land surface temperature, Land use, Artificial Neural Network, Scenario Analysis, Remote Sensing

## Ⅰ. Introduction

The increase in the artificial environment, which is the main cause of the urban heat island, is directly associated with changes in land use and land cover(Streutker, 2003). Land use and land cover can be viewed as resulting from constant change by human activities from the past to the present, and these changes can be considered the fundamental cause of the destruction of the ecosystem(Singh, 1995; Voogt and Oke, 2003). Therefore, for accurate judgment of the urban environment, climate, response, management, collection, and accumulation of highly precise land use and land cover data of the latest information is required(Assefa, 2004).

* 대구대학교 조경학과 조교수 (주저자: wslee@daegu.ac.kr)
** 경북대학교 조경학과 정교수 (교신저자: sgjung@knu.ac.kr)

Analysis tools in GIS(Geographic Information System) and RS(Remote sensing) are used to analyze urban climate and identify spatial characteristics and environmental characteristics; in particular, land surface temperature(LST) extracted from satellite images is being used to identify temperature rises and heat island phenomena in cities(Voogt and Oke, 2003; Small, 2006; Hais and Kučera, 2009).

However, despite the number of studies, in thermal environment analysis of a city through land use and land cover, high-resolution data have not been easily accessed so far due to data limitations. In addition, impact factors on the thermal environment have been identified in several previous studies but there are few studies predicting the changes in LST according to the changes in the urban environment in terms of urban and environmental planning.

Thus, this study develops the prediction models of LST by using detailed environmental factors extracted from a high-resolution land cover and land use map, and other indexes extracted from satellite images. Also, it analyzes the change in the LST depending on changes of spatial characteristics through the optimal model and the scenario analysis. Through this study, we will be able to identify the influence of the thermal environment in a city by using highly precise spatial data and predicting LST in the future.

## Ⅱ. Literature Review

Looking into major research using LST, Carnahan and Larson(1990) identified the temperature difference between urban and suburban areas of Indianapolis on a meso-scale unit by using Landsat Thematic Mapper images, and Weng(2003) studied the pattern of LST targeting Guangzhou, China, and analyzed the relationship between LST and land cover. Also, Li et al.(2009) identified that the expansion of industrial areas and the Manhattanization of commercial buildings are the main causes of increasing LST; they did this by analyzing the change pattern of LST according to changes in land use using Landsat TM images of two periods targeting Shanghai. In addition, studies applying LST are under way in various fields of study such as the impact of terrain type on LST(Geiger et al., 2003; McCune, 2007; Hais and Kučera, 2009; Li et al., 2010), the impact of types and characteristics of land use and land cover on LST(Voogt and Oke, 2003; Weng et al., 2004; Xian and Crane, 2006; Amiri, 2009; Zhou et al., 2011), the impact of vegetation status such as NDVI(Normalized Difference Vegetation Index) on LST(Gallo and Owen, 1999; Weng et al., 2004; Wang et al., 2006; Yuan and Bauer, 2007; Raynolds et al., 2008), among other areas.

On the other hand, in general to analyze the relationship between LST and other impact factors, linear regression analysis is used a lot. Linear regression analysis has the advantages that it can realize a model within a relatively short time through simple statistical processing and can be easily applied through various statistical packages(Lin et al., 1986; Moore, 2008). However, it has limitations in that the accuracy of the model is low in the prediction of the complex relationship and important variables tend to be excluded depending on the level of significance and various applications of the model is difficult(Deshpande and Subbarayan, 2000; Kagie and Van Wezel, 2007). The predictive model technique recently highlighted is an artificial neural network(ANN) designed to perform the same function as the human brain structure. ANN is used to find the optimal mathematical algorithm model through numerous repetitive learning processes(Haykin, 1999)[1]. For example, ANN has proved to have higher prediction accuracy than linear regression analysis, logit model, ARIMA model, and others in many previous studies(Ottenbacher et al., 2001; Xu et al., 2005; Wang and Elhag, 2007; Yilmaz, 2009).

In comparing with previous studies, this study has some different characteristics. The high-resolution spatial data with land use and land cover were used, the highly precise LST was predicted by comparing ANN model and linear regression model, and the change in the LST depending on changes of spatial characteristics was quantitatively predicted by the scenario analysis.

## Ⅲ. Materials and methods

### 1. Study area

This study was set in Changwon[2], South Gyeongsang Province, which is South Korea's first planned city. Changwon is located in the Southeastern part of the Korea peninsula; the city is surrounded by the Naknam Mountains starting from Mt. Jiri and has excellent natural resources because the south-west side faces the southern sea(Figure 1). The area of Changwon, the target site, is approximately 292.7㎢ and is divided into 15 administrative district; approximately 502,727 people live there. Regarding the city's climate, it shows the characteristics of an oceanic climate that has four seasons and is heavily influenced by the monsoon. The annual average temperature is about 15℃, and the annual average precipitation is about 1,395 mm.

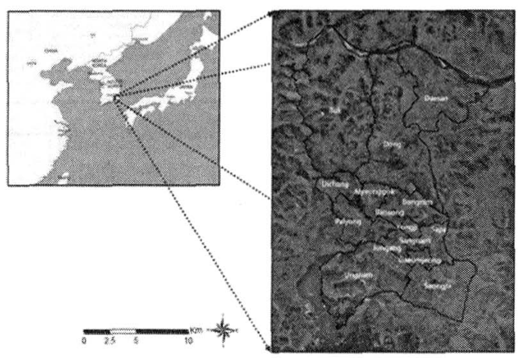

Figure 1. The location of study area

On the other hand, for Changwon, a planned city, the characteristics of land use are clearly classified. In this way, Changwon emphasized efficient use of land by planning land use separately by space but since spatial characteristics have a negative impact on the urban environment and are concentrated, many environmental problems such as the heat island phenomenon, regional disproportion of green area, etc. are occurring. Hence, Changwon was selected as study area in order to explode the change of LST within a planned city.

## 2. Research design

The research process was largely divided as shown in Figure 2. In the first step, basic data required for analysis were collected and built. LST, NDBI(Normalized Difference Built-up Index), and NDVI data were extracted from satellite images, and building area, impervious area, and vegetation area were generated from the land cover map and eight details such as residential area, commercial area, industrial area, etc. were generated from the land use map. The raw data for land use and LST were based on the data of previous study(Lee et al., 2011). Since LST is measured based on thermal infrared emitted from the earth's surface, LST data corrected through the process of correction and temperature extraction were built.

In the second step, to product GIS-based thematic maps with the thermal environment and built spatial data, the space unit was set at 500m×500m of the vector grid. This was done because the minimum space range at which spatial characteristics of one point affect LST can be seen at 500 m and this was determined as the size at which characteristics of land use can be classified clearly(Ng et al., 2006; Yoon & An, 2009). Total vector grid of the target site is 1301 and thematic maps by each spatial

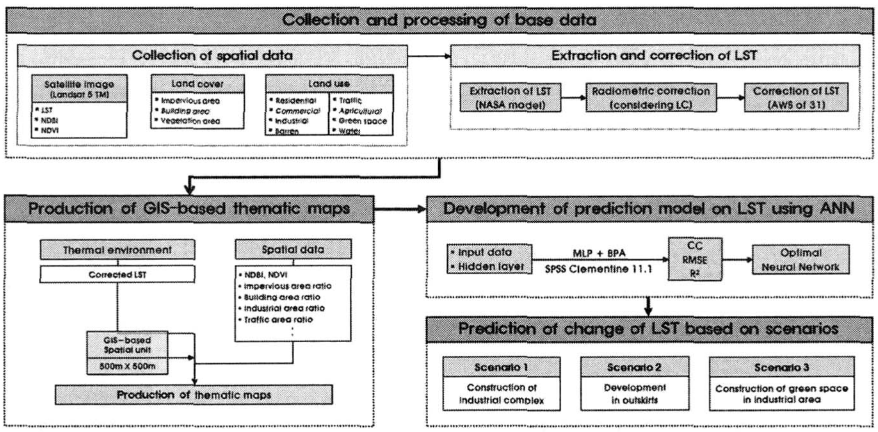


Figure 2. The process of this study

characteristic were made based on this.

In the third step, the optimal LST predictive model was developed using ANN. Since prediction accuracy can be changed significantly in the predictive model according to input data, input data were classified into video data, land cover data, land use data, and the predictive model was created by changing a hidden layer of neural network structures into 1~3.

Among various models exist in ANN[3], this study used the Back Propagation Algorithm(BPA) of MLP in SPSS Clementine 11.1 as an analysis tool. Also, Multiple Linear Regression(MLR) was carried out to compare it with the existing traditional predictive technique. On the other hand, accuracy analysis of a model is the basis on which to judge the similarity based on the degree of observed value and predictive value. This study used RMSE and coefficient of determination($R^2$) of predictive value. After comparing the accuracy of the model estimated in this way, the optimal neural network to predict LST was selected.

In the last step, after setting 3 scenarios by considering the direction of urban planning of Changwon, the change in the thermal environment of a city according to scenarios was predicted. Prediction of LST progressed by setting the occupation ratio of changed land use as input data and applying it to an optimal neural network model that showed the highest prediction accuracy; then the result was derived.

## 3. Data collection and image pre-processing

For satellite images, Landsat 5 TM images(Path 114/Row 36), which were taken on May 13, 2007, were used. As the pre-treatment process of images, geometric correction and orthorectification were conducted by using PG-STEAMER 4.1 and then LST was extracted after going through temperature correction from the thermal infrared band[4]. Also, NDBI and NDVI were calculated from the 3, 4, and 5 bands.

On the other hand, the land cover map and land use map were based on KOMPSAT-Ⅱ, high-resolution(1m) satellite images taken in December 2007 and May 2008, and high-resolution(10cm) digital color aerial photographs of Changwon taken in 2007, and they were made into a highly precise map of 1:1,000 scale through the application of several field surveys and verification processes. Building area, impervious area, and vegetation area data were extracted from the high-resolution land cover map, and 8 detailed land use types such as residential area, industrial area, green space, etc. were extracted from the land use map.

## 4. Extraction and correction of LST

There are various techniques to extract temperature from the Landsat TM thermal infrared band but this study used NASA(National Aeronautics and Space

Administration) model extraction by converting figures of unique digital numbers images. Since correction according to radiation characteristics of the target site was not done on LST extracted in this manner, radiation correction was done by applying unique emissivity by land cover characteristics based on the law of Stefan-Boltzmann(Wang et al., 2005)[5].

Though radiation correction was conducted, LST was significantly different from the actual temperature of urban space, that is, observed temperature. Since temperature extraction using satellite image data, though radiation correction was conducted, is based on thermal infrared coming from the surface of the earth, it is significantly different from the actual temperature of urban space, which is observed temperature(Park and Jung, 1999). Therefore, correction was carried out by analyzing the relative temperature as measured with an automatic weather system(AWS) and calculated LST. First, since the range of land use affecting meteorological observation points is generally determined at about a 500m~1,000m radius(Kwon, 2006; Yoon and An, 2009), this study set the range of influence of points at 500m. To analyze this, average LST reflecting the influence range was calculated by using neighborhood statistics of ArcGIS 9.3.

Next, to compare LST and observed temperature, 31 AWS points included in one section of Landsat 5 TM images were extracted[6]. Finally, as a result of regression analysis on AWS observed temperature and LST of images, the coefficient of determination of regression equation was shown to be 0.513(correlation coefficient : 0.716), and a constant and LST were significant within 1% significance level. By applying the equation derived through the above analysis, LST values extracted from images were corrected into observed temperature.

## 5. Design of ANN model

To explore the optimal predictive model by applying ANN, cases were classified into 3 according to the form of input data. Case 1 set NDBI and NDVI extracted from satellite images as input variables, Case 2 set building area, impervious area, and vegetation area extracted from land cover map as input variables, and Case 3 determined 8 detailed land use types extracted from the land use map as input variables. Also, a total of 9 types of cases were set by subdividing each case into 3 types according to the number of hidden layers. Node numbers composing a hidden layer were set to be changed from 1 to 5n, equivalent to 5 times the input variables, and corrected LST was input as variables of the output layer.

On the other hand, to compare the neural network model by type, random seed was fixed in the same condition and the initial constant(Eta) was input as 0.9 and alpha was set as 0.3. Also, in the case of the activation function, it was set as the sigmoid function. In the learning step, 651(corresponding to 50% of 1301 spatial units) was used, and in the inspection step, 650, the remaining 50%, was used. Also, in the inspection step, to compare the traditional prediction method and ANN result, MLR analysis was conducted.

## 6. Setting of Scenario

Scenario 1 assumed that the industrial complex was expanded into an area adjacent to a city(Table 1; Figure 3). This area is where industrial complex development was started in 2010; its size is 11ha and completion is set at 2013. The land use map to be changed was made based on industrial complex planning drawing provided by Changwon, and temperature was predicted based on it.

Table 1. The setting of 3 scenario types

| Scenario type | Purpose of plan (Location) | Area (ha) |
|---|---|---|
| 1 | Construction of industrial complex (Cheonsun-dong 467) | 11 |
| 2 | New town development (Buk-myeon Gamgye-ri) | 108 |
| 3 | Development of green space (Seongsan-dong 76) | 35 |

Scenario 2 was established that urban development was progressed to the outskirts

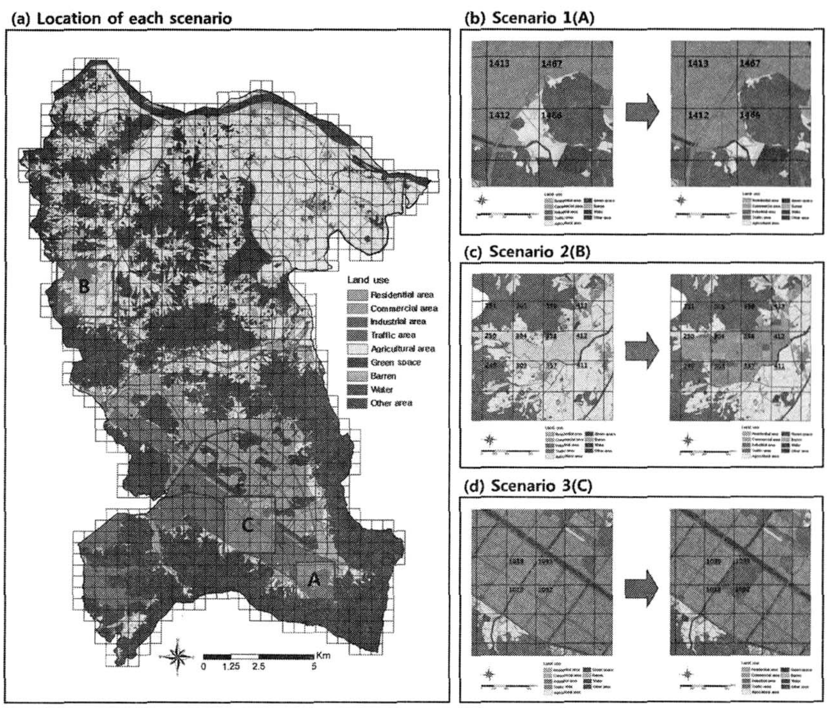


Figure 3. The applying area and change of land use by each scenario

of a city. The main purpose of this area is to develop residential complexes and its area is about 108ha; development was started in 2008 and will be completed in 2012. The land use map was built based on the urban development plan provided for Changwon, and variation was calculated by comparison with current land use.

Scenario 3 was set that some space in the industrial area was converted into green space. Although development is not scheduled for this area, it is where prediction was conducted on a pilot basis to reduce a high LST for an industrial complex; the total area is approximately 35ha.

## IV. Results

### 1. Status of thermal environment and spatial characteristics

To perform analysis by a spatial unit of 500m×500m vector grid targeting Changwon,

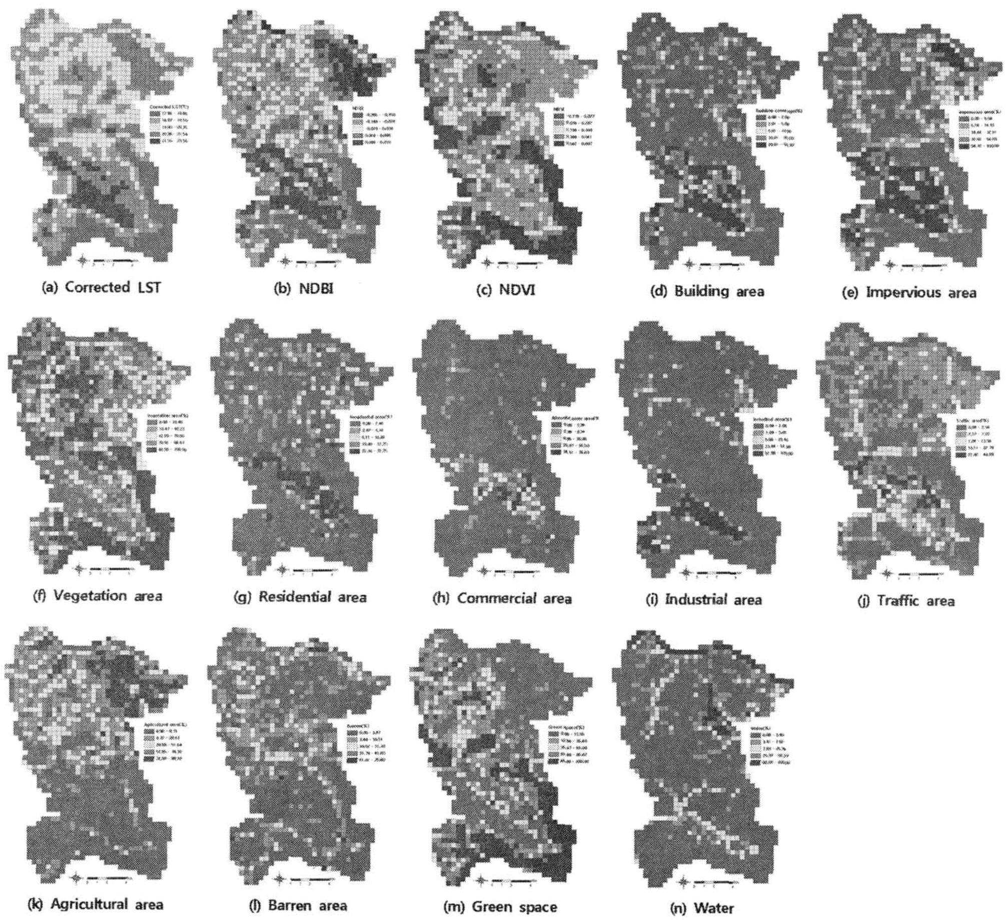


Figure 4. The base map for spatial analysis

14 basic theme maps such as LST and others were produced from Landsat 5 TM images, land cover, and the land use map(Figure 4). In examining the LST distribution map, the average temperature at 10:00 A.M. on May 13, 2007, in Changwon was shown in 19.93℃. The area that showed the highest LST was the Ungnam region in the central city, and it was analyzed as about 23.94℃; conversely, a low temperature distribution of about 17.8℃ was shown in southeastern Mt. Beolmo(Figure 3a). Examining characteristics by area, a significant temperature difference between the outskirts area and the central city can be checked, and the slight difference between east and west of the northern area can be observed. In particular, the temperature appeared high along the southwestern industrial area in the southern portion of the central city and the northeastern residential area showed a relatively low distribution. Also, the northeastern area where farmland facilities such as greenhouses are located showed a higher temperature distribution than surrounding areas.

Looking at the distribution pattern of spatial characteristics, NDBI, an impervious area showed the form similar to distribution of LST; in particular, NDBI was analyzed to show a high value in the large northeastern area and central city. Also, the temperature of the building area appeared high, centering on the urban area located in the south. On the other hand, unlike the above factors, NDVI and vegetation area showed a low value in the urban central part and a high value was distributed along forests on the outskirts. In the case of land use, the temperatures of the residential area, commercial area, industrial area, and traffic area appeared high along the urban central part but showed different distribution patterns. This is because Changwon was deliberately planned to place the same type of land use intensively to increase the spatial efficiency of land. On the other hand, green space showed a high proportion in the northwestern area and on the outskirts of a city, and the agricultural area showed a high proportion in the northern area. Also, barren areas were scattered across the city, and there was a high proportion of water in Junam Reservoir and Nakdong River, the large river in the north, and a relatively high proportion along Changwon River and Nam River in the urban center.

## 2. Development of the prediction model

ANN was driven by using input data, initial specifying function, parameters, etc., and the optimal model according to each case was derived as Table 2 through numerous repetitive processes within a model. The node number of the hidden layer was set automatically by selecting the model with the best accuracy according to the

Table 2. The node structure and prediction accuracy of optimized ANN by case

| Case type | | Hidden layer | | | Learning data | | Verification data | | Driving time |
|---|---|---|---|---|---|---|---|---|---|
| | | H1 | H2 | H3 | RMSE | $R^2$ | RMSE | $R^2$ | |
| Case 1 | Case 1-1 | 5 | - | - | 0.514 | 0.761 | 0.569 | 0.712 | 1s |
| | Case 1-2 | 5 | 2 | - | 0.500 | 0.773 | 0.570 | 0.712 | 28s |
| | Case 1-3 | 9 | 8 | 2 | 0.500 | 0.774 | 0.564 | 0.717 | 3m 7s |
| | MLR | - | | | 0.507 | 0.767 | 0.568 | 0.714 | - |
| Case 2 | Case 2-1 | 10 | - | - | 0.469 | 0.801 | 0.484 | 0.792 | 10s |
| | Case 2-2 | 9 | 9 | - | 0.473 | 0.798 | 0.492 | 0.785 | 2m 7s |
| | Case 2-3 | 11 | 11 | 7 | 0.463 | 0.806 | 0.477 | 0.798 | 17m 48s |
| | MLR | - | | | 0.552 | 0.724 | 0.544 | 0.738 | - |
| Case 3 | Case 3-1 | 11 | - | - | 0.466 | 0.803 | 0.464 | 0.809 | 11s |
| | Case 3-2 | 34 | 7 | - | 0.454 | 0.813 | 0.458 | 0.814 | 10m 51s |
| | Case 3-3 | 39 | 39 | 4 | 0.454 | 0.813 | 0.455 | 0.816 | 6hr 1m 27s |
| | MLR | - | | | 0.460 | 0.809 | 0.458 | 0.813 | - |

condition of case. For Case 1, the model with the node structure of 5, 5-2, 9-8-2, respectively, as hidden layer increases was analyzed to be optimal. For Case 2, the structure of 10, 9-9, 11-11-7 was derived as the optimal model, and for Case 3, the structure of 11, 34-7, 39-39-4 was derived as the optimal model according to the change in hidden layer.

Next, to select the optimal model, accuracy was calculated as shown in Table 2 by using RMSE and R2. For Case 1, RMSE appeared low, 0.564, in Case 1-3 where there are 3 hidden layers, and R2 was also analyzed as the highest in Case 1-3. Also, for Case 2, the same as for Case 1, RMSE and R2 of Case 2-3 were assessed to have a high accuracy, 0.477 and 0.798, respectively. Also, for Case 3, Case 3-3 with 3 hidden layers was analyzed as the model with the highest accuracy. Examining differences according to case, the result of Case 3 using land use data was shown to have higher accuracy than other cases. Of course, since the number of input data differs, comparison of accurate results may be difficult. However, since it was reported that if the number of input data is more than 2, the impact on accuracy of a model is not that great(Zhang et al.. 2001; Kim, 2008), it can be determined that land use data can be more accurate to predict LST compared to other input data. On the other hand, as a result of comparing the results of neural network and MLR results, the traditional method, the prediction result of MLR was also shown to be high and, therefore, there are cases having higher predictive power according to the node number of the hidden layer, but as a whole, in all cases, prediction accuracy was assessed lower than for the optimal neural network model. These findings have already been proved in several studies(especially Ottenbacher et al., 2001; Xu et al., 2005; Yilmaz, 2009), in the study of Xie et al.(2009), as a result of comparing prediction accuracy of LST of ANN and MLR, it was found that ANN has a remarkably higher accuracy. According to the time taken to realize a model, the time of Case 1-1 was the shortest, 1 second; Case 3-3 was the longest at 6 hours 1 minute 27 seconds. Case 3-3 was analyzed to have the highest prediction accuracy, but actually, the difference between Case 3-2 and $R^2$ is just 0.002. Therefore, in considering temporal efficiency of a model, Case 3-2 can be said to be the more efficient model compared to Case 3-3.

Since the purpose of this study is to predict LST accurately, Case 3-3, which showed the highest accuracy, was selected as the optimal neural network model. RMSE of the predicted results for Case 3-3 is 0.455 and $R^2$ is 0.816.

In examining relatively important analysis results between input variables through sensitivity analysis of the optimal neural network model, traffic area(0.282) and industrial area(0.275) were shown to be the variables with the greatest impact on LST(Figure 5). Since the importance of the two variables was analyzed as two times higher than that of other variables, it can be determined that the impact on LST is high. Actually, the study of Amiti et al.(2009) showed that traffic area and industrial area increased LST; in particular, LST was analyzed as the highest in the areas such as road area.

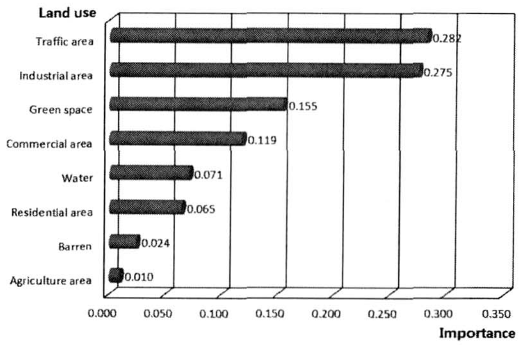


Figure 5. The importance[7] of each variable

## 3. Prediction of change of LST using scenario analysis

### 1) Scenario 1

Scenario 1 represents area A adjacent to the city and predicted a change in LST in that new industrial complexes are expanded or developed near the existing industrial area(Figure 5b). As the change pattern of land use, agricultural area, residential area,

Table 3. The change of land use and LST at scenario 1

| ID | Change of land use(%) | | | | | | | Change of LST(℃) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Residential area | Industrial area | Traffic area | Agricultural area | Green space | Barren | Water | Before | After | Difference |
| 1412 | -1.18 | 29.78 | 1.05 | -18.73 | -4.63 | -4.29 | -2.02 | 20.23 | 21.84 | 1.61 |
| 1413 | -2.95 | 5.94 | 0.75 | -0.34 | 0.00 | -3.30 | -0.10 | 21.12 | 22.15 | 1.03 |
| 1466 | -0.66 | 7.17 | -0.19 | -5.08 | -0.39 | -0.91 | 0.05 | 19.31 | 19.46 | 0.15 |
| 1467 | -2.10 | 2.67 | 0.83 | -0.66 | -0.48 | -0.26 | 0.00 | 20.7 | 20.44 | -0.26 |

green space, etc. decreased and industrial and traffic areas increased in most areas(Table 3). Especially in the case of area ID1412, while agricultural area decreased by 18.73%, industrial area increased by 28.78%, and therefore this area was shown to be the biggest area of change in land use.

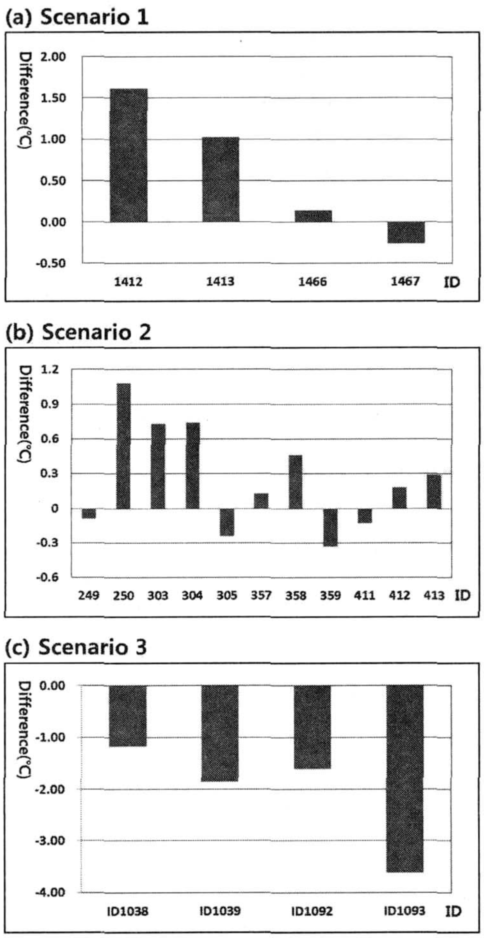


Figure 6. The change of LST by each scenario

In the predictions of LST according to scenario 1, it was analyzed that LST of area ID1412, where there were many changes from agricultural to industrial area, would rise by 1.61℃, and in area ID1413, it was predicted that LST would rise by 1.03℃ due to an increase in the industrial area(Table 3; Figure 6a).

On the other hand, in the case of area ID1467, changes to the industrial area were not much, but LST was shown to decrease by 0.26℃, and this is the result of errors in the model and is occurs because existing green space is greater than in other areas.

### 2) Scenario 2

Scenario 2 is area B, which is located on the outskirts of the city, and the predicted change of LST in case that land use pattern is changed by new urban development(Figure 4c). According to the change pattern of land use, it was shown that residential area increased by 50% in areas ID250, ID304, and ID358 but that agricultural area, green space, barren area, etc. were shown to decrease(Table 4). For areas ID303, ID357, and ID412, it was confirmed that other land use was decreasing due to an increase in the residential area. On the other hand, in the case of area ID303, since LST for the industrial area and the traffic area appeared large and were shown to increase by 28.41% and 5.65%, respectively, the rise of LST after urban development can be expected.

Examining the prediction results of LST through Table 4 and Figure 6b, LST of

Table 4. The change of land use and LST at scenario 2

| ID | Change of land use(%) | | | | | | | | Change of LST(℃) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Residential area | Commercial area | Industrial area | Traffic area | Agricultural area | Green space | Barren | Water | Before | After | Difference |
| 249 | 0.00 | 0.00 | 0.63 | 2.76 | -2.36 | 0.15 | -0.50 | 0.00 | 19.7 | 19.61 | -0.09 |
| 250 | 56.35 | 6.18 | 0.00 | 7.41 | -30.87 | -13.89 | -24.03 | -1.16 | 19.68 | 20.76 | 1.08 |
| 303 | 12.44 | 0.00 | 28.41 | 5.65 | -44.53 | 12.06 | -11.79 | -1.99 | 20.38 | 21.11 | 0.73 |
| 304 | 59.73 | 13.87 | 0.00 | 9.04 | -26.28 | 5.42 | -60.06 | -1.73 | 20.22 | 20.97 | 0.74 |
| 305 | 4.72 | 0.00 | 0.00 | -0.10 | -1.49 | -2.58 | -0.55 | 0.00 | 19.32 | 19.07 | -0.24 |
| 357 | 23.61 | 2.31 | -0.61 | 7.07 | -14.18 | 0.90 | -17.64 | -1.37 | 20.53 | 20.66 | 0.13 |
| 358 | 69.12 | 10.12 | 0.00 | 7.80 | -15.90 | 1.67 | -71.57 | -1.24 | 20.51 | 20.97 | 0.46 |
| 359 | 8.41 | -0.68 | -0.58 | 1.64 | -5.41 | -3.00 | -0.22 | -0.17 | 19.81 | 19.48 | -0.33 |
| 411 | 1.08 | 0.00 | 0.00 | 6.36 | -5.61 | -0.12 | -1.71 | 0.00 | 20.44 | 20.31 | -0.13 |
| 412 | 35.01 | 0.99 | 0.00 | 5.75 | -7.78 | 0.46 | -33.64 | -0.78 | 20.55 | 20.73 | 0.18 |
| 413 | 6.80 | 9.43 | -1.88 | 2.92 | -17.03 | 6.16 | -2.80 | -3.59 | 20.34 | 20.62 | 0.29 |

ID250 area was predicted to show the greatest change by rising by 1.08℃. This was because land use having a correlation with the amount of LST such as residential area, traffic area, and commercial area, etc. increased about 70% in this area; and green space, barren area, and agricultural area, etc. decreased. Next, it was determined that LST of areas ID303 and ID304 will rise by 0.73℃ and 0.74℃, respectively. Area ID303 was expected to raise LST due to industrial area development and area ID250 was similarly predicted with area ID250. On the other hand, though the small size of the residential area increased, LST was predicted to decrease in areas ID305 and ID359. LST was predicted to be low because these areas hold a relatively large amount of green space compared to other areas: 65% of green space.

### 3) Scenario 3

Scenario 3 is area C, which is located in the industrial complex area of the city, with change of LST when part of the industrial complex is removed and green space is created(Figure 5d). According to the change pattern of land use of Scenario 3, the industrial area was decreased in all of 4 areas and green space was increased as much as the industrial area decreased(Table 5). Especially in area ID1093, the percentage of green space converted from industrial area appeared the highest, 69.17%.

Table 5. The change of land use and LST at scenario 3

| ID | Change of land use(%) | | Change of LST(℃) | | |
|---|---|---|---|---|---|
| | Industrial area | Green space | Before | After | Difference |
| 1038 | -9.37 | 9.37 | 23.08 | 21.91 | -1.17 |
| 1039 | -16.28 | 16.28 | 23.56 | 21.70 | -1.86 |
| 1092 | -19.56 | 19.56 | 23.52 | 21.92 | -1.60 |
| 1093 | -69.17 | 69.17 | 23.43 | 19.82 | -3.61 |

Looking at the reduction effect of LST in the industrial area followed by the creation of green space, it was predicted that approximately 3.61℃ was reduced in area ID1093 where the percentage of conversion to green space was high, and it was also analyzed that there was more than 1℃ of reduction effect in area 3(Table 5; Figure 6c). On the other hand, it was found that although the area converted into a green space in area ID1038 was less than that in area ID1092, 0.3℃ of LST was a greater reduction. This is because the percentage of traffic area, which was shown to have the greatest impact on LST, is 4.71%, relatively lower than 14.74% of area ID1092.

As above, it could be judged that the green space in the city relieves the heat island phenomenon by reducing ambient temperature and is an essential requirement for a pleasant urban environment(Spronken-Smith and Oke, 1998; Maco and McPherson, 2003; US EPA, 2007). Also, it is judged that it will be necessary to remove artificial areas such as buildings and roads and to convert them into pervious areas such as green space and water.

## V. Discussion and conclusions

This study develope the prediction models of LST based on high-resolution land cover and land use map targeting Changwon, South Korea, and predicted changes of LST according to the scenarios of urban development. The results and discussion from the analysis can be summarized as follows.

As a result of exploring the prediction models of LST through a neural network, it was analyzed that using land use data(Case 3) shows higher accuracy than if using data extracted from image data(Case 1) or land cover data(Case 2). Of course, for land use data, the condition that there are many variables is different, but according to the previous studies, it was analyzed that the number of data input layers in a neural network did not have a significant impact on accuracy(Zhang et al.. 2001; Kim, 2008), and therefore, it can be judged that land use had a significant impact on the LST. Also, the optimal ANN was analyzed to have higher accuracy than MLR.

According to the result of Case 3-3 selected as the optimal neural network, the importance of the traffic area appeared the highest, 0.282, followed by industrial area and green space, 0.275 and 0.155, respectively. These findings appeared to be similar in previous studies(Weng et al., 2004, Amiti et al., 2009), but in the case of Changwon, the city was created by separate land use intentionally and, therefore, it was judged to show a more remarkable difference than was seen in other studies.

In the prediction result of LST, if a new industrial complex is created in the area adjacent to the existing industrial complex, it was shown that LST would rise due to the increase in artificial areas such as buildings and roads, etc. Also, if a large-scale housing complex is created on the outskirts of the city, it was analyzed that LST would rise according to the ratio of artificial surface occupied per unit space. On the other hand, if green space is created in the industrial area that showed high LST, it was analyzed that LST would decrease by showing a significant difference.

As above, this study built the optimal model to predict LST through various approaches and LST changes were predicted according to changes in land use. Especially, it could be judged that the green space reduces ambient temperature in the city. Thus, these findings form this study can be used a basic data to propose the green spaces of proper scale and proportion in the planning stage, when trying to create a new large-scale housing and industrial complex. Also, it can be utilized a guideline to develop a high accurate prediction model on LST.

However, it did not consider the impact of structure or layout pattern of spatial characteristics such as land use, etc., on LST. Also, it has the limitation that factors shown to greatly affect LST such as elevation, slope, air pollution, height of artifacts, and shade(Nichol and Wong, 2005; Qin et al., 2011; Geiger et al., 2003) were not considered. Thus, in the future, it is judged that accurate models should be developed by considering more diverse indicators and a specific direction should be taken for a reduction in LST. In the case of ANN, it has the advantage that it can be generally analyzed with high prediction accuracy but has the disadvantage that it is difficult to understand the fundamental relationships between indexes and identify the exact internal structure of the model. Therefore, in order to apply the neural network model correctly, it is judged that the analysis of relationship for each parameter should be preceded preferentially.

---

Note 1. ANN has the advantages of having a higher prediction accuracy; ANN does not exclude variables and can be applied to various studies(Ottenbacher et al., 2001; Kumar, 2005).

Note 2. Changwon was declared to be "Environmental Capital" in 2006.

Note 3. Various models exist in ANN such as Multi-Layer Perceptron(MLP), Radial Basis Function(RBF), Self-Organizing Feature Map(SOFM), and others(Haykin, 1999).

Note 4. The spatial resolution of thermal band in Landsat TM 5 is 120 meters.

Note 5. In the previous study, it was reported that radiation correction according to land cover characteristics can increase the accuracy of LST by removing errors caused by application of average emissivity of NASA model(Um, 2006).

Note 6. Since the image time of the target site of Landsat 5 TM is about 10:30 A.M., AWS observed temperatures at each location between 10 and 11 A.M. were collected and averaged(Sabins, 1997).

Note 7. The importance was computed by sensitivity analysis of ANN. Also, it means the effect standard, which each independent variables affect dependent variable(Hunter et al., 2000).

## References

1. Amiri, R., Weng, Q., Alimohammadi, A., and Alavipanah, S.K., 2009. "Spatial-temporal dynamics of land surface temperature in relation to fractional vegetation cover and land

use/cover in the Tabriz urban area, Iran", *Remote Sensing of Environment,* 113(12): 2606-2617.
2. Assefa, M.M., 2004. "Spatiotemporal dynamics of land surface parameters in the Red River of the North Basin", *Physics and Chemistry of the Earth,* 29: 795-810.
3. Carnahan, W.H., and Larson, R.C., 1990. "An analysis of an urban heat sink", *Remote Sensing of Environment,* 33: 65-71.
4. Deshpande, A.M., and Subbarayan, G., 2000. "A System for First Order Reliability Estimation of Solder Joints in Area Array Packages", *Journal of Electronic Packaging,* 122(1): 6-12.
5. Gallo, K.P., and Owen, T.W., 1999. "Satellite based adjustments for the urban heat island temperature bias", *Journal of Applied Meteorology,* 38: 806-813.
6. Geiger, R., Aron, R.H., and Todhunter, P. 2003. *The Climate Near the Ground,* (6th ed.) Lanham, MD: Rowman and Littlefield Publishers.
7. Hais M. and Kučera, T., 2009. "The influence of topography on the forest surface temperature retrieved from Landsat TM, ETM C and ASTER thermal channels", *ISPRS Journal of Photogrammetry and Remote Sensing,* 64: 585-591.
8. Haykin, S., 1999. *Neural Networks: A Comprehensive Foundation* (2nd ed.), New York: Macmillian College Publishing Company.
9. Hunter, A., Kennedy, L., Henry, J., and Ferguson, R.I., 2000. "Application of Neural Networks and Sensitivity Analysis to improved prediction of Trauma Survival", *Computer Methods and Algorithms in Biomedicine* 62: 11-19.
10. Jauregui, E., 1997. "Heat island development in Mexico city", *Atmospheric Environment,* 31(22): 3821-3831.
11. Kagie, M., and Van Wezel, M., 2007. "Hedonic price models and indices based on boosting applied to the Dutch housing market", *Intelligent Systems in Accounting, Finance and Management,* 15: 85-106.
12. Kim, Y.S., 2008. "Comparison of the decision tree, artificial neural network, and linear regression methods based on the number and types of independent variables and sample size", *Expert Systems with Applications,* 34: 1227-1234.
13. Kumar, U.A., 2005. "Comparison of neural networks and regression analysis: A new insight", *Expert Systems with Applications,* 29(2): 424-430.
14. Kwon, Y.A., 2006. "Analysis of urban thermal environment properties using Landsat ETM+ in Seoul", *The Korean Urban Geographical Society,* 9(1): 147-157.
15. Lee, S.K., Jung, S.G., Lee, W.S., and Park, K.H., 2011. "A predictive model for urban temperature using the Artificial Neural Network", *The Journal of Korea Planners Association,* 46(1):129-142.
16. Li, J., Wang, X., Wang, X., Ma, W., and Zhang, H., 2009. "Remote sensing evaluation of urban heat island and its spatial pattern of the Shanghai metropolitan area, China", *Ecological Complexity,* (6)4: 413-420.
17. Li, S., Zhao, Z., Miaomiao, X., and Wang, Y., 2010. "Investigating spatial non-stationary and scale-dependent relationships between urban surface temperature and environmental factors using geographically weighted regression", *Environmental Modelling & Software,* 25(12): 1789-1800.
18. Lin, B.S., Mackenzie, D.L., and Gulledge Jr., T.R., 1986. "Using ARIMA models to predict prison populations", *Journal of Quantitative Criminology,* 2(3): 251-264.
19. Maco S.E., and McPherson E.G., 2003. "A practical approach to assessing structure,

function and value of street tree populations in small communities", *Journal of Arboriculture,* 29(2):84-97.

20. McCune, B., 2007. "Improved estimates of incident radiation and heat load using non-parametric regression against topographic variables", *Journal of Vegetation Science,* 18(5): 751-754.
21. Moore, J.H., 2008. "Analysis of Gene-Gene Interactions", *Current Protocols in Human Genetics,* 59: 1.14.1-1.14.10.
22. Nichol, J., and Wong, M.S., 2005. "Modeling urban environmental quality in a tropical city", *Landscape and Urban Planning,* 73(1): 49-58.
23. Ottenbacher, K.J., Smith, P.M., Illig, S.B., Linn, R.T., Fiedler, R.C., and Granger, C.V., 2001. "Comparison of logistic regression and neural networks to predict rehospitalization in patients with stroke", *Journal of Clinical Epidemiology,* 54(11): 1159-1165.
24. Park, K.H., and Jung, S.G., 1999. "Analysis on Urban Heat island Effects for the Metropolitan Green Space Planning", *Journal of the Korean Association of Geographic Information Studies,* 2(3): 35-45.
25. Qin Q., Zhang N., Nan P., and Chai L., 2011. "Geothermal area detection using Landsat ETM+ thermal infrared data and its mechanistic analysis: a case study in Tengchong, China", *International Journal of Applied Earth Observation and Geoinformation,* 13(4):552-559.
26. Raynolds, M.K., Comiso, J.C., Walker, D.A., and Verbyla, D., 2008. "Relationship between satellite-derived land surface temperatures, arctic vegetation types, and NDVI", *Remote Sensing of Environment,* 112: 1884-1894.
27. Sabins, F.F., 1997. *Remote Sensing: Principles and Interpretation* (3rd ed.), New York: W.H. Freeman and Company. 69pp.
28. Singh, R.B., 1995. *Global Environmental Change: Perspectives of Remote Sensing and Geographic Information System,* Rotterdam: Balkema Publishers. 321pp.
29. Small, C., 2006. "Comparative analysis of urban reflectance and surface temperature", *Remote Sensing of Environment,* 104: 168-189.
30. Spronken-Smith R.A., and Oke T.R., 1998. "The thermal regime of urban parks in two cities with different summer climates", *International Journal of Remote Sensing,* 19(11): 2085-2104.
31. Streutker, D.R., 2003. "Satellite-measured growth of the urban heat island of Houston, Texas", *Remote Sensing of Environment,* 85(3): 282-289.
32. Um, D.Y., 2006. "A study on the accuracy improvement of land surface temperature extraction by remote sensing data", *Journal of the Korean Association of Geographic Information Studies* 9(2): 159-171.
33. US EPA, 2007. Heat island effect. Available URL: http://www.epa.gov/heatislands/index.html (accessed 5 June, 2012).
34. Voogt, J.A., and Oke, T.R., 2003. "Thermal remote sensing of urban climates", *Remote Sensing of Environment,* 86: 370-384.
35. Wang K., Li Z., and Cribb M., 2006. "Estimation of evaporative fraction from a combination of day and night land surface temperatures and NDVI: a new method to determine the Priestley-Taylor parameter", *Remote Sensing of Environment,* 102: 293-305.
36. Wang, K., Wan, Z., Wang, P., Sparrow, M., Liu, J., Zhou, X., and Haginoya, S., 2005. "Estimation of surface long wave radiation and broadband emissivity using Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature/ emissivity products", *Journal of Geophysical Research,*

110: D11109, 1-12.

37. Wang, Y.M., and Elhag, T.M.S., 2007. "A comparison of neural network, evidential reasoning and multiple regression analysis in modelling bridge risks", *Expert Systems with Applications*, 32(2): 336-348.
38. Weng, Q., 2003. "Fractal analysis of satellite-detected urban heat island effect", *Photogrammetric Engineering and Remote Sensing*, 69: 555-566.
39. Weng, Q., Lu, D., and Schubring, J., 2004. "Estimation of land surface temperature -vegetation abundance relationship for urban heat island studies", *Remote Sensing of Environment*, 89(4): 467-483.
40. Xian, G., and Crane, M., 2006. "An analysis of urban thermal characteristics and associated land cover in Tampa Bay and Las Vegas using Landsat satellite data", *Remote Sensing of Environment*, 104(2): 147-156.
41. Xie, Y., Sha, Z., Yu, M., Bai, Y., and Zhang, L., 2009. "A comparison of two models with Landsat data for estimating above ground grassland biomass in Inner Mongolia, China", *Ecological Modelling*, 220: 1810-1818.
42. Xu, L., Chow, M.Y., and Gao, X.Z., 2005. "Comparisons of logistic regression and artificial neural network on power distribution systems fault cause identification", *Proceedings from IEEE Mid-Summer Workshop on Soft Computing in Industrial Applications*, Espoo, Finland, 28-30 June, pp. 128-31.
43. Yilmaz, I., 2009. "Landslide susceptibility mapping using frequency ratio, logistic regression, artificial neural networks and their comparison: A case study from Kat landslides (Tokat-Turkey)", *Computers & Geosciences*, 35(6): 1125-1138.
44. Yoon, M.H., and An, D.M., 2009. "An application of satellite image analysis to visualize the effects of urban green areas on temperature", *Journal of the Korean Institute of Landscape Architecture*, 37(3): 46-53.
45. Yuan, F., and Bauer, M.E., 2007. "Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery", *Remote Sensing of Environment*, 106: 375-386.
46. Zhang, G.P., Patuwo, B.E., and Hu, M.Y., 2001. "A simulation study of artificial neural networks for nonlinear time-series forecasting", *Computers & Operations Research*, 28: 381-396.
47. Zhou, W., Huang, G., and Cadenasso, M.L., 2011. "Does spatial configuration matter? Understanding the effects of land cover pattern on land surface temperature in urban landscapes", *Landscape and Urban Planning*, 102(1): 54-63.

논 문 투 고 2013-09-30
심 사 완 료 2013-12-10
수 정 일 2014-01-09
게 재 확 정 일 2013-12-10
최 종 본 접 수 2014-01-14