IMPERVIOUS SURFACE ESTIMATION USING REMOTE SENSING IMAGES AND TREE REGRESSIOIN

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ABSTRACT Impervious surface is an important index for the estimation of urbanization and environmental change. In addition, impervious surface has an influence on the parameters of rainfall-runoff model during rainy season. The increase of impervious surface causes peak discharge increasing and fast concentration time in urban area. Accordingly, impervious surface estimation is an important factor of urban rainfall-runoff model development and calibration. In this study, impervious surface estimation is performed by using remote sensing images such as landsat-7 ETM+ and high resolution satellite image and regression tree algorithm based on case study area – Jungnang-cheon basin in Korea.

KEY WORDS: Impervious surface estimation, Remote sensing images, Regression tree algorithm

1. INTRODUCTION

1.1 General Descriptions

Generally, impervious surfaces are any man-made construction that doesn't allow natural infiltration of water, such as buildings, residential areas, industrial areas, roads and parking lots made from asphalt, concrete or bricks(Vikhamar et al., 2005). Impervious surface is an important index for the estimation of urbanization and environmental change. In addition, impervious surfaces have an influence on the short-term rainfall-runoff process during rainy season. The increase of impervious surface causes hydrological change like peak discharge increasing and faster concentration time in urban area. Therefore, the estimation of impervious surface is an important factor of urban rainfall-runoff model and the parameters calibration of one.

The main objective of this study is the estimation of impervious surface using remote sensing images such as landsat-7 ETM+ and high resolution satellite image, and regression tree algorithm based on case study area(Jungnang-cheon) in South Korea.

Many researches for the impervious surfaces estimation using remote sensing images such as Landsat Thermatic Mapper(TM), high resolution satellite images(e.g. IKONOS, DOQQ), and high resolution aerial photograph are continued for a long time. These researches have some methodology for the impervious surfaces estimation. Herold et al.(2003) have performed the estimation of percent impervious surface and canopy cover using classification and regression tree(CART) technology for landsat-7 Enhanced Thermatic Mapper plus(ETM+). Yang et al.(2003) and Vikhamar and Kastdalen(2005) have applied regression tree algorithm to landsat-7 ETM+ and high resolution satellite images or aerial photographs.

2. APPLICATION DATA

2.1 Case study area

In this study, case study area is Jungnang-cheon basin in South Korea. Jungnang-cheon is first tributary to Han-river including Seoul and Uijeongbu. In addition Jungnang-cheon basin with 299.60 ㎢ area, 37.17 ㎞ channel length and 8.06 ㎞ mean width of basin is typical urban stream basin and shown as figure 1.

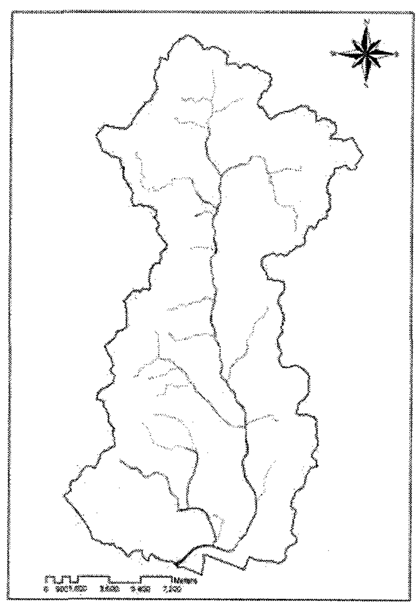

Figure 1. Jungnang-cheon basin

2.2 Data sets

Authors collect remote sensing images such as landsat-7 ETM+ and high resolution satellite image for the impervious surface estimation of Jungnang-cheon basin.

Data quality of landsat-7 ETM+ is superior to its predecessors with significant improvement of on-flight radiometric and geometric calibration including a 15m resolution panchromatic band and an improved 60m spatial resolution thermal infrared band(Yang et al., 2003) and landsat-7 ETM including Jungnang-cheon basin is shown as figure 2. Landsat-7 ETM+ of this research has 30m×30m spatial resolution in UTM coordinate system with WGS84 ellipsoid at September 23, 2001. High resolution satellite image of this research has 1m×1m spatial resolution in TM coordinate system with Bassel ellipsoid. High resolution satellite image is shown as figure 3 having geometric calibration, radiometric calibration and terrain correction at from February to June 2002.

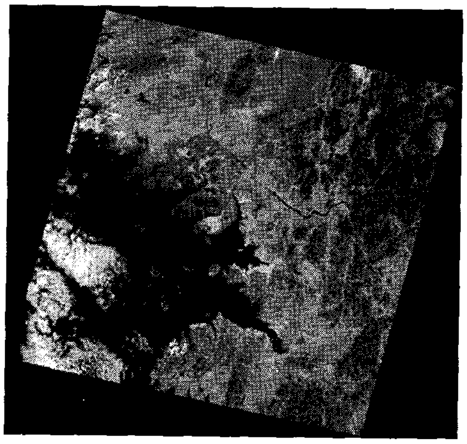

Figure 2. Landsat-7 ETM+

Figure 3. High resolution satellite image

2.3 Image processing

A coordinate transformation which converts TM coordinate system to UTM coordinate system is performed for high resolution satellite image in order to remove the error of matching remote sensing images. Authors select a tasselled cap transformation image and Normalized Difference Vegetation Index(NDVI) as various input data. A tasselled cap transformation of landsat-7 ETM+ is performed by tasselled cap coefficients based satellite reflectance(Huang et al., 2002) shown as table 1. NDVI transformation is performed by equation (1) for landsat-7 ETM+.

$$NDVI = \frac{NearIR - Red}{NearIR + Red} \tag{1}$$

where $NearIR$ = the 4th band of landsat-7 ETM+
Red = the 3rd band of landsat-7 ETM+

Table 1. Tasselled cap coefficients(Huang et al., 2002)

Index	B1	B2	B3	B4	B5	B7
Brightness	0.3561	0.3972	0.3904	0.6966	0.2286	0.1596
Greeness	-0.3344	-0.3544	-0.4556	0.6966	-0.0242	-0.2630
Wetness	0.2626	0.2141	0.0926	0.0656	-0.7629	-0.5388

3. REGRESSION TREE ALGORITHM

The regression tree algorithm is a binary recursive partitioning process and a ruled-based model for the prediction of continuous variables based on training data. The process spilts each parent node into two child nodes and the process is repeated, treating each child node as a potential parent node(Breiman et al., 1984). The basic concept of regression tree algorithm is shown as figure 4. Each rule set defines the conditions under a multivariate linear regression. The regression tree algorithm estimates the nonlinear relationship between predictor and independent variables for all continuous and discrete input data sets. The tree regression algorithm apply to many research of remote sensing analysis and image processing(Huang et al., 2001 ; Huang and Townshend, 2003). Authors can use a commercial software called Cubist(http://rulequest.com/cubist-info.html).

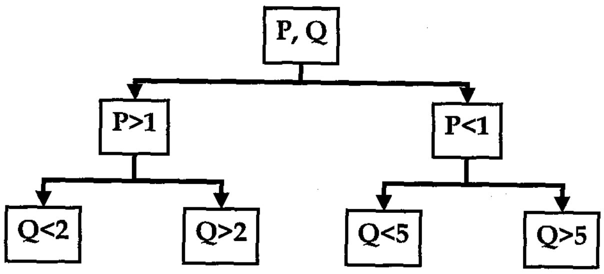

Figure 4. The concept of regression tree algorithm

4. IMPERVIOU SURFACE ESTIMATION

4.1 Training - test data collection

Impervious surface is estimated by collecting training – test data, applying regression tree algorithm to training – test data, and modelling prediction of spatial information. The procedure of impervious surface estimation is shown as figure 5. The results of modelling using tree regression algorithm rely on the quality of training - test data. It is necessary to collect a large number of training – test data for impervious surface estimation. In this study, training – test data sets are collected by overlaying between landsat-7 ETM+ and high resolution satellite image with different spatial resolution. For example, Authors can overlay about 900 pixels of 1m resolution satellite image on 1 pixel of 30m resolution landsat-7 ETM+. Then, impervious surface is calculated by the 1m pixel percent(%) of high resolution satellite image within 1 pixel of 30m resolution landsat-7 ETM+.

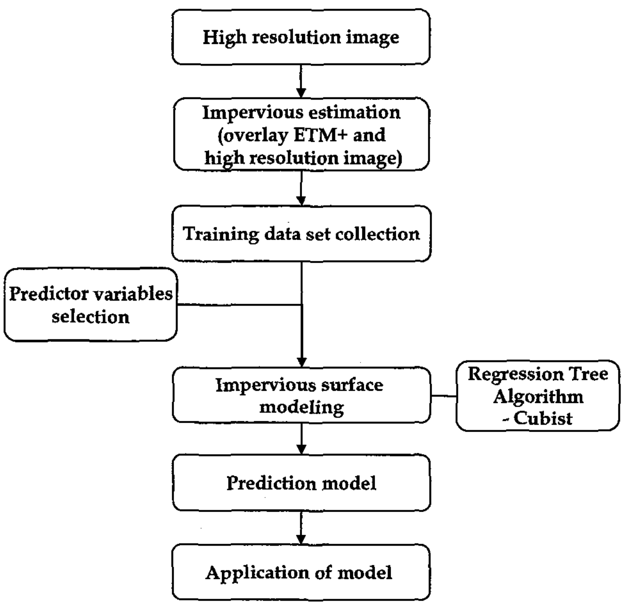

Figure 5. The procedure of training and test data collection

4.2 Application of regression tree algorithm

Authors would select the predictor variables for efficient and fast prediction modelling using regression tree algorithm. In this study, the predictor input variables are selected as band 3(red), band 4(near IR), band 5(mid IR), band 7(mid IR) of landsat-7 ETM+, greenness and wetness of a tasselled cap transformation image, and NDVI. The independent variable is a continuous impervious percent (%). Then, initial regression tree algorithms apply to training - test data.

Once the initial regression tree algorithm application was built, it is possible that the modelling is improved by considering input variables combination conditions. Final regression tree algorithm application was made, the accuracy is compared by all variable combination conditions.

4.3 The results

Test case results considering predictor input variable conditions are shown as table 2. Here, B3, B4, B5, and B7 mean band 3, band 4, band 5, and band 7 of landsat-7 ETM+, respectively. TC2 and TC3 mean greenness and wetness of a tasselled cap transformation image, respectively. RME means a relative mean error and r mean a correlation coefficient between input data and result value. In thess results, test 2, 3, and 4 have the highest correlation coefficients as 0.79 and the lowest relative mean error as 0.59. However, test 5 has the lowest correlation coefficient as 0.69 and the highest relative mean error as 0.71. Accordingly, Authors know that band 3, 4, 5, and 7 of landsat-7 ETM+ and NDVI are the main effect factors of impervious surface estimation. Finally, Authors are mapping the impervious surface using the combination of main factors. The map of impervious surface is shown as figure 6.

Table 2. Test case results

Test	B3	B4	B5	B7	TC2	TC3	NDVI	RME	r
1	O	O	O	O	O	O	O	0.61	0.77
2	O	O	O	O	O		O	0.59	0.79
3	O	O	O	O		O	O	0.59	0.79
4	O	O	O	O			O	0.59	0.79
5	O	O	O	O	O	O		0.71	0.69
6	O	O	O	O				0.70	0.69

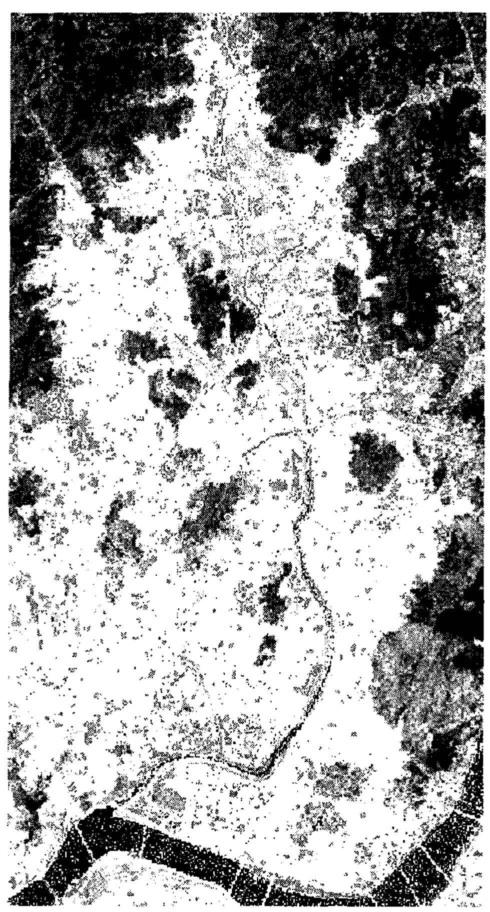

Figure 6. Impervious surface estimation

5. CONCLUSIONS

In this study, impervious surface estimation is performed by collecting training - test data for remote sensing images and modelling using regression tree algorithm. Then, the results of impervious surface estimation are compared by input variables condition. The conclusions of this study are as follows.

(1) Impervious surface can be estimated by using remote sensing images such as landsat-7 ETM+ and high resolution satellite image and regression tree algorithm.
(2) The main effect factors of impervious surface estimation are band 3, 4, 5 and 7 of landsat-7 ETM+ and NDVI.

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