PRACTICAL IDENTIFICATION METHOD FOR VEGETATION IN URBAN REGION USING TWO SPECTRAL EDGE IN HIGH RESOLUTION SATELLITE IMAGERY

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The accurate information on vegetation-covered area as a pervious surface is necessary to improve the accuracy of runoff analysis for non-point pollutant loading and groundwater recharge in urban region. In this study, practical bisection method for distinguishing vegetation from non-vegetation in urban regions was proposed. The Green Bias Index (GBI) which is derived from the strong relationship between the red edge and green edge in high resolution satellite image stands for the pigment property of vegetation as the bias terms of the green reflectance between near-infrared and red reflectance. Through the application of the GBI in study area, the vegetation higher than 99.7% to ground truth data could be identified, while the misidentification rate from non-vegetation is lower than 0.2% and 0.1% in roof and road, respectively. The width error between identified and measured vegetations was zero to one pixel for eleven sites selected in the study area. Finally, the spatial and temporal variance of GBI was investigated with five satellite images obtained on different date and location.

Key Words: vegetation, urban region, runoff analysis, high resolution satellite

1. INTRODUCTION

As landcover conditions provide essential information for runoff simulation on the effective rainfall, it is important to classify the surface into several types with the basis on types of rainfall loss. Especially, urban region is covered with diverse landcover types, like roof, road, vegetation, and soil. Moreover, these surfaces are complicatedly distributed over the urban region.

Hijioka et al.1) carried out landcover classification for urban runoff with the detailed digital information of 10m grid landuse. They classified urban surface into roof, road and pervious area. Since the detailed distribution and size of vegetation-covered area including roof garden, street plants and plant zone within building sites, were not quantitatively taken into account, runoff hydrograph showed a little disagreement between observed and simulated outflow in early part of rainfall event. Hence, the detailed information on both area (size) and distribution of pervious surface is required to enhance the model accuracy for runoff analysis of rainfall and non-point pollutant loading. Cowen et al.2) recommended that the medium-scale image of 1 to 5m resolution needs to be acquired for interpretation of landuse and landcover classification level III specified by the United States Geological Survey.

Fortunately, remarkable advances in satellite sensor technology have made feasible the use of a high resolution satellite image for urban landuse classification. The satellite sensors like QuickBird and IKONOS provide a significant high-resolution available from 0.64m to 1.0m panchromatic and 2.4m and 4m multispectral (blue, green, red and near-infrared) in space-acquired land observation.
In terms of estimating a vegetation cover ratio, Spectral Mixture Analysis (SMA) has been frequently used to derive subpixel vegetation information from remotely sensed imagery in urban areas, which models remotely sensed pixels as a combination of pure endmembers from a spectral library. Since we should always know the information on endmember variability for the successful use of this method, nevertheless its good performance for estimating a vegetation cover ratio in urban region, it was not practically utilized. Spectral vegetation indices (VIs) are widely used indicator of temporal and spatial variations in vegetation structure and biophysical parameters. Most VIs combine information contained in two spectral bands, visible red and near-infrared. Among them, the NDVI (Normalized Difference Vegetation Index) is the most commonly used one, and had been found to be highly correlated to the amount of green leaf biomass in early Landsat MSS applications. Hashiba et al. suggested a possibility of extraction of the distribution of small-scale vegetation about one square meter or bigger with NDVI in urban region using the high-resolution satellite image data by IKONOS. Meanwhile, considerable effort has been expended in improving the NDVI. These efforts can be summarized in three following aspects; 1) indices to minimize soil noise such as SAVI (Soil Adjusted Vegetation Index), and its family (TSAVI, MSAVI, and OSAVI) 2) indices to minimize atmospheric noise such as GEMI (Global Environmental Monitoring Index), and ARVI (Atmospherically Resistant Vegetation Index), and 3) indices to minimize complex noise such as EMI (Enhanced Vegetation Index).

Some of those VIs should be accompanied with securing experimental parameters or immense ground truth data properly to conduct vegetation identification; however it is nearly impossible to determine the parameters such as a soil line in urban region, comparing to large-scale farm and forest area upon the monotonous background. Although soil area is an important factor to determine the critical vegetation area, there is limited soil area in urban region, which is mostly distributed on a playground and park. In addition, the background of vegetation is concrete and asphalt in many cases. Hence, the critical factor to identify a vegetation area is a building area rather than a soil area in urban region. Because a roof is a dominant component, as well as it is covered with various paints and materials, in some case; the paint contains thermal insulating materials which bring about the increase of near-infrared reflectance in roof area. Some researchers pointed out that blue roof, rubber-covered track of stadium, and soil represent high NDVI value using IKONOS images in urban region.

From the view-point of rainfall runoff simulation, the method for vegetation identification using remote sensed data in urban region requires to be considered that; firstly, it is important not only to identify vegetation area with high accuracy but also properly to exclude the non-vegetation area (especially roof and road) from the vegetation area, because there is critical difference between vegetation and non-vegetation area in estimating an effective rainfall. Secondly, as the users are nonspecialist in the remote sensing, the method should be easy to use without experimental parameters and with the least field work to obtain the ground truth data for selecting a critical threshold value between vegetation and non-vegetation.

In this study, the effectiveness for application of existing several VIs to urban region was investigated. The VIs was chosen on account of that they do not need of experimental parameter or have a generalized parameter in their formulation. Then, the practical method was proposed to identify the vegetation in urban region using the combination of two typical spectral edges (i.e. red edge and green edge).

2. MATERIALS AND METHODOLOGY

(1) Vegetation indices based on a red edge

NDVI, SAVI and ARVI as vegetation indices using the reflectance contrast between near infrared and visible red (red edge) are chosen to investigate their effectiveness for identifying the vegetation area in urban region. Each index given in (1), (2) and (3) stands for basic index, index using soil line, and atmospherically corrected index, respectively.

\[
\text{NDVI} = \frac{(\text{NIR}-R)}{(\text{NIR}+R)} \quad (1)
\]

\[
\text{SAVI} = \frac{(\text{NIR}-R)(1+L)}{(\text{NIR}+R)+L} \quad (2)
\]

where, \( L = 0.5 \)

\[
\text{ARVI} = \frac{(\text{NIR}-RB)}{(\text{NIR}+RB)} \quad (3)
\]

where, \( RB = R - \gamma (B-R), \quad \gamma = 1.0 \)

The B, R and NIR represent the reflectance in visible blue and red, and near-infrared, respectively. The constant \( L = 0.5 \) given in Eq. (2) has been adjusted to account for first-order soil background variation. Although, the \( \gamma \) given in Eq. (3) depends on the aerosol type, the value is fixed to 1.0, because the aerosol model is not available.

(2) Vegetation index based on green edge

Gitelson et al. suggested the “Green” NDVI (GNDVI) for chlorophyll estimation. The GNDVI is much sensitive to the Chl concentration in a wide range
of Chl variations than the original “red” NDVI. The Green NDVI is expressed as follows;

\[ \text{GNDVI} = \frac{\text{NIR}-\text{G}}{\text{NIR}+\text{G}} \]  

(4)

where, G and NIR represent the reflectance in visible green and near-infrared ray, respectively. The GNDVI considers the reflectance in G instead of the reflectance in R as the sensitive term in NDVI.

(3) Green Bias Index (GBI)

Compared to the vegetation index of which value quantitatively corresponds to a biological activity, the practical bisection method for distinguishing vegetation from non-vegetation in urban region with the least spatial and temporal variance is proposed in this study. It is derived from the strong linear relationship between the (NIR-G) as an indicator of chlorophyll content and the (NIR-R) as an indicator of a basic green leaf biomass. According to Aoki et al.16), as the reflectance in the visible range is governed mainly by pigment content and composition, relationship of reflectance with chlorophyll content at specific wavelengths remain quantitatively the same in leaves of different and unrelated plant species. Hence, the linear relationship between the (NIR-G) and (NIR-R) is expected to be kept in vegetation during green leaf.

The Green Bias Index (GBI) which represents the pigment property of vegetation as the bias term of green reflectance between near-infrared and red reflectance is expressed by

\[ \text{GBI} = \frac{\text{NIR}-\text{G}}{\text{NIR}-\text{R}} \]  

(5)

where, NIR, G and R represent the reflectance at near-infrared, visible green and visible red band, respectively.

This method is based on the following assumptions;

1) The vegetation fraction (VF) is higher than 60% in urban region. Compared to agricultural region where is left a marginal soil background of the crop considering growth conditions, vegetation identification for urban region takes account of mostly matured tree and shrub of which mean LAI (Leave Area Index) is generally much higher than 117). On the conditions of VF > 60%, the green reflectance value shifts between NIR and R. It is based on that the relation of R<G<NIR is kept in vegetation when chlorophyll contents is yellowish-green to dark-green6), 15).

2) Theoretically, the NDVI value for healthy vegetation is usually as low as 0.118). The condition of NDVI>0.1 (i.e. NIR>1.22R) is adopted to avoid the misidentification of roof due to the color effect in relatively low NIR reflectance.

3) A mixed pixel problem over vegetation fringe is ignored. The GBI is desirable to be used for the remote sensed data scanned during the biological activity of vegetation is flourishing. Finally, the vegetation in urban region is determined in the range of 0 < GBI < 1 with NIR > 1.22R.

(4) Study area and used data

The five high-resolution satellite images from four areas where are Itabashi ward (Tokyo), Mito city (Ibaraki prefecture), Kumamoto city (Kumamoto prefecture) and Hanoi city (Vietnam) were used in this study. The brief of the used satellite images is summarized in Table 1. Only vegetation is selected in the images of Mito, Kumamoto and Hanoi.

As a principal test area, the Shimura district in Itabashi Ward, Tokyo with area of 12.1 ha was selected to investigate the applicability of conventional VIs for urban region and reflectance properties of several representative urban landcover types at IKONOS satellite imagery. The IKONOS satellite image of the area is shown in the left side of Fig.1. Its product specifications are summarized in Table 2.

The selection of the Shimura district as a principal test area is based on that;

1) The area comprises representative urban-landcovers over the whole area, e.g. vegetation, building, road and soil which are defined as a typical urban land cover in this study according to their distinguished difference in effective rain-fall.

Table 1 Image brief of satellite image used in this study.

| Location            | Date     | Pixel number | Image type & SR* |
|---------------------|----------|--------------|------------------|
| Itabashi (the study area) | Sep. 2004 | 31,965       | IKONOS, 1m       |
| Mito city           | Dec. 2000| 8,467        | IKONOS, 4m       |
| Mito city           | May 2001 | 8,491        | IKONOS, 4m       |
| Kumamoto city       | May 2002 | 6,260        | IKONOS, 1m       |
| Hanoi city          | Nov. 2002| 9,026        | QuickBrid, 2.4m  |

*Spatial resolution

Table 2 Meta data of IKONOS satellite image.

| Item                  | Feature                                      |
|-----------------------|----------------------------------------------|
| Processing Level      | Orthorectified, TOA* (Mito:Standard Geometrically Corrected) |
| Interpolation Method  | Cubic Convolution                            |
| Multispectral Algorithm | Projective                                   |
| MTFC** Applied        | Yes                                          |
| DRA*** Applied        | No                                           |
| Stereo                | Mono                                         |
| File Format           | GeoTIFF (11bits/pixel/band)                 |

*TOA : Top Of Atmosphere  **MTFC : Modulation Transfer Function Compensation  ***DRA : Dynamic Range Adjust
2) The distribution of vegetation is much complicated, e.g. tree overspreading a walk through a park as well as vegetation planted on the road and roof. Nevertheless these vegetation should be considered as a pervious area in rainfall runoff simulation, those areas have been regarded as an impervious area in classification with only conventional GIS data, e.g. Tokyo Metropolitan City Planning Geographic Information.

The boundary of the study area was determined according to adjacent main road, considering independent drainage system for the surface flow of rainwater.

The right side of Fig.1 shows two kinds of ground truth data. First one is polygon data of vegetation, roof, road and soil area which are silhouetted by black polygon, hatched line, dark gray polygon and gray polygon with a bold frame, respectively. Those are determined through visual interpretation of IKONOS image and field survey. Here, detailed classification between tree and turf which are presumed to have a difference in the reflection characteristics was ignored in this study, because their rainfall loss can be regarded as equal in runoff simulation. And as the soil area is too small in the study area, additional sampling for soil area was carried out in other IKONOS satellite images, which are selected from the playground of elementary school and middle school in Nerima and Katsushika ward in Tokyo, respectively. The product specifications of images are same to Shimura area.

The pixels extracted from each category are used to investigate the reflectance property of vegetation distinguished from other representative urban landcovers. Secondly, eleven sites induced by dotted line from vegetation area in the Fig.1 were selected to assess the identification accuracy of vegetation by different methods. A field survey to measure a vegetation width was carried out on May 2007.

3. RESULTS AND DISCUSSIONS

(1) Reflectance property of urban vegetation

The reflectance property of vegetation distinguishable from other urban landcovers (roof, road and soil) is investigated in the study area. Fig.2 represents the fitted curve for the whole reflectance value for the given four landcover types in visible blue (B), green (G), red (R) and near infrared (NIR) band. The reflectance was given by dividing a digital number by radiometric resolution (11bit=2040) of IKONO image in each band. The reflectance of four bands was arranged in ascending order based on the blue band which has the least standard variation. The determination coefficient ($R^2$) and the root mean square errors (RMSE) for each curve are summarized in Table 3.

As a well-known reflectance characteristic of vegetation, the high reflectance difference between visible band and NIR band is also clearly observed in Fig.2. Especially, the distance between NIR and R and between NIR and G is more uniform and larger in vegetation then any other landcovers. The relative magnitude relation of $R>G<NIR$ is kept over the whole range of vegetation. The consistency of the relative magnitude among the R, G and NIR is a unique characteristic of vegetation not to be found in other landcover types.

In order to investigate the ability to distinguish the vegetation from other urban landcovers with the contrast between two reflectance value in four bands in IKONOS image, the six combinations of reflec-
The B, G, R and NIR reflectance to the whole pixels sorted by ascending order for four landcover types (*the pixel number of soil area consists of the sum of 2875, 3627 and 596 selected from Nerima, Katsushika and Shimura, respectively).

### Table 3: Determination coefficient ($R^2$) and RMSE of each curve to all pixel.

| Categories | Vegetation | Roof | Road | Soil |
|------------|------------|------|------|------|
| B          | R$^2$ 0.93 | 0.95 | 0.89 | 0.99 |
|            | RMSE 0.006 | 0.017| 0.014| 0.002|
| G          | R$^2$ 0.94 | 0.91 | 0.88 | 0.95 |
|            | RMSE 0.008 | 0.034| 0.022| 0.010|
| R          | R$^2$ 0.92 | 0.84 | 0.85 | 0.89 |
|            | RMSE 0.010 | 0.046| 0.027| 0.017|
| NIR        | R$^2$ 0.32 | 0.79 | 0.81 | 0.86 |
|            | RMSE 0.040 | 0.052| 0.031| 0.017|

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The index value was calculated to two places of decimals for four landcover types given as ground truth data, i.e. vegetation, roof, road and soil. The percentage of pixels included in each class interval (0.02) of NDVI, SAVI, ARVI and GNDVI is plotted in Fig.4 in range of -0.16~0.50, -0.07~0.30, -0.12~0.84 and -0.38~0.44, respectively. The intersecting point distinguishing between vegetation and non-vegetation areas clearly appeared in NDVI, SAVI and GNDVI. However, clear intersecting point is not found in ARVI, due to much vegetation area is overlapped with roof area. In order to determine the critical threshold value between vegetation and non-vegetation in each VI, five values near the intersecting point in each VI were selected in interval of 0.02. The percentage exceeding each five threshold value is plotted by black dots for vegetation and by gray-hued bars for non-vegetation in Fig.5. In the case of NDVI, the most vegetation (more than 99%) can be identified by the threshold value up to 0.14, at the same time, pixels more than 1.1%, 0.4% and 0.0% in roof, road and soil, respectively are also extracted as a vegetation. In the case of SAVI, the most vegetation (more than 99%) can be identified by the threshold value up to 0.09, at the same time, pixels more than 0.8%, 0.1% and 0.0% in roof, road and soil, respectively are also extracted as a vegetation. ARVI appeared to be inadequate to distinguish the vegetation from non-vegetation in urban region.

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(2) Vegetation identification with NDVI, SAVI, ARVI and GNDVI

Considering that not only the red edge (NIR-R) but also green edge (NIR-G) are good indicators to distinguish the vegetation from other landcover in urban region, three red edge based vegetation indices (NDVI, SAVI and ARVI) and one green edge based vegetation index (GNDVI) were applied to the study area to investigate the effectiveness for identifying urban vegetation.

The index value was calculated to two places of decimals for four landcover types given as ground truth data, i.e. vegetation, roof, road and soil. The percentage of pixels included in each class interval (0.02) of NDVI, SAVI, ARVI and GNDVI is plotted in Fig.4 in range of -0.16~0.50, -0.07~0.30, -0.12~0.84 and -0.38~0.44, respectively. The intersecting point distinguishing between vegetation and non-vegetation areas clearly appeared in NDVI, SAVI and GNDVI. However, clear intersecting point is not found in ARVI, due to much vegetation area is overlapped with roof area. In order to determine the critical threshold value between vegetation and non-vegetation in each VI, five values near the intersecting point in each VI were selected in interval of 0.02. The percentage exceeding each five threshold value is plotted by black dots for vegetation and by gray-hued bars for non-vegetation in Fig.5. In the case of NDVI, the most vegetation (more than 99%) can be identified by the threshold value up to 0.14, at the same time, pixels more than 1.1%, 0.4% and 0.0% in roof, road and soil, respectively are also extracted as a vegetation. In the case of SAVI, the most vegetation (more than 99%) can be identified by the threshold value up to 0.09, at the same time, pixels more than 0.8%, 0.1% and 0.0% in roof, road and soil, respectively are also extracted as a vegetation. ARVI appeared to be inadequate to distinguish the vegetation from non-vegetation in urban region.

Finally, In the case of GNDVI, the most vegetation
(more than 99%) can be identified by the threshold value up to 0.02, at the same time, pixels more than 0.5%, 0.2% and 0.0% in roof, road and soil, respectively are also extracted as a vegetation.

The value of 0.14, 0.09 and 0.02 were selected as a critical threshold value of NDVI, SAVI and GNDVI, respectively to identify vegetation area in the study area. Fig.6 shows the vegetation area identified with NDVI, SAVI and GNDVI. The identified vegetation area is 1.6ha, 2.0ha and 1.4ha, respectively. The distribution of vegetation area represents a good correspondence to the distribution of vegetation observed on the IKONOS image in all cases.

However, as shown in Fig.6, a blue-tinged slate roof such as b1, b2 and b3 highlighted by dotted circle in (a) and (b), and a red-tinged slate roof such as r1 and r2 highlighted by dotted circle in (c) remained even after removing the lower value than the given threshold value of NDVI, SAVI and GNDVI, respectively.

The reflectance in G, R and NIR of vegetation and non-vegetation is plotted in the R-NIR plane (a) and the G-NIR plane (b) in Fig.7. The whole pixels of the ground truth data are critically divided into two groups between vegetation and non-vegetation by the given isoline (e.g. NDVI = 0.14, SAVI=0.09 and GNDVI=0.02). However, some pixels of bluish or reddish roofs are plotted in the range of vegetation in each plane. There are contrary results on exclusion of the bluish and reddish roof with the red edge-based index and the green edge-based index. The bluish roof can be excluded from vegetation by the green edge-based index, but cannot be excluded by the red edge-based index. Meanwhile, the reddish roof can be excluded from vegetation by the red edge-based index, but cannot be excluded by the green edge-based index.

Hence, it is impossible simultaneously to distinguish the bluish and reddish roof from vegetation using the only one relationship between R and NIR or between G and NIR, because the NIR reflectance of those roofs is much higher than usual roof and the bluish and reddish roof color has much effect on the reflectance in the R and G band. The value of NDVI, SAVI and GNDVI in those roofs is in the range of 0.14~0.32, 0.09~0.15 and 0.08~0.26, respectively.
(3) Vegetation identification with Green Bias Index (GBI)

Although the NDVI, SAVI and GNDVI represented a good performance for distinguishing vegetation from other landcovers, there are still some restrictions in their practical use as follows;

- Much ground truth data for the elaborated selection of a threshold value is necessary to guarantee the satisfactory accuracy in vegetation identification.

- Some reddish or bluish roofs mainly made of slate could not be simultaneously distinguished from vegetation area using the single reflectance difference between NIR vs. R and NIR vs. G alone.

It is most important critically to distinguish vegetation and roof as far as possible. However, the problems above are mostly due to various materials and colors of roof.

In Fig.8, all pixel of four landcovers (vegetation, roof, road, and soil) was plotted in the coordinate space between (NIR-R) and (NIR-G) which are numerator and denominator of GBI given in eq. (5). Vegetation is found to be substantially lined between two isolines of (NIR-G) = (NIR-R) and (NIR-G) = 0 with high correlation ($R^2 = 0.97$), while non-vegetation is clouded under the line of (NIR-G) = 0. In addition, it is found that the bluish and reddish roofs critically are separated from vegetation by the two isolines.

Generally, concrete and tile which are most common roof materials keep the relationship of spectral reflectance in $B<G<R<\text{NIR}$ \cite{19}. However, adiabatic treatment increases the NIR reflectance and painting changes the reflection intensity in certain visible band. Fig.9 shows the average reflectance in all roof, reddish (r1&r2) and bluish (b1~b3) roof area, respectively. And the example of bluish roof (b1) is represented in Photo 1. Different trend of reddish/bluish roof with average for all roof is partially found in reflectance for each band, e.g. high NIR reflectance in reddish roof and low red reflectance in bluish roof. Therefore, it is considered that the conceptual use of G band together with the relationship between R and NIR is effective to identify vegetation from such reddish/bluish roof of which reflectance is disturbed in certain spectral band due to its material and color.

All pixel of $0<\text{GBI}<1$ with $\text{NIR}>1.22R$ in IKO-
NOS satellite image of the study area was represented in Fig.10. The estimated vegetation area shows outstanding correspondence with the vegetation area determined through the visual interpretation of IKONOS image and field survey. In addition, most blue/red-tinged roofs (the b1, b2, b3, r1, and r2 marked by dotted circles in Fig.10 completely correspond to those in Fig.6) are successfully excluded.

In Table 4, the percentage included in the range of 0<GBI<1 with NIR>1.22R is compared with the percentage exceeding the range of NDVI>0.14, SAVI>0.09 and GNDVI>0.02 for vegetation, roof, road and soil area. All cases represent a good identification performance higher than 99%.

The identification accuracy for vegetation using the GBI is assessed through the comparison of an identified vegetation width with a measured vegetation width. The comparison was carried out for the eleven sites as shown in Fig.1. The measured vegetation width and the difference value with the vegetation width identified by NDVI, SAVI, GNDVI and GBI in each site are summarized in Table 5. Since the mixed pixel effect was out of account in this study, the error within one or two pixel is considered as a rational result. Considering sample number, selecting accuracy of the threshold value and measuring error, the GBI shows almost equal or a little better ability for distinguishing between vegetation and others.

(4) Spatial and temporal variance of the GBI

The spatial and temporal variance of the relationship between (NIR-R) and (NIR-G) for vegetation is investigated with additional four high resolution satellite images which are obtained on a different date and location. The description of the used satellite image is summarized in Table 1. Average monthly temperature of the given areas is 23.5°C(Sep. of Tokyo), 5.1°C(Dec. of Mito), 16.3°C(May of Mito), 19.7°C(May of Kumamoto), and 21.9°C(Nov. of Hanoi), respectively (JMA20 and WWIS21).

Fig.11 shows the relationship between (NIR-R) and (NIR-G) for the pixels of vegetation extracted from the different five areas. The pixels was determined mainly from park tree in each areas easy to identify using only the visual interpretation of satellite image. In Fig.11, most vegetation is concentrated on an extension line of the vegetation of study area (IT) with a high correlation. Considering the seasonal condition and geographical position of each images, the vegetation at Kumamoto of May (KU), which is expected to be the most active condition among the given vegetations, represents a high contrast both to (NIR-R) and (NIR-G). While, the vegetation at Mito of December (MI(1)) represents the lowest contrast both to (NIR-R) and (NIR-G), additionally some of them represent a minus value in (NIR-G) due to the effect of significant decrease in chlorophyll contents. It is related to the low bioactivity caused by seasonal condition. Since the GBI is desirable to be used for the remote sensed data scanned during the biological activity of vegetation is flourishing, the image of MI(1) is out of account in this study.
4. CONCLUSIONS

Two reflectance difference between NIR and R, and NIR and G are found to be the most prominent indicators for distinguishing vegetation from non-vegetation in urban region. Three vegetation indices based on the NIR-R contrast (NDVI, SAVI and ARVI) and a vegetation index based on the NIR-G contrast (GNDVI) are applied for vegetation identification in the study area. The NDVI, SAVI and GNDVI represented a good performances for distinguishing vegetation from non-vegetation, although the ARVI appeared to be inadequate to urban region.

In order to practically identify vegetation in urban area for estimating effective rainfall in rainfall runoff simulation without experimental parameters or immense ground truth data to determine the parameters such as a soil line and threshold value, as well as with keeping the identifying accuracy similar to conventional vegetation indices above, the Green Bias Index (GBI) which represents the pigment property of vegetation as the bias terms of green reflectance between near-infrared and red reflectance is proposed as follows

\[
\text{GBI} = \frac{(\text{NIR-G})}{(\text{NIR-R})}
\]

where, NIR, G and R represent the reflectance at near-infrared, visible green and red band, respectively. From the strong linear relationship between the chlorophyll content and basic biomass in vegetation under three assumptions that are VF > 60%, NDVI > 0.1 and ignorance of mixed pixel effect, the urban vegetation is determined in the range of 0 < GBI < 1.

We could achieve both the identifying accuracy of vegetation higher than 99.7% and misidentification rate of blue/red-tinged roof lower than 0.2% through the application of the GBI to test area. In addition, we could find out that the spatial and temporal variances of the relationship between (NIR-G) and (NIR-R) in vegetation is well arranged within the given vegetation isolines of the GBI in four different dated and positioned satellite images.

Although statistical verification for effectiveness of the GBI through applying into various field, the quantitative consideration between the GBI performance and other factors (e.g. vegetation species and mixed pixel effect), verification for various roof color, and so on remain as challenges of the future, the GBI as a practical identification method of urban vegetation without the hard work to obtain much ground truth data will be helpful for advanced runoff analysis to assess non-point pollutant loading and recharge of subsurface water quantitatively.

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