The Effect of Topographic Correction on SPOT6 Land Cover Classification in Water Catchment Areas in Bandung Basin, Indonesia

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Summary

Currently, there is no generally accepted topographic correction method to be applied in different landscape contexts. This study derived land cover maps in Ci Kapundung and Ci Sangkuy upper water catchment areas, which are located in a rugged terrain in mountainous areas in Bandung Basin, Indonesia, using object-based classification of satellite images. Under these conditions, a modified sun-canopy-sensor correction (SCS+C) was chosen as topographic correction method. Its performance was evaluated based on the Overall Accuracy (OA). Result shows that the correction method could improve the accuracies to 77% and 87.58% for the first and second case studies respectively.

KEYWORDS: land cover, object-based classification, forest classifier, remote sensing, topographic correction

1. Introduction

Forest classification through remote sensing is a significant topic because the analysis and monitoring of land use changes is key to successful climate change mitigation and adaptation, e.g. the REDD scheme. However, a topographic effect can alter the radiance values recorded by the satellite sensors, thus leading to the misinterpretation of land cover (Ediriweera, et al., 2013). The problem can be more clearly seen in rugged terrain landscapes than in flat terrain, such as mountainous area, where different illumination could be found in slopes, resulting in distinct reflectance value for similar land cover (Veraverbeke, et al., 2010 *cited in* Vanonckelen, et al., 2013).

This study proposes the application of a modified sun-canopy-sensor/SCS+C as a topographic correction (TC) method, for the development of land cover maps in mountainous area in Indonesia, using an object-based classification. SCS+C was used to test the applicability of the method on improving the classification accuracy.

Object-based classification has been used in previous work (Moreira & Valeriano, 2014), to evaluate the classification accuracy on a Landsat 5 TM image after TC. The study showed that C-Correction, SCS+C and Minnaert methods could reduce the topographic effect, without atmospheric correction being performed. Therefore, this paper intends to evaluate SCS+C as TC method, on object-based classification using SPOT 6 images.

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2. Materials and Methods

2.1. Study area

The case studies are located in Ci Kapundung and Ci Sangkuy upper water catchment areas (WCA) in Bandung Basin, Indonesia (Figure 1). The two catchments encompass areas of 102.88 sq.km and 98.91 sq.km respectively, and consist of rugged terrain with an elevation varying between 760 and 2,337 m above sea level. The landscapes are predominantly covered by agriculture, settlements, and forest.

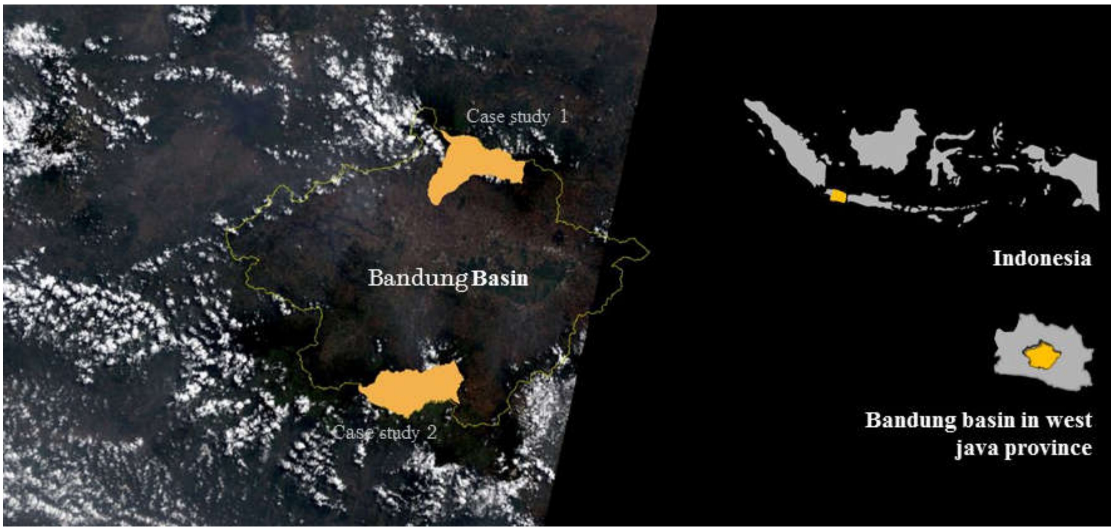
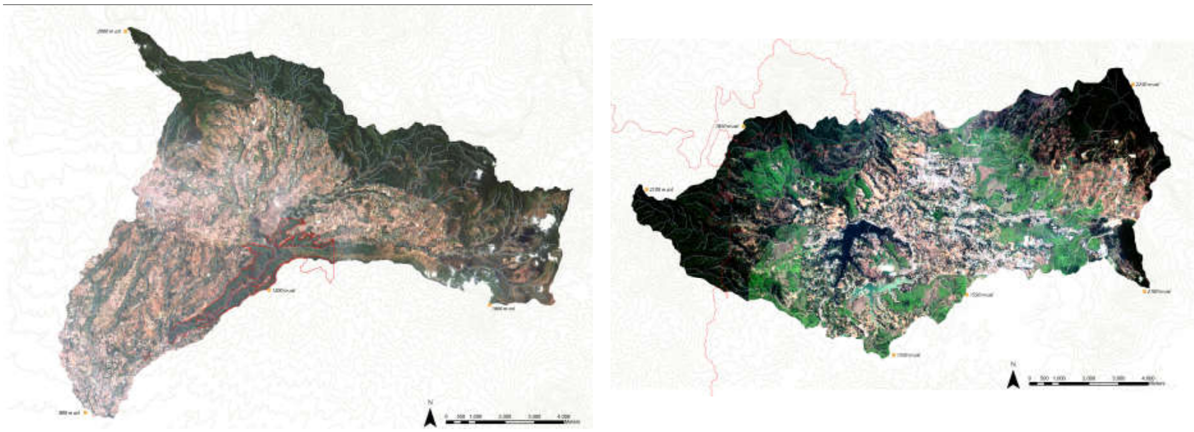


Figure 1 Location of Ci Kapundung and Ci Sangkuy upper water catchment areas in Bandung Basin, Indonesia

2.2. Data sources

SPOT 6 satellite images (three colors and an IR band) of the two case studies were purchased from Airbus. The images were taken on 20 September 2015, with solar elevation angle of 59.37^{o} (Figure 2). Clouds cover are 0.13% and 0% for the first and the second case studies respectively. The geometric calibration has been done previously by Airbus. The digital elevation model (DEM) used in this study is the space shuttle radar topography mission (SRTM) at resolution levels of 1 arc sec (approx. 30 m x 30 m), which was resampled to a pixel size of 6 m x 6 m to match the SPOT datasets.



(a) (b)

Figure 2 The SPOT 6 image of Ci Kapundung (a) and Ci Sangkuy (b) upper water catchment areas in natural color before image pre-processing

A field survey was conducted in July-September 2016 to identify landscape structures in a designated number of plots in both water catchment areas, in which the locations were recorded through transect walks. Due to the lack number of plot areas, land cover data derived from visual interpretation of the images from Esri's basemaps (DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, and the GIS User Community), as well as maps from Perhutani and PTPN (state-owned forest and agriculture enterprises in Indonesia), were also used to identify land cover, especially forest plant communities. Mixed forests are mainly located in remote areas at the higher altitude. The forests are surrounded by productive forests, which are comprised of various plant communities, such as *Altingia excelsa* and *Eucalyptus* (broad-leaved trees) and Conifers. Based on the site surveys and maps, the land cover classes of the area were reclassified into six broad classes (developed area, agriculture and grass, conifers, mixed plant communities, plantation, and water bodies). The classified land cover data will be used to simulate land use changes and run a hydrology model, as part of our research project assessing different landscape structures, which can reduce flood risk in Bandung Basin.

2.3. Data processing and evaluation

Topographic correction (TC) methods have been proposed in various studies, and their application to increase the classification accuracy in different landscape setting have been assessed. Some of the TC methods are C-Correction/CC and Statistical-Empirical/SE (Teillet et al., 1982), sun-canopy-sensor/SCS (Gu and Gillespie, 1998), a modified sun-canopy-sensor/SCS+C (Soenen et al., 2005), pixel-based Minnaert/PBM (Lu, et al., 2008, *cited in* Vanonckelen, 2013), etc. However, there is no single method, which is acknowledged as the best method, since different evaluation procedures have been used in different case studies (Sola, et al., 2016).

The combination of Transmittance Function as atmospheric correction method and PBM has been proved to increase the classification accuracy for the Romanian Carpathian Mountains (Vanonckelen et al., 2013). On the other hand, CC, SE and SCS+C have been argued to outperform other methods, including Minnaert and PBM (Sola, at al., 2015). Specifically, the SCS+C method is proposed for forest images and suitable for steep slopes (Soenen, 2005).

The methodology for this study is shown in Figure 3. The uncorrected (UI) and corrected (CI) images were developed, and object-based classification was performed on both images. The classification results from the images were then evaluated to assess the classification accuracy.

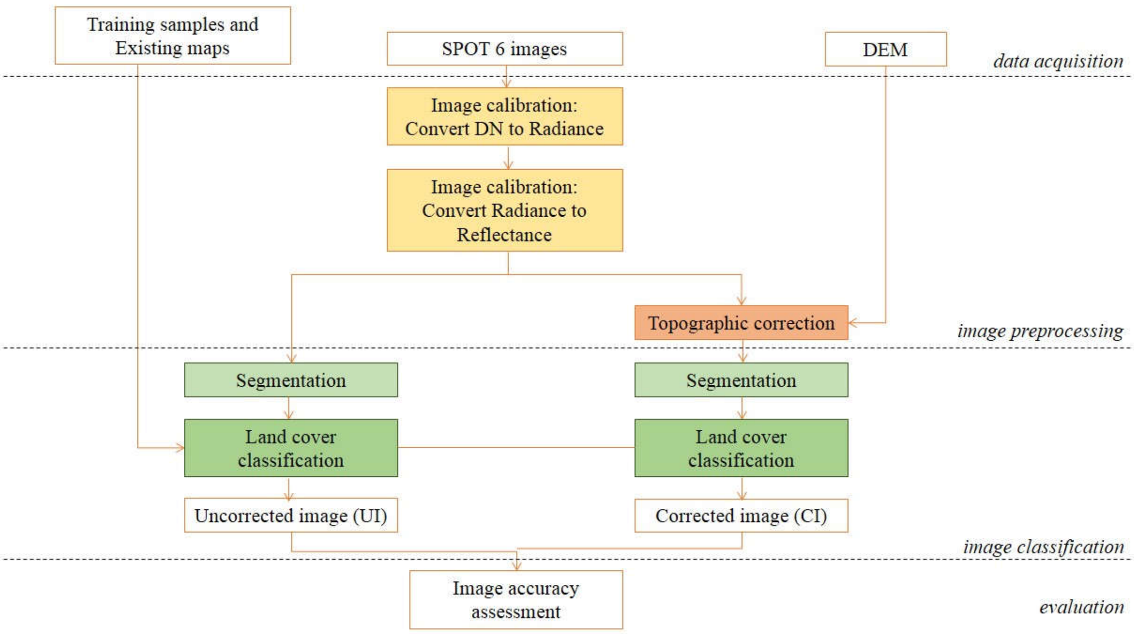


Figure 3 The methodology used in the study

The digital numbers (DN) of the SPOT 6 images were calibrated to at-satellite radiance ($L_{s,\lambda}$), (Eq. 1). Then, the values were converted to at-surface reflectance ($\rho_{T,\lambda}$) using Equation 2. It requires radiance value ($L_{s,\lambda}$), the relative Earth-Sun distance in astronomical units for the day of image acquisition(d^2), solar exoatmospheric spectral irradiances($ESUN_{\lambda}$), and the sun zenith angle(θ_s). The Earth-Sun distance for the image is determined based on the image acquisition date (Chander, et al., 2009).

$$L_{s,\lambda} = DN\ x\ gain + \ offset \tag{1}$$

$$\rho_{T,\lambda} = \frac{\pi\ L_{s,\lambda} d^2}{ESUN_{\lambda} \cos\theta_s} \tag{2}$$

The at-surface reflectance values from objects covered with clouds could not be retrieved because clouds block all radiation reflected from the Earth's surface (Lu, 2007 *cited in* Liu, et al., 2011). Therefore, the areas covered with clouds were excluded from the topographic correction and image classification process. Cloud masking was performed based on the at-surface reflection values, following the method described by Candra, et al. (2014). Using the same method, specific threshold for Green and NIR bands were used to identify water bodies in the images, thus water is excluded in the further image classification process.

After the at-satellite radiances were directly converted to at-surface reflection, SCS+C as TC method was performed to develop the CI using Equation 3 and 4 (Soenen, et al., 2005). On the other hand, no TC was applied on the development of the UI.

$$\rho_{H,\lambda} = \rho_{T,\lambda} \frac{\cos\theta_t \cos\theta_s + C_{\lambda}}{\cos i + C_{\lambda}} \tag{3}$$

with

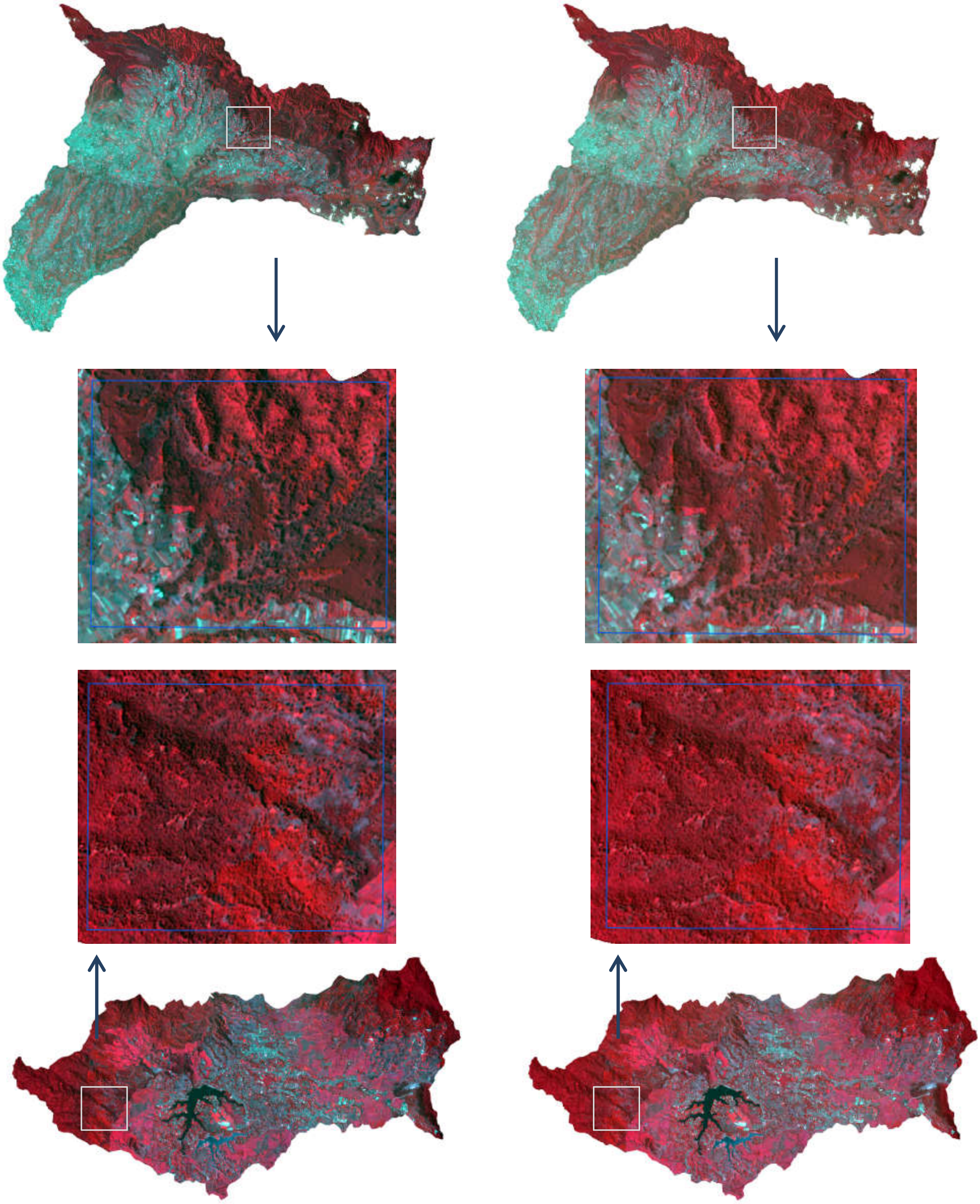
$$\cos i = \ \cos\theta_s\ \cos\theta_t + \ \sin\theta_s \sin\theta_t \cos(\emptyset_s - \emptyset_t) \tag{4}$$

$\rho_{H,\lambda}$ is the normalized reflectance; i is the solar incident angle; θ_t is the slope angle; θ_s is the solar zenith angle; $\emptyset_s$ is the solar azimuth angle; $\emptyset_t$ is the aspect angle; C_{λ} is empirical parameters (c=b/m, c is a function of the regression slope (b) and intercept (m)), which was acquired using regression between *cos i* and $\rho_{T,\lambda}$. 10.013 sample points were assigned in different terrain and illumination condition to derive *cos i* value.

Training samples were assigned and object-based classification was performed on UI and CI of the two case studies. The process consists of the segmentation for objects with similar reflectance and shape properties (Baatz and Schape, 2000, *cited in* Moreira and Valeriano, 2014). Support Vector Machine (SVM) classifier was used to classify the images, which was suggested to have a better result than the other classifiers (Huang, et al., 2002). Overall accuracy (OA) (Congalton, 1991) was assessed to evaluate the classification results for the uncorrected and corrected images using 2,001 test samples (stratified random sampling).

3. Results and discussions

Figure 4 and 5 show the comparison of infrared images and classification results from the UI and CI. Topographic effects are clearly seen in the rugged terrain in the UI. As the result of topographic correction, the slope facing away from the illumination source in the CI appear brighter than the same slope in UI.



(a) (b)

Figure 4 The uncorrected (a) and corrected (b) infrared images of the first and second case studies

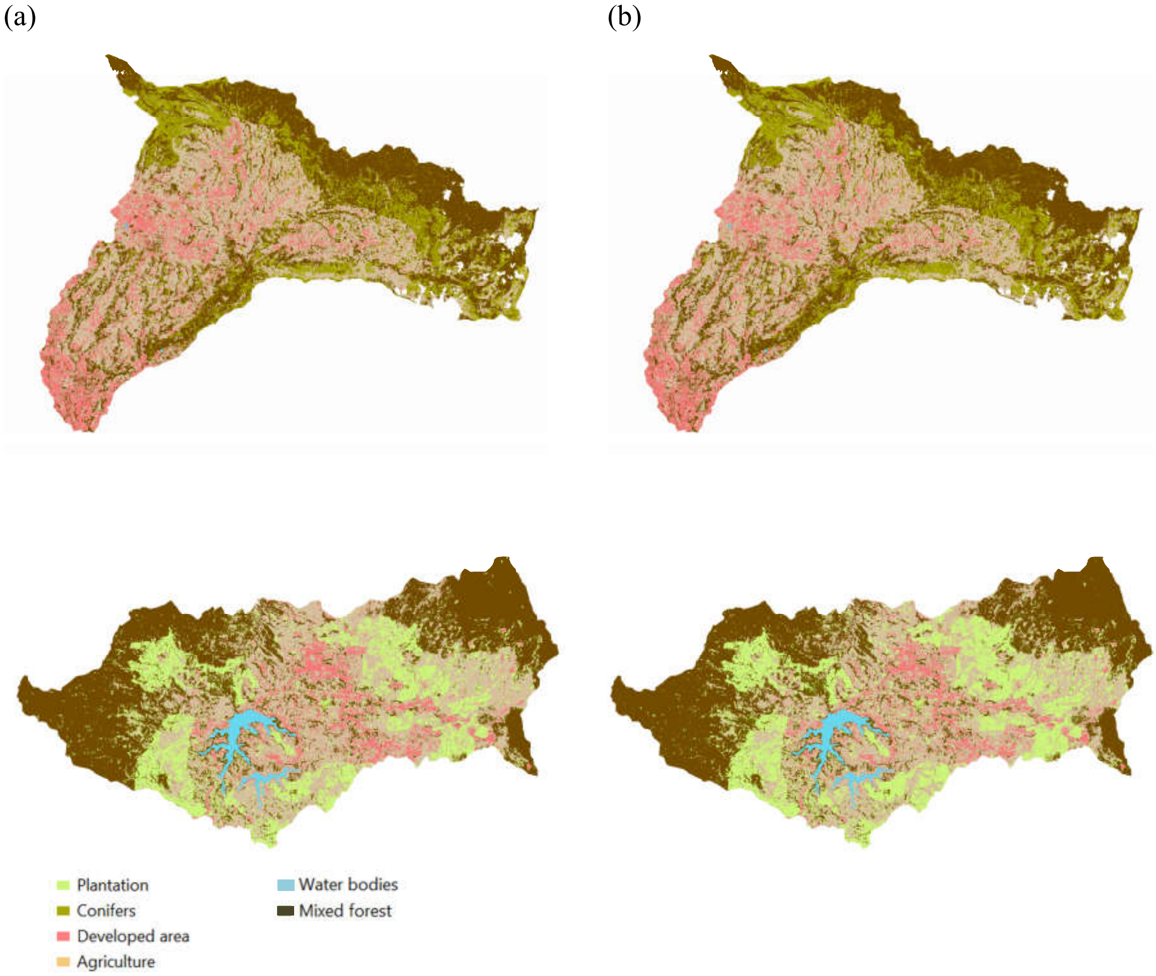


Figure 5 The classification results from the uncorrected (a) and corrected images (b) for the two case studies

Table 1 to 4 show the classification accuracy (OA) for the UI and CI of the two case studies. Water bodies were excluded in the accuracy assessment. The OA for the first and the second case studies increase from 74.25% to 77%, and 80.44% to 87.58% respectively, after TC being performed. Generally, forest classes have low accuracies between 30% and 75.44% for the UI due to the topographic effect. Most of the forests are located in rugged terrain, which contributes to the different illumination of slopes.

Different reflectance values of conifers and mixed plant communities result in the two classes could be separated in different classes. However, cloud shadows which are mainly located in the mountainous area in Ci Kapundung WCA altered the actual DN, thus prompted the misclassification of the two forest types. This also affected to the lower OA of the WCA image classification compared to the classification of the other case study.

A similar increase in accuracy for image classification through the application of the SCS+C method was also achieved in a study conducted in Kheyround Kenar forest in Iran (Ghasemi, et al., 2011). The study showed that the TC could improve the accuracy from 75.22% to 82.13%.

Table 1 OA for the first case study UI

	Reference dataset					
Classified image	Developed	Agriculture and Grass	Conifers	Mixed plant communities	Total	User Acc. (%)
Developed area	49	11	0	1	61	80.33
Agriculture and Grass	15	156	2	12	185	84.32
Conifers	0	15	38	29	82	46.34
Mixed plant communities	0	15	29	129	173	74.57
Total	64	197	69	171	501	0.00
Producer Accuracy (%)	76.56	79.19	55.07	75.44	0.00	74.25
Overall Accuracy: 74.25%						
Kappa statistic: 0.63						

Table 2 OA for the first case study CI

	Reference dataset					
Classified image	Developed	Agriculture and Grass	Conifers	Mixed plant communities	Total	User Acc. (%)
Developed area	46	12	0	0	58	79.31
Agriculture and Grass	9	162	7	7	185	87.57
Conifers	0	12	48	28	88	54.55
Mixed plant communities	1	20	19	129	169	76.33
Total	56	206	74	164	500	0.00
Producer Accuracy (%)	82.14	78.64	64.86	78.66	0.00	77.00
Overall Accuracy: 77%						
Kappa statistic: 0.67						

Table 3 OA for the second case study UI

	Reference dataset						
Classified image	Developed	Plantation	Agriculture and Grass	Conifers	Mixed plant communities	Total	User Acc. (%)
Developed area	22	0	0	11	0	33	66.67
Plantation	1	74	2	19	2	98	75.51
Agriculture and Grass	0	2	152	24	5	183	83.06
Conifers	6	9	10	152	0	177	85.88
Mixed plant communities	0	0	6	1	3	10	30.00
Total	29	85	170	207	10	501	0.00
Producer Accuracy (%)	75.86	87.06	89.41	73.43	30.00	0.00	80.44
Overall Accuracy: 80.44%							
Kappa statistic: 0.72							

Table 4 OA for the second case study CI

Classified image	Reference dataset Developed	Plantation	Agriculture and Grass	Conifers	Mixed plant communities	Total	User Acc. (%)
Developed area	24	1	1	4	0	30	80.00
Plantation	0	92	6	14	1	113	81.42
Agriculture and Grass	0	2	171	2	4	179	95.53
Conifers	4	11	3	147	0	165	89.09
Mixed plant communities	0	0	9	0	3	12	25.00
Total	28	106	190	167	8	499	0.00
Producer Accuracy (%)	85.71	86.79	90.00	88.02	37.50	0.00	87.58
Overall Accuracy: 87.58%							
Kappa statistic: 0.82							

4. Conclusions

This paper proposes an evaluation of SCS+C as TC method, on object-based classification using SPOT 6 images. The study showed that SCS+C method could significantly reduce the topographic effect particularly in such a steep and forested terrain. There is an improvement of classification accuracy on the corrected image compared to the uncorrected image from 74.25% to 77% and from 80.44% to 87.58% for the first and second case studies respectively. To improve the accuracy, atmospheric correction and the topographic correction are suggested being implemented for such mountainous and forested terrain before image classification process.

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6. Biography

Medria Shekar Rani is a PhD student in the Department of Landscape, the University of Sheffield. Her research is focused on landscape structure and flood risk simulation on water catchment areas.

Dr. Olaf Schroth is a lecturer in Landscape Planning, in the Department of Landscape, the University of Sheffield. His works include the development of technologies for environmental modeling and landscape visualisation.

Dr. Ross Cameron is a senior lecturer in the Department of Landscape, the University of Sheffield. His research interests are green infrastructure and climate change mitigation, emphasising on plant species in regard to ecosystem services.

Prof. Eckart Lange is a professor in the Department of Landscape, the University of Sheffield. His research focuses on the influences of landscape architecture and environmental planning on landscape change.

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