

DERIVING LAND USE AND CANOPY COVER FACTOR FROM REMOTE SENSING AND FIELD DATA IN INACCESSIBLE MOUNTAINOUS TERRAIN FOR USE IN SOIL EROSION MODELLING

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ABSTRACT:

Soil erosion is one of the severe land degradation problems in many parts of the world. It not only affects on decreasing agricultural productivity but also it causes disasters such as siltation of reservoirs and flooding in low lying areas in case of high rainfall events. To predict soil losses various models are available the results of which can be used for formulating soil conservation planning. In order to run the predictive models, one of the crucial data required is the land cover/land use and the canopy cover information. While land cover data can be used to derive information on effective soil hydrological depths and to estimate kinetic energy of leaf drainage, vegetation canopy cover will give information on rain interception factor, both of which are important input in calculating runoff and soil loss. These data may not be easily available in many mountainous areas because of inaccessibility problem. In this situation remote sensing data becomes very important. For classification of remote sensing data, however, one has to keep into account the problem due to illumination variations induced by variations in topography in mountainous areas, which may not lead to normal distribution of training samples, an assumption required by maximum likelihood classification. To solve this problem, illumination variation was removed using different techniques. The resulting data was classified to generate land use map. The result shows improvement in classification accuracy. The cover factor or the C factor is generally estimated using normalized difference vegetation index (NDVI) assuming a linear relationship which may not be the case always. The surface cover includes not only vegetation canopy cover but also plant residue and soil surface cover. In this study C-factor is derived by using in first place field assessment and then followed by calculating normalized difference vegetation index (NDVI). Correlation is carried out and a curve is fitted. The estimated C-factor represents the percent ground cover for each land cover type, as well as the presence of plant residue. The result was tested for its reliability and estimation error using field data, which shows that the coefficient of efficiency was higher (0.77) and the root mean square error was 0.03. The study was applied in a watershed in northern Thailand

1. INTRODUCTION

1.1 General Introduction

Land use changes due to population pressure from forest to agricultural land, can result in major changes in soil physical properties such as bulk density, soil structure, and organic carbon content that affect soil hydraulic properties and water retention characteristics as shown by various studies (Prachansri, 2007; Suriyaprasit, 2008; Zhou et al., 2008). Reduction of organic matter with cultivation depletes soil aggregate stability (Six et al., 2000). Overall effect is the increase in soil erosion. Soil erosion not only affects on decreasing agricultural productivity but also it causes disasters such as siltation of reservoirs and flooding in low lying areas in case of high rainfall events. In order to prevent land degradation and formulate conservation plan, it is essential to know the magnitude of erosion problem. In order to run the predictive models, one of the crucial data required is the land cover/land use and the canopy cover information. While land cover data can be used to derive information on effective soil hydrological depths and plant height, vegetation canopy cover will give

information on rain interception factor, both of which are important input parameters in calculating runoff and soil loss. These data may not be easily available because of inaccessibility problem in many mountainous areas. In this situation remote sensing data becomes very important. But for classification of remote sensing data there is inherent problem of illumination variations which may not lead to normal distribution of training samples, an assumption required by maximum likelihood classification (Shrestha and Zinck, 2001). In order to remove topography related constrains in remote sensing data, various researchers have applied different techniques such as the use of intensity normalization, and topography normalization using solar azimuth and solar elevation (Colby, 1991; Gupta et al., 2007; Shrestha and Zinck, 2001). It will be important to assess the usefulness of these techniques to see which one gives better results in terms of classification accuracy in mountainous areas.

The normalized difference vegetation index (NDVI) is generally used to derive cover factor, the C factor used in erosion modelling. Methods to convert NDVI to C values can be done by following linear least square method (de Jong, 1994)

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or by exponential function (Van der Knijff et al., 1999). In the tropics the rain interception is not only by vegetation canopy cover but also by plant residue after crop harvest and soil surface cover, etc.. Thus direct conversion of NDVI to C values, without field verification can be mis-leading and does not represent the real situation. It will be necessary to derive C values taking into account all the above mentioned conditions. A case study area in northern part of Thailand was used to test: the usefulness of correcting illumination variations caused by topography induced constrains for improving land use classification and the estimation of optimal C-factor using NDVI and field data.

1.2 Study area

Study area is in Nam Chun watershed in Petchabun province, about 400 km north of Bangkok, Thailand (Figure1). It lies between 16° 40' and 16° 50' North latitudes and between 101° 02' and 101° 15' East longitudes covering 67 km². The climate is tropical with distinct variation between dry and wet seasons. Average annual rainfall is 1075 mm and average annual temperature is 28 °C with highest reaching 37.5°C in April and lowest of 17.4 °C in December.

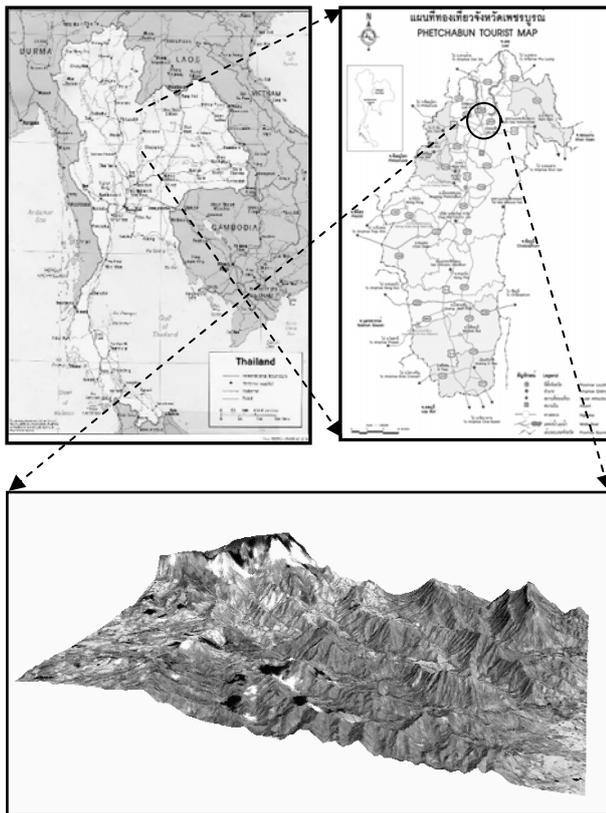


Figure 1: Study area in Namchun watershed, Thailand

2. METHODS

2.1 Field estimation of cover factor

Fieldwork was carried out during September 2007. Sufficient training samples were collected for classification, a similar set

of samples was collected for the purpose of classification validation. In addition, field estimation of cover factor, C was carried out in different land cover and land use types. In total C factor was estimated at 138 locations. Their map coordinates were recorded using GPS receivers.

The C factor was estimated in the field (C_f) using prior land use (PLU), canopy cover assessed for different cover types (CC), and surface cover (SC) following the method explained for RUSLE (Renard et al., 1997) as follows:

$$C_f = PLU \cdot CC \cdot SC \cdot SR \tag{1}$$

The prior-land-use subfactor (PLU) expresses the influence on soil erosion of subsurface residual effects from previous crops and the effect of previous tillage practices on soil consolidation, for the study case a value of 0.5 given for forest areas while a value of 1.0 is given for agricultural areas. Canopy cover is estimated using fraction of land surface covered by canopy (F_c) and height (mm) that raindrops fall after striking the canopy (H) as follows:

$$CC = 1 - F_c \cdot \exp^{-0.1 \cdot H} \tag{2}$$

The surface cover is estimated from the percentage of area covered by soil surface (Sp), random roughness (Ru) and an empirical coefficient (b) as:

$$SC = \exp \left(-b \cdot Sp \cdot \left(\frac{0.24}{Ru} \right)^{0.08} \right) \tag{3}$$

Finally surface roughness (SR) is also estimated using random roughness as follows:

$$SR = \exp^{-0.66 \cdot (Ru - 0.24)} \tag{4}$$

2.2 Removal of illumination variations and land use classification

Landsat TM data of the area obtained on 3 March 2007 was available. Similarly digital elevation data with 5m spatial resolution was available from the Land Development Department, Bangkok, Thailand. After geo-referencing the satellite data, two techniques for removing topographic influence were applied to check their usefulness in resulting classification accuracy. The first method is the use of intensity normalization as described in Shrestha and Zinck (2001), using the equation:

$$B_i Normal = \left(\frac{B_i}{\sum_{i=1}^n B_i} \right) \times 255 \tag{5}$$

Where: B_i Normal is normalized individual band of any sensor, B_i is individual band of any sensor, I is number of bands (from 1 to n bands) and 255 is the compensation factor to fit the 8 bit data range of 0-256. Topographic removal was also carried using solar azimuth and solar elevation, together with elevation data using the equation (Colby, 1991):

$$B_{V_{Normal}} \lambda = \frac{(B_{V_{Observed}} \lambda \cos(e))}{(\cos(ki) \times \cos(ke))} \quad (6)$$

Where, $B_{V_{Normal}} \lambda$ is normalized brightness values, $B_{V_{Observed}} \lambda$ is the observed brightness values, $\cos(e)$ is the cosine of the incidence angle, $\cos(i)$ is the cosine of the existence angle, or slope angle, k is the empirically derived Minnaert constant.

After topographic correction, the data was subjected to maximum likelihood classification with sufficient training samples for classification. Classification results were assessed for accuracy using test samples.

2.3 Canopy cover factor estimation

For generating canopy cover values, normalized difference vegetation index was computed using near infrared (NIR) and red band (R), and using the conventional equation:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \quad (7)$$

The resulting NDVI values has range of -1 to 1 which should not be interpreted as percent vegetation cover. In order to convert NDVI into canopy cover values, the field estimated 138 C factor samples were used and plotted against NDVI values. Regression function was used and curve was estimated (Figure 2) following an exponential relationship (adjusted R2 value of 0.78), the equation of which is given by:

$$C = 0.227 \cdot \exp^{(-7.337 \cdot NDVI)} \quad (8)$$

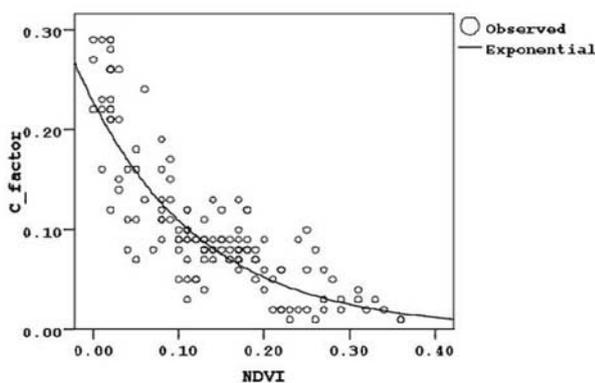


Figure 2: Relationship between NDVI and C-factor values

The reliability of generated C-factor map was evaluated by comparing predicted C-factor values from NDVI with field validation data, collected separately during field work. For this purpose coefficient of efficiency (C.E.) and root mean square error (RMSE) were calculated as follows:

$$C.E. = \frac{\sum_{i=1}^n (Xval_i - \overline{Xval})^2 - \sum_{i=1}^n (Xp_i - Xval)^2}{\sum_{i=1}^n (Xval_i - \overline{Xval})^2} \quad (9)$$

where, $Xval_i$ is validated C-factor values, \overline{Xval} is mean validated C-factor values and Xp_i is predicted values. The C.E. values close to 1 indicate better prediction. Similarly root mean square error (RMSE) was calculated.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Xp_i - Xval_i)^2}{n - 1}} \quad (10)$$

3. RESULTS

The land use/cover classification of the area was carried out using maximum likelihood classifier for three data sets: with topography normalisation technique, with intensity normalization technique and without correcting topographic effects. Classification was carried out for five land use classes: forest, degraded forest, grassland, agriculture areas and orchard. The areas covered by different classes are summarised in Table 1. The results were assessed for accuracy using 125 test samples collected during fieldwork (Table 2). Classification accuracy was also estimated for the three results which show that correction of illumination variation by topography normalization technique helps increase classification accuracy (Table 3). Classification accuracy of Land TM bands without using illumination correction is 67 percent. Highest accuracy was obtained by using topographic normalization technique (74 percent).

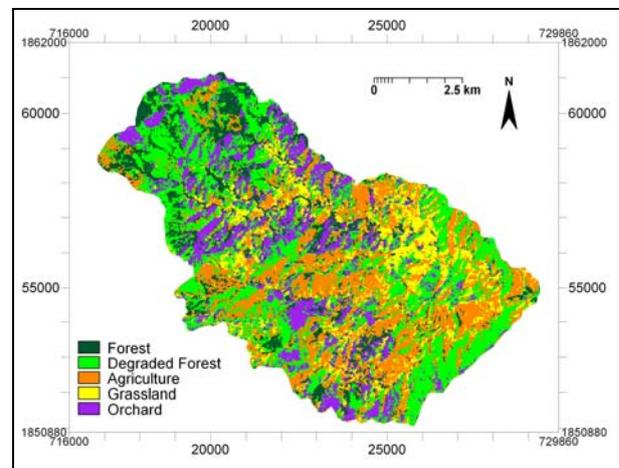


Figure 3: Land use classification

Land use/cover	Hectares	Percent
Forest	857	13
Degraded Forest	2267	34
Grassland	1686	25
Agriculture	778	12
Orchard	1070	16
Total	6658	100

Table 1: Land use classification in Namchun watershed

Class	Ref. total	Total classified	No. correct	Accuracy	
				Producer	User
Forest	25	15	12	48	80
Deg.Forest.	25	21	18	72	86
Agriculture	25	23	20	80	87
Grassland	25	34	22	88	65
Orchard	25	32	21	84	66
total	125	125	93		

Overall classification accuracy = 74.4%

Table 2: Contingency table

Classification accuracy (%)		
Without correcting topographic effects	Using Intensity normalization	Using topographic normalization
67	69	74

Table 3: Classification accuracy

Canopy cover factor was generated using equation 8 which resulted in C-factor map (Figure 4). The result was assessed for its reliability using 125 validation data collected during fieldwork. The coefficient of efficiency is estimated at 0.77 (value 1 means the best prediction) and with lower root mean square error (0.03).

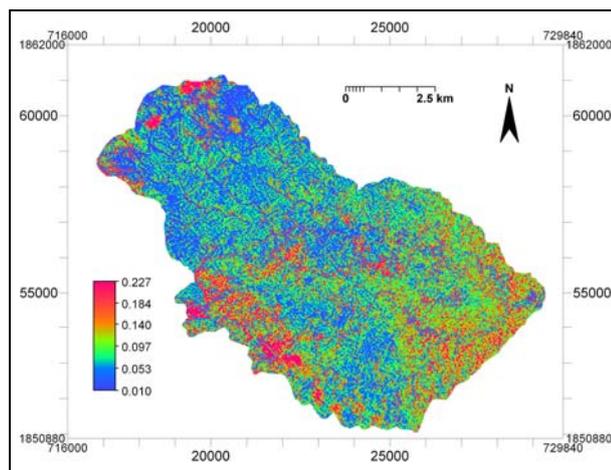


Figure 4: Canopy cover factor map

The results show that land use classification can be improved in mountainous areas by correcting illumination variations on satellite data using topographic normalization technique. In case of unavailability of digital elevation data, illumination variation can be corrected using intensity normalization procedure. The result also shows that canopy cover factor values (C-factor) can

be best estimated using field estimation and correlating with NDVI values.

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