Empirical Method for Topographic Correction in Aerial Photographs

T. Svoray and Y. Carmel

***Abstract*—We suggest an empirical method to correct topographic effects on vegetation classification of panchromatic aerial photographs. The method is based on the use of spatial interpolation technique that constructs a luminance surface from targets of high brightness values. The luminance surface is then used to correct the topographic effects differentially, by increasing brightness values in shaded areas and decreasing brightness values of lightened areas. For this purpose, the use of a trapezoidal function was found successful in the reduction of standard deviation of brightness values of trees, shrubs, and herbaceous plants after empirical correction. This method outperformed a frequently used digital elevation model-based topographic correction in terms of overall classification accuracy of the resulting images.**

***Index Terms*—Classification error, geostatistics, topographic effect, vegetation mapping.**

I. INTRODUCTION

TOPOGRAPHY has a strong effect on both irradiation and reflectance of a slope, and terrain may strongly affect the quality of vegetation classification [1]. There have been many attempts to correct these attenuations, with varying degrees of success (see summary in [2]). Typically, parametric models that use information on local incidence angle are used to correct pixel values, in order to reduce topographic effects. Models to recalculate the local incidence angle include a number of approaches (reviewed recently in [3]): exact derivation of the dependence of vegetation canopy reflectance on terrain slope [4]; nonparametric modeling of radiance [5]; and more comprehensive, physically based models that include atmospheric, illumination and reflectance correction to reduce topographic effects [1]. Common to the parametric models is the need for an accurate digital elevation model (DEM) to derive local topography. However, readily available DEMs are contour-based and therefore often provide low vertical resolution with both random and systematic errors [6]. DEMs of high accuracy and high-resolution are expensive and therefore often unavailable [3].

In this study, we suggest an empirical method for topographic corrections, as an alternative to the mechanistic models that require the use of DEMs. Our method is based on a two-step process: 1) manual location of a single bright target in each local region (referring to bare rock, "local" is defined here as a block in a grid overlaid on the image), and interpolation of the "bright targets" layer into a "luminance surface" using kriging interpolation technique and 2) differential topographic correction of the original image using the luminance surface combined with a trapezoidal function, which increases brightness values in shaded areas and decreases brightness values of lightened areas. Although demanding manual calibration of each scene, the method is easy-to-use and can be applied using available image processing and GIS software.

Based on previous studies that have used aerial photos for vegetation mapping [5], [13] we expect that the topographic correction will restore the potential uniqueness of image brightness of each vegetation class that was destroyed due to the bias caused by variation in local incidence angle. Removal of this bias is expected to significantly improve accuracies of classification of vegetation formations from aerial photographs.

We evaluate the performance of our method against a standard DEM-based method [9] assessing: 1) the change in standard deviation of pixels within each class and 2) accuracy of a classification of the resulting images of each of these two methods relative to that of the original image. A method that results in a lower standard deviation (STD) of a given class is considered more effective [3]. However, a reduced intraclass variation by itself does not ensure improved classification (e.g., if interclass variation is reduced more than intraclass variation, classification accuracy may be reduced). In the present study, improved classification is the goal of topographic normalization, thus we use overall classification accuracy as an additional performance index.

II. METHODS

The study site is part of the Judean Hills of Israel at an altitude range of 390–630 m above mean sea level. Slope range is between 0° to 36°, with a mean slope decline of 13°. Rock formations are mainly carbonates including limestone, dolomite, and chalks, and the dominant soil formation is Brown Rendzina. The climate is Mediterranean, and the vegetation includes three dominant formations: Aleppo pine trees (Pinus halepensis), shrubs (mainly Quercus calliprinos and Pistacia lentiscus), and annual grassland of various species.

A. Empirical Method

The empirical method suggested here begins with grid sampling of bright targets to create a luminance surface for the entire study area. This surface is assumed to represent the variation in pixel brightness of bare rocks due to changes in local incidence angle. We then use this surface to correct pixel brightness in the

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T. Svoray is with the Department of Geography and Environmental Development, Ben-Gurion University of the Negev, Beer-Sheva 84105, Israel (e-mail: tsvoray@bgumail.bgu.ac.il).

Y. Carmel is with The Technion—Israel Institute of Technology, Haifa 32000, Israel (e-mail: yohay@tx.technion.ac.il).

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raw data. The empirical method was applied to the study area in two steps.

1) Construction of a Luminance Surface: A grid of blocks was overlaid on the entire study area. The size and number of blocks may vary due to the level of spatial variation in rock cover and topographic conditions. Here, we selected block size of 50 × 50 m, which resulted in a grid of 220 blocks. Using visual interpretation, a sample of "bright target" pixels was chosen in each block. The "bright targets" corresponded to areas of exposed rocks only, with brightness values much higher than the other pixels in the block. The choice of sample size would depend on local conditions, and in particular, on the pattern of bare rock in the study area and the internal variation in their brightness values. Here, we chose a sample of at least ten pixels, fully covered by bare rocks, per block.

Due to the fact that the rocks in the study area are carbonates and the soil is Brown Rendzina, the rock targets can be easily traced by the operator. Given the internal variation in brightness of bare rocks in each block, we calculated the sample average of bare rock in each block, and assigned it to the block's centroid. This step culminated in a lattice of points that covered the entire study area, where each point represents the mean brightness value of bare rock in each block. Next, these points were interpolated to create a continuous luminance surface with a spatial resolution of 0.27 m per pixel. We applied ordinary Kriging using the spatial analysis tool of ARCGIS 8.3. Cross validation [7] was used to assess interpolation quality.

2) Correction of Original Image Using the Luminance Surface: The luminance surface was used to correct the raw image based on a trapezoidal function. This function was used in several studies, e.g., [8]. We developed a form of a conditional expression (1) to make specific use of properties of the luminance surface histogram in bright flat areas for the application of our empirical correction. To do so we used samples of image brightness from bright and flat surfaces located in three remote locations in the study area. In general, the identification of flat and bright targets in the study area can be done using topographic maps backed by information from a field survey

$$\begin{aligned} x' &= x + (\delta - \psi) \bullet \left(1 - \tfrac{\delta - x}{\delta - \gamma}\right), && \text{if } L < \beta \\ x' &= x, && \text{if } \beta < L < \gamma \\ x' &= x - (\psi - \alpha) \bullet \left(1 - \tfrac{x - \alpha}{\beta - \alpha}\right), && \text{if } L > \gamma \end{aligned} \quad (1)$$

where x and x' are pixel values in the original image and the empirically corrected image, respectively; L is the respective pixel value in the luminance surface; α and δ are the minimum and maximum brightness values of the bright targets luminance surface; β, ψ, and γ are the minimum, median, and maximum, respectively, of the brightness values of a bright target at flat surface (see Fig. 1). The values assigned for our particular case study are based on a statistical analysis of the image histogram: $\alpha = 210$, $\beta = 235$, $\psi = 240$, $\gamma = 245$, and $\delta = 255$.

B. DEM-Based Method

There are many methods for topographic correction using DEMs; see [3] for a review. We chose (2) to calculate the local

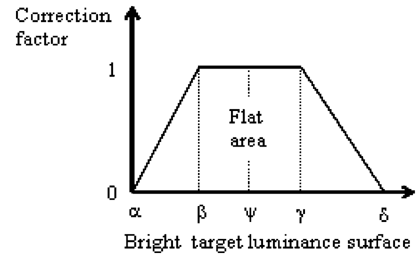

Fig. 1. Differential topographic correction based on the distance from the image brightness of flat surface.

angle of incidence. This correction assumes isotropic reflection, which is suitable in cases of high sun elevation angle in hilly terrain [9]

$$\begin{aligned} x' &= x \cos\theta_i \\ &= x(\cos\theta_n \cos\theta_z + \sin\theta_n \sin\theta_z \cos\phi_z \cos\phi_n \\ &\quad + \sin\theta_z \sin\phi_z \sin\theta_n \sin\phi_n) \end{aligned} \quad (2)$$

where x and x' are pixel values in the original image and the corrected image, respectively where θ_z and ϕ_z are the zenith and azimuth angle of the sun, θ_n and ϕ_n are the zenith and azimuth angles of the normal to the surface, and θ_i is the angle between the direct radiation and the surface normal [10].

Calculation of the local angle of incidence for each pixel requires accurate coregistration of each image to the DEM. In our case, the resultant root mean square error of the registration was less than one pixel (0.27 × 0.27 m in size). The panchromatic aerial photo, recorded digitally, was acquired at 14/04/2003 at 14:07:11 covering an area of 750 × 750 m. At this time, at the site location—34:45N 35:04E—the sun azimuth was 48.8 and zenith 243.3. The DEM was generated from two stereoscopic aerial photos, using the Orthobase-Pro tool of ERDAS Imagine [11].

C. Model Performance

The relative performance of the two methods was evaluated using two different measures. First, the standard deviation of each class in the training sets was calculated for each of the three images: raw data; empirically corrected; and DEM-based corrected. Second, a maximum-likelihood algorithm was used to classify the three images. We distinguished four land cover types that dominate the study area: pine trees, shrubs, herbaceous vegetation, and bare rock. The training sets where derived using data collected in the field. Confusion matrices were calculated based on a dataset of 100 locations to compare classification performance between the three images. Manual interpretation was used as a reference for the classification algorithms. Manual interpretation was found reliable for accuracy assessments to the four land covers studied here in several similar landscapes [12], [13] and in our preliminary analysis of the study area.

III. Results

A. Empirical Method

1) Construction of a Luminance Surface: The selection of 220 bright targets was a rapid and an easy task. The brightness of

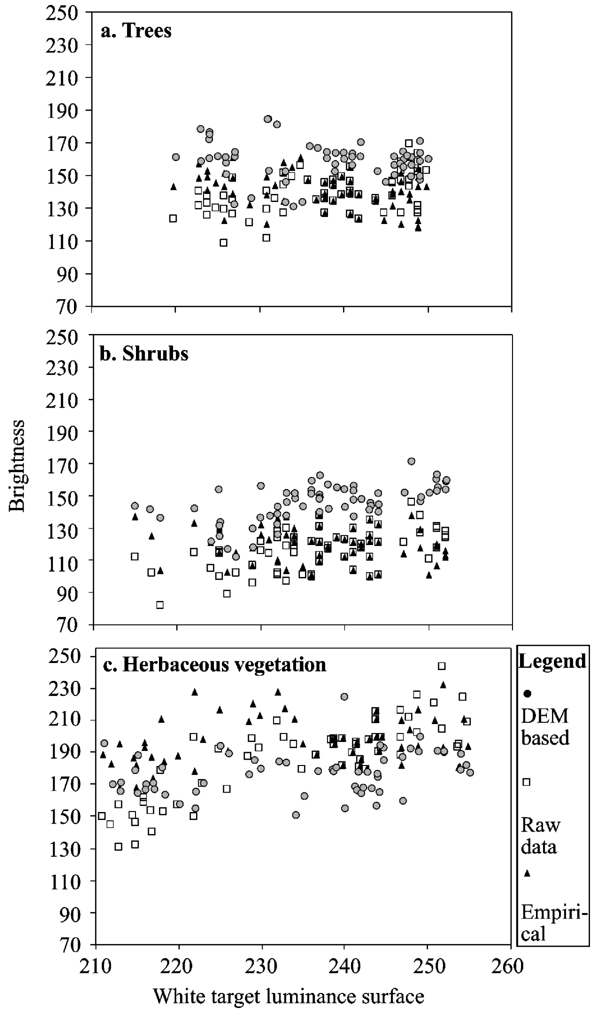

Fig. 2. Samples of image brightness of (a) trees, (b) shrubs, and (c) herbaceous vegetation plotted against their equivalent white target brightness. The plots show how bias in the row data points is corrected in the points of both topographic corrections.

the limestone rocks was significantly different than the brightness of the three vegetation formations, soil, and artificial objects. The high cross-validation results ($R^2 = 0.96$) show that the interpolated surface reliably reflects the variability in brightness of similar bright objects across the image.

2) Correction of Original Image Using Luminance Surface: Fig. 2 shows samples of brightness values of the three vegetation formations in the study area plotted against their equivalent values in the luminance surface. In the raw data sample, brightness values are biased by topography; pixels of low luminance have lower brightness and vice versa. This phenomenon is particularly prominent in the case of herbaceous vegetation. According to Fig. 2, the empirical correction was successful in correcting the bias in the brightness values of all three vegetation formations.

B. DEM-Based Method

The variability in brightness values of each of the vegetation formations was reduced by the DEM-based method. The result is a flat distribution of brightness values regardless of the effect of topography, as illustrated by the luminance surface values [Fig. 2(a)–(c)]. However, the DEM-based method decreased separability between trees and herbaceous vegetation, since their distributions became more similar (i.e., their brightness clouds overlap). In contrast, shrubs remained distinguishable after the DEM-based correction. Fig. 3 shows that the DEM-based method outperformed the empirical method in reducing the variability of trees and shrubs. Yet, the smaller overlap between class distributions indicates that separability was higher when the empirical method was used.

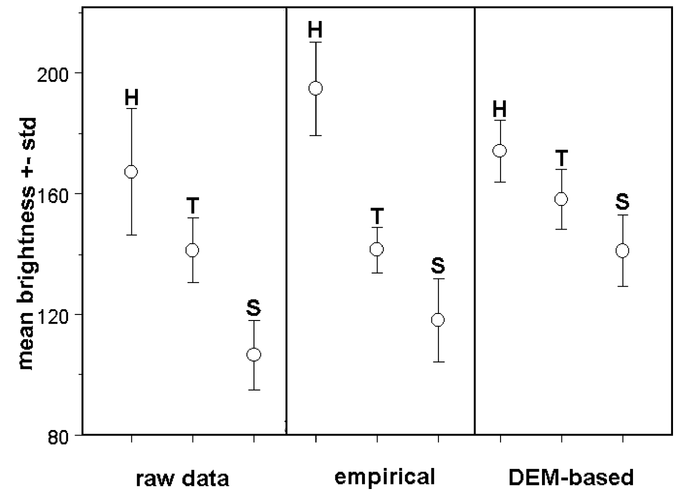

Fig. 3. Brightness (mean $\pm$ standard deviation) of the verification points, for three vegetation formations (H—herbs, T—trees, S—shrubs), resulting from the raw image, empirically corrected image, and DEM-based corrected image.

C. Model Performance

Classification accuracy of the DEM-based corrected image was lower than that of the raw data classified image (74% versus 88%, respectively; see Table I). In contrast, the empirical correction has yielded the highest overall accuracy (92%). This result could be expected, since the DEM-based correction increases overlap between the brightness values of trees and herbaceous vegetation.

The classification of rock cover had the highest accuracy in all three classified images. The empirical method yielded similar classification accuracy results for the three vegetation formations, with some confusion between trees and shrubs and to a lesser degree between trees and herbaceous vegetation. In the classification of the raw data, highest accuracy was achieved for herbaceous vegetation, then shrubs and finally trees. Confusion between these formations was similar to the case of the empirical image. The DEM-based classification had reasonable accuracy for shrubs, and much lower accuracy for the other classes.

IV. Discussion

The empirical method for topographic correction of aerial photographs was found to be both rapid and accurate. The luminance surface was used successfully to correct topographic effects differentially, using the trapezoidal function.

Overall classification accuracy was highest when the empirically corrected aerial photo was used. This superiority was contributed mainly by the improved accuracy of shrubs and trees.

TABLE I
CONFUSION MATRICES OF THE IMAGE CLASSIFICATIONS

Raw image Overall accuracy 88%	*Pine trees*	*Shrubs*	*Herbaceous vegetation*	*Rock*	Row total
Pine trees	**83**	15	10	0	108
Shrubs	12	**85**	0	0	97
Herbaceous vegetation	5	0	**88**	3	96
Rock	0	0	0	**97**	97
Column total	100	100	98	100	398
Empirical correction Overall accuracy 92%	*Pine trees*	*Shrubs*	*Herbaceous vegetation*	*Rock*	
Pine trees	**89**	9	10	0	108
Shrubs	8	**91**	0	0	99
Herbaceous vegetation	2	0	**88**	3	93
Rock	1	0	0	**97**	98
Column total	100	100	98	100	398
DEM-based correction Overall accuracy 74%	*Pine trees*	*Shrubs*	*Herbaceous vegetation*	*Rock*	
Pine trees	**68**	18	10	0	96
Shrubs	11	**76**	5	0	92
Herbaceous vegetation	10	4	**61**	13	88
Rock	11	2	22	**87**	122
Column total	100	100	98	100	398

Herbaceous vegetation, despite its large internal variation, was classified relatively accurately in the raw data, and the empirical correction method did not improve classification results further.

The DEM-based method is automatic, does not require calibration for each scene, and does not require operator's subjective decisions. However, in spite of reducing the variability within each group, this method does not necessarily increase classification accuracy, and in some instances it may even decrease accuracy (as in our case). In contrast, the empirical method is more accurate under certain conditions, is DEM-free, and relatively easy to apply.

Luminance surface can be predicted using spatial interpolation techniques and the trapezoidal function used here was successful in correcting the topographic effect differentially, by increasing brightness values in shaded areas and decreasing brightness values of lightened areas. The "bright targets" suggested here can be applied by tracing rocks in areas of bright carbonate rock cover that is exposed within the vegetation strata.

The use of rocks is likely to be less effective in basaltic areas and in areas of dense vegetation cover. Global abundance of carbonates in the terrestrial surface is almost 25% [14]; thus, it is expected that the use of rock as "bright targets" will be indeed useful at least in those parts of the world. In areas covered by basaltic rocks, for example, where it is difficult to distinguish between rocks and soil, other targets with unique and relatively homogenous brightness values can replace the rocks in creating the luminance surface. Shadows, for example, were found useful in representing luminance gradients across a panchromatic aerial photo in a case study of computerized vegetation classification [13].

The empirical method developed here may be useful and cost effective for studies of small areas, but may not be proper for large areas because many bright targets have to be selected by the operator to generate the luminance surface. Given the method was applied for one dataset only, further research is needed to study model behavior with other datasets, other land cover types, and other sources (e.g., satellite imagery).

V. CONCLUSION

An empirical method for topographic correction was developed as an alternative to commonly used DEM-based methods. The empirical method increased the variation between the classes and improved classification accuracy comparing with both raw data and the DEM-based method mainly for the classes of trees and shrubs. The method should be useful particularly when accurate and detailed DEMs are not available and for small scale projects.

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