Radiometric-topographic normalization in mountainous terrain for Landsat-TM-based forest parameter assessment by the kNN method

Tatjana Koukal, Werner Schneider & Franz Suppan
Institute of Surveying, Remote Sensing and Land Information, Department of Landscape, Spatial Sciences and Infrastructure, BOKU - University of Natural Resources and Applied Life Sciences, Vienna, Austria

Keywords: forest inventory, radiometric-topographic normalization, kNN

ABSTRACT: The kNN method of combining a terrestrial forest inventory with remote sensing image analysis is applied in mountainous terrain. This poses problems of radiometric-topographic normalization, which are addressed in this paper. The SCS (sun-canopy-sensor) method, extended for including diffuse sky radiation, is found to be particularly suited for this. Estimating parameters of radiometric-topographic correction algorithms (such as the ratio of direct sun radiation and diffuse sky radiation in case of the extended SCS method) from the image itself by regression of forest pixels arbitrarily selected at different topographic conditions relies on the assumption that the forest pixels selected at different irradiation conditions represent (in the statistical average) identical forest conditions. This assumption can hardly be proved to be valid. The estimation of this ratio by tuning within the kNN cross-validation procedure, on the other hand, represents a sound method, making use of the large amount of forest information available from terrestrial forest inventories. The practicability of this method depends on the number and thematic distribution of field plots on one single scene, for which homogenous atmospheric conditions can be assumed.

1 FOREST INVENTORY BY TERRESTRIAL SURVEY AND BY REMOTE SENSING

In many countries, terrestrial forest inventories are being carried out since decades, and valuable inventory data are being collected which form the basis for various political, administrative and economic decisions. These terrestrial inventories are based on statistical sampling methods. In Austria, for instance, the national forest inventory is based on a systematic sampling grid with a grid width of slightly less than 4 km. At every grid point, there are 4 circular plots arranged at the corners of a square of 200 m side length. Inventory data are regularly collected since the early 1960s.

There are, however, two major problems with the results of this inventory: Firstly, one cannot produce maps (with the exception of very small scale maps showing the grid points in raster format). There is no information available between the grid points. In particular, one cannot use the result for planning purposes on a regional scale. Only statistical information is produced. The second problem is that even statistical information can be given only for large areal entities. In Austria one obtains very reliable and statistically significant results for the whole country, for provinces, but not for smaller forest districts, where there might be only a few forest plots in one district.

One solution is to use remote sensing data, especially Landsat type images, to fill the area in between the terrestrial sample plots by deriving the needed forest information from the spectral signatures of the images, and to use the terrestrial sample plots as a reference to calibrate the remotely
sensed spectral information. A method to do this has been developed in Finland, and it has been implemented in the Finnish forest inventory (Kilkki and Päivinen, 1987; Tomppo, 1993). This method is based on the kNN (k-nearest-neighbour) algorithm.

The application of this method in mountainous terrain poses problems, which are addressed in this paper.

2 THE KNN METHOD

Only the basic idea of the kNN method for forest inventory purposes making use of information from terrestrial sample plots is described here: There is a number of pixels that coincide with the terrestrial plots where forest information is available. These pixels may be called plot pixels. For any other pixel not being a plot pixel the forest parameters are to be estimated. The spectral signature of such a pixel is compared with the spectral signatures of plot pixels in the same image. A number of k plot pixels is selected that are most similar to the pixel under consideration. k is a small number, e.g. between 1 and 10. The Euclidean distance in multispectral feature space may be taken as similarity measure. The forest information at the k plot pixels is used to assess the forest parameters of the pixel under consideration. In this way, estimates of all the forest parameters that have been surveyed at the plots are obtained for all pixels.

The estimated variables can be both continuous and categorical, using either the k-nearest-neighbour’s mean or mode.

Promising features of the kNN-method are the following:

• kNN is simple to implement but powerful if some preconditions are fulfilled (e.g. sufficient amount of representative terrestrial data).
• As no assumptions are made regarding the shape of distributions in feature space, deviations from normality do not harm the accuracy of the estimations.
• The kNN-method may include spatial information into the estimation process. Varying site properties, e.g. climate and soil, that are responsible for gradients and local characteristics of many forest attributes such as forest composition, can be taken into account by restricting the selection of plot pixels to those from strata with similar site properties.

Estimation accuracy can be assessed by leave-one-out cross-validation. In cross-validation, the sampling data set (in our case: the set of plot pixels) is randomly split into K disjoint subsets of approximately equal size. Each subset is used as a test set in turn, and the other K-1 subsets are put together to form the training set (K-fold cross-validation). When K equals the number of observations n, the procedure is called leave-one-out cross-validation. The system is trained and tested n times (Efron and Tibshirani, 1993).

In the kNN-forest-inventory method, cross-validation is used

• for the tuning of the kNN-parameters und
• for accuracy assessment.

In the method described here, cross-validation is used in addition for the tuning of the parameters of radiometric-topographic normalization.

3 RADIOMETRIC-TOPOGRAPHIC NORMALIZATION

One might argue that the kNN method, being a completely nonparametric method, working without any precondition with regard to spectral signature distributions, should be able to cope with the problem of radiometric-topographic distortions automatically, if one properly defines the neighbourhood for selecting nearest neighbours: One merely has to look for plot pixels at slopes of similar inclination and of similar exposition. However, when narrowing down the set of plot pixels for
spectral comparison by topographic conditions too much, one may not find enough plot pixels of similar forest properties. One therefore has to apply some radiometric-topographic normalization procedure.

One approach would be to apply radiometric topographic normalization as a separate pre-processing step, and to perform kNN classification afterwards. It is however advantageous to use the kNN procedure itself to find the optimal method and the optimal parameters of the radiometric-topographic normalization. Thus the huge amount of forest reference data originating from the field inventory is used in order to improve radiometric-topographic normalization.

There are different normalization methods to choose from. They are listed in table 1:

<table>
<thead>
<tr>
<th>Correction Method</th>
<th>Non-Lambert. reflection</th>
<th>Diffuse sky radiation</th>
<th>Canopy geometry</th>
<th>Object independence</th>
<th>Oblique sensor directions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cosine</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>C-Correction</td>
<td>--</td>
<td>✓</td>
<td>--</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Minnaert</td>
<td>✓</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>✓</td>
</tr>
<tr>
<td>SCS original</td>
<td>✓ (forests)</td>
<td>--</td>
<td>✓</td>
<td>✓ (forests)</td>
<td>--</td>
</tr>
<tr>
<td>SCS extended</td>
<td>✓ (forests)</td>
<td>✓</td>
<td>✓</td>
<td>✓ (forests)</td>
<td>--</td>
</tr>
</tbody>
</table>

The cosine correction accounts for varying irradiation of surfaces of different angle in relation to the incident sun radiation only. The so-called c-correction is similar to the cosine correction, but, in addition, allows for diffuse sky radiation. These two methods assume Lambertian surfaces. They are, therefore, not particularly suited for forest canopy surfaces. The Minnaert correction is applicable for non-Lambertian surfaces and is widely used. It has, however, two deficiencies: It is object-dependent, that means one has to know the surface characteristics before one can apply the correction. Of course, one has to perform the correction before one can classify an image, which in turn is a prerequisite for determining the surface characteristics. Thus one has a circular problem,
and the best one can do is to apply an iterative procedure. The second problem with Minnaert is even more profound: Although the Minnaert correction accounts for non-Lambertian surface characteristics, it works only with the angles between direction to the sun, direction to the sensor, and surface normal. It does not account for the distinguished status of the vertical direction - it does not account for the fact that trees are growing vertically. If comparing sloped terrain and flat terrain with the same angles between sun direction, surface normal and sensor direction, then Minnaert gives identical results, which means that trees are assumed to grow as indicated in Fig. 1. As a consequence, the Minnaert correction may be good for soils, for rocks and similar surfaces, but not for forest.

There is another normalization method, which does not have these problems of the Minnaert method. It is the so-called SCS (surface-canopy-sensor)-method, introduced by Gu and Gillespie in 1998. In this method, special forest characteristics like tree crown shape and crown closure have no influence. It is therefore not required to know the forest type beforehand. Moreover, the vertical direction has a prominent status - the method accounts for the fact that trees are growing vertically.

The independence of the SCS method from canopy characteristics sounds incredible. The explanation for this can be found in a simplifying assumption: all shadow areas as seen from the sensor are assumed to have no radiance at all. Only direct sun radiation is taken into account, diffuse sky radiation and multiple reflections are neglected. The resulting model is very simple and elegant.

The radiation-surface-interaction of forested surfaces is considered at three levels, tree elements (leaves and branches), tree crown and canopy.

Since the habit of trees is not affected by topography, interactions at the first two levels are considered to be independent of topography. Consequently, the direct irradiance (i.e. energy per unit area) on the sunlit portions of individual tree crowns is not affected by topography.

The total area of the sunlit portions of the canopy, however, depends on topography. Therefore, the SCS-approach normalizes the canopy’s sunlit area in order to remove topographic effects. The

![Figure 2. Horizontal projection of the area per pixel of the sunlit part of the canopy on sloped terrain ($A_0$) and on horizontal terrain ($A_N$)
radiation on the sunlit canopies is kept invariant and the sun-crown-geometry is preserved.

In order to formulate the SCS-model it has to be found out, how the canopy’s sunlit area per pixel varies with topography. More precisely, the sunlit area per pixel is a function of the geometry between sun, sensor and terrain as well as forest canopy characteristics, such as forest cover type, age, and tree density.

Gu and Gillespie arrive at the relationship described in equations (1) and (2) (see also Fig. 2):

\[
\frac{A_O}{A_N} = \frac{L_O}{L_N} = \frac{\cos i}{\cos \alpha \cdot \cos \vartheta_s} \tag{1}
\]

\[
L_N = L_O \cdot \frac{\cos \alpha \cdot \cos \vartheta_s}{\cos i} \tag{2}
\]

\(A_O\) ... horizontal projection of the area of the sunlit part of the canopy on the sloped terrain
\(A_N\) ... horizontal projection of the area of the sunlit part of the canopy on the horizontal terrain
\(L_O\) ... radiance arriving at the sensor from pixels on the sloped terrain
\(L_N\) ... radiance arriving at the sensor from pixels on the horizontal terrain
\(\alpha\) ... slope of the terrain surface
\(i\) ... sun incidence angle measured from the surface normal
\(\vartheta_s\) ... sun zenith angle

Diffuse sky radiation is neglected here. We put up an empirical equation in which the dependence of \(L_0\) on the slope angle is restricted to a fraction \(c_S\) of the total radiance \(L_N\), while the remaining fraction \((1 - c_S)\) is considered independent of the slope angle. \(c_S\) and \((1 - c_S)\) correspond to the proportions of direct solar radiation and of diffuse sky radiation.

\[
L_O = c_S \cdot L_N \cdot \frac{\cos i}{\cos \alpha \cdot \cos \vartheta_s} + c_D \cdot L_N \tag{3}
\]

\[
L_N = L_O \cdot \frac{\cos \alpha \cdot \cos \vartheta_s}{c_S \cdot \cos i + c_D \cdot \cos \alpha \cdot \cos \vartheta_s} \tag{4}
\]

\(c_S\) is estimated from the image itself as described below.

4 PARAMETER TUNING BY CROSS VALIDATION

Fig. 3 shows the overall workflow of the kNN method. Starting from the two input data sets “inventory data” and “satellite image data”, maps and statistics for predefined areal entities may be produced, together with figures of accuracy of these data products.

The kNN parameters governing the prediction (classification) process include weights of the different spectral bands used to calculate spectral similarity, parameters describing the weighting function for the spectral distance, characteristics of the spatial neighbourhood (e.g. maximal geographical distances in horizontal and vertical directions for the search of similar plot pixels), and the value of k.
Figure 3. Workflow of kNN method

Starting with an initial choice of the kNN parameters, the performance of the classification algorithm is evaluated by leave-one-out cross validation. The root-mean-square difference between estimated and observed forest parameters at the plot pixels or the overall classification accuracy is used as performance parameter. The kNN parameters are then varied until the set with the best estimation performance is found. Manual trial-and-error or automated optimisation methods (e.g. downhill simplex method) may be used.

The radiometric-topographic normalization can be included in this parameter optimisation loop. Both the type of normalization and, if applicable, parameter(s) of the normalization (e.g. the $c_s$ value of the extended SCS-method) may be optimized.

5 STUDY AREA AND RESULTS

The study was conducted in two areas:
Study area 1: This study area is located in Lower Austria (eastern part of Austria) and represents optimal conditions referring to topography, availability of topographic information (DTM 25 m), number of available training data and cloud cover.
Study area 2: This study area is located in Tyrol (western part of Austria) and was selected as it is a challenge in many respects. It is in the alpine region and contains only a small number of training data due to scene size (quarter scene) and cloud cover.

Various parameter tuning runs were performed with these data sets.

In study area 1, the Minnaert method and the SCS methods showed equal performance, which seems to be due to the moderate topographic situation. The performance of the Minnaert method, however, depends on the use of appropriate Minnaert factors that are specific for forest characteristics (e.g. tree species, age, density). They are available for the sample plots in the training sample, but not for other pixels for which the forest parameters are to be estimated.

In study area 2, the enhanced SCS method yielded best results. Problems arose, however, from the fact that few plot pixels are available, and that they are very unequally distributed over the classes of forest cover type. Therefore, the prediction error assessed by cross-validation was not very reliable, and the correction methods could not be evaluated satisfactorily.
“Conventional” estimation of the the \( c_S \) value with the help of linear regression was used here in addition to parameter estimation by kNN tuning. A larger number of pixels from a wide range of irradiation conditions was used. Fig. 4 shows the regression coefficients for different values of \( c_S \) for TM2 to TM5 and TM7. The optimal values of \( c_S \) are indicated by a regression coefficient of 0, whereas positive and negative coefficients indicate undercorrection and overcorrection respectively. \( c_S \) optimisation successfully counteracts overcorrection in areas that are poorly irradiated. However, this method of estimating radiometric-topographic correction parameters by regression relies on the assumption that the forest pixels selected at different irradiation conditions represent (in the statistical average) identical forest conditions – an assumption that remains unproved.

Employing the enhanced SCS method, the quality of forest cover type estimation by the kNN method, as measured by the overall classification accuracy, could be increased by approximately 5%.

6 CONCLUSION AND OUTLOOK

The SCS method, extended for including diffuse sky radiation, is found to be particularly suited for radiometric-topographic correction of forest areas on satellite images. It significantly enhances the accuracy of the assessment of forest parameters by the kNN method in mountainous terrain. It is easy to implement so that it is considered to be suitable for operational applications.

Estimating parameters of radiometric-topographic correction algorithms (such as the ratio of direct sun radiation and diffuse sky radiation in case of the extended SCS method) from the image itself by regression of forest pixels arbitrarily selected at different topographic conditions relies on the assumption that the forest pixels selected at different irradiation conditions represent (in the statistical average) identical forest conditions. This assumption can hardly be proved. The estimation of this parameter by tuning within the kNN cross-validation procedure, on the other hand, represents a sound method, making use of the large amount of forest information available from terres-
trial forest inventories. The practicability of this method depends on the number and thematic distribution of field plots on one single scene, for which homogenous atmospheric conditions can be assumed.

Improvements are to be expected from enhancements of the method - which so far is completely nonparametric - by atmospheric and/or forest-spectral models.

ACKNOWLEDGEMENT

This work was performed within a project financed by the Austrian Federal Ministry of Agriculture, Forestry, Environment and Water Management, in collaboration with the Austrian Federal Office and Research Centre for Forests.

REFERENCES


