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OBJECT-DEPENDENT SPATIAL VARIATIONS OF SPECTRAL SIGNATURES ON INFRARED COLOUR AERIAL PHOTOGRAPHS

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Abstract

Methods for determining object-specific spatial distributions of colour density on aerial photographs are described. The distributions are obtained by adjustment calculation from density measurements on sample areas imaged at least twice on neighbouring photographs.
Examples of data on space-dependent colour densities of tree species deduced by these methods are presented. Improvements in classification accuracy after preprocessing steps compensating these spatial variations are demonstrated. Finally, a classification method making deliberate use of the object-specific spatial distributions of colour density is described.

1. Introduction

Infrared colour aerial photographs represent, in a qualified sense, three-channel radiometric data that can be used for automatic object identification and thematic mapping. A major difficulty, however, arises from the fact that spectral signatures of objects usually depend on the view angle (α, β) at which the objects are sensed, and hence on their position (x, y) on the aerial photograph.

As a consequence of this spatial variation of signatures, clusters of object classes in the three-dimensional signature space tend to spread out, thus affecting the selectivity of a classification based on these signatures.

It is therefore highly desirable to obtain detailed information on the space-dependence of signatures in order to be able to compensate it in a preprocessing step.

In principle one could try to quantify the individual components contributing to this space dependence, such as

- view-angle dependent object reflectivity (mainly caused by a view-angle dependent ratio of sun-lit and shadowed areas) $\varrho(\alpha, \beta)$ [1-3],
- atmospheric transmission $\tau_A(\alpha, \beta)$ [4],
- atmospheric path radiance (haze) $E_A(\alpha, \beta)$ [4],
- off-axis illumination loss of camera lens and filters $\tau_L(\alpha, \beta)$ [5]
- and non-uniform development [6].

Tracing the image formation process from the illumination conditions of the scene to the final development of the photographic image, one could then determine the overall effect of spatial density variation on the aerial photograph:

$$D_i^{(j)}(x,y) = f^{(j)}\left[x, y, \left(E^{(j)} \cdot \varrho^{(j)}(\alpha,\beta) \cdot \tau_A^{(j)}(\alpha,\beta) + E_A^{(j)}(\alpha,\beta)\right) \cdot \tau_L^{(j)}(\alpha,\beta) \cdot t\right] . \qquad (1)$$

In this equation, j denotes the spectral channel, $D_i^{(j)}(x,y)$ is the colour density of object i in spectral channel j measured at position (x,y) on the photograph, $f^{(j)}(x,y,E)$ represents the space-dependent transfer characteristic of the photographic material, $E^{(j)}$ is the irradiance of the scene in channel j , and t is the exposure time.

This procedure, however, would be too complicated to be applied in practice.

On the other hand, it is possible to derive the spatial variations of signatures directly from a set of objects each of which is imaged at least twice in the overlapping regions of neighbouring photographs. In this communication, a new method based on this idea is described in the context of other techniques for determining spatial signature variations. Data on space-dependent colour densities of tree species deduced by this method are presented. Improvements in classification accuracy after preprocessing steps compensating these spatial variations are demonstrated. Finally, a classification method making deliberate use of the object-specific spatial dependence of spectral signatures is described (as proposed e.g. in [7]).

2. Determination of the spatial variation of signatures by adjustment calculation

In the following, it is assumed that the objects to be identified on aerial photographs can be classified into distinct categories. The spatial dependence of the colour densities of all objects belonging to a given category A may be described by functions

$$D_i^{(j)}(x,y) = g_A^{(j)}\left(D_{io}^{(j)}, x, y\right), \qquad (2)$$

where $D_{io}^{(j)}$ is the "standardized" density for colour j of object i (colour density that would have been observed for object i located at position (0, 0)). No assumptions are made on the homogeneity of the colour densities within one category (e.g. tree species). It can even be divided into subclasses (e.g.according to degree of stress) of distinguishable spectral signatures, as long as the functions describing the spatial variations of signatures are identical for all subclasses.

The image coordinate system is assumed to have its origin at the principal point of the image, with the x-axis parallel to the direction of incident sunlight (fig. 1). In this case it can be assumed that the spatial variations of signatures (except the contribution of nonuniform development) is symmetrical with respect to the x-axis, i.e., the corresponding functions are even functions of y.

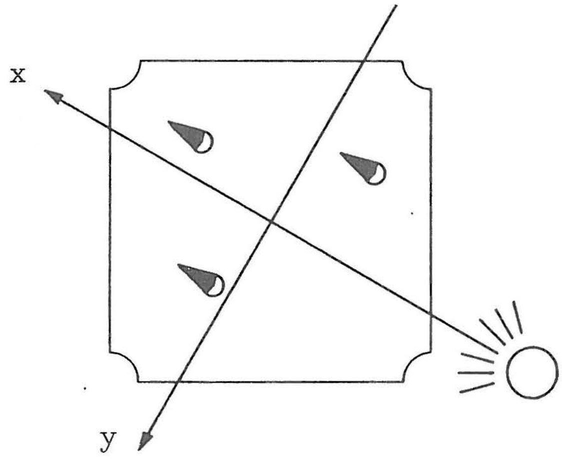

Fig. 1: Image coordinate system

In order to be able to determine functions $g_A^{(j)}$ by adjustment calculation from measurements on the aerial photographs, certain assumptions concerning the type of these functions have to be made. Using the model described by equ. (1), the following cases can be distinguished (index j is omitted from now):

a) Linear relationship between density D and the logarithm of exposure:

$$f(x,y,E\cdot t) \equiv K(x,y) + \gamma(x,y)\cdot \log(E\cdot t)\,. \tag{3}$$

In equ. (3), $K(x,y)$ represents the segment of the characteristic curve on the density axis, and $\gamma(x,y)$ is the gradation [6] .

This assumption will be satisfied mainly for low-contrast black-and-white films. For colour films only under certain circumstances (low contrast objects, optimum exposure conditions).

aa) Uniform photographic development conditions: $\gamma(x,y) = \gamma_c$, $K(x,y) = K_c$.
Films processed by automatic processing machines will more likely satisfy this condition than films processed by rewind methods.

aaa) Negligible atmospheric path radiance: $E_A = 0$.
This case may apply at clear weather conditions, at low sun angles, and for long-wavelength channels. Only multiplicative factors are left, which modify the irradiance (i.e., additive terms modifying the photographic density) [8]:

$$D_i(x,y) = D_{io} + a(x,y)\,. \tag{4}$$

aaaa) Quasi-random distribution of samples of the various subclasses of one category [8]: The average signal at each position (x,y) on the photograph (calculated by multiple regression) then is a measure of the spatial dependence of the signatures. If an adjustment function of second degree of the form $a_0 + a_1x + a_2x^2 + a_3y^2$ (in agreement with the above-mentioned symmetry with respect to the x - axis) is determined, then the additive term of equ. (4) is obtained as

$$a(x,y) = a_1x + a_2x^2 + a_3y^2\,. \tag{5}$$

aaab) Arbitrary distribution of samples of the various subclasses of one category: For every pair of density values $D_i(x_1, y_1)$, $D_i(x_2, y_2)$ obtained from one and the same object imaged in the overlapping region on two adjacent photographs the difference between the "standardized" densities D_{io} calculated from both values according to equ. (4) should be a minimum. Again substituting a second-degree polynomial for $a(x,y)$, the unknown coefficients a_1, a_2, a_3 can be calculated by adjustment of the "observation equations"

$$v = D_i(x_1,y_1) - D_i(x_2,y_2) - a_1(x_1-x_2) - a_2(x_1^2-x_2^2) - a_3(y_1^2-y_2^2). \tag{6}$$

aab) In the presence of atmospheric path radiance it is advisable to take the antilogarithm of equ. (3) substituted in equ. (1) and to work with irradiances [8]:

$$E_i(x,y) = \frac{1}{t} \cdot 10^{\frac{D_i(x,y) - K_c}{\gamma_c}} \tag{7}$$

The spatial variations of the irradiances are now characterized by a multiplicative and an additive term (the latter representing the influence of atmospheric path radiance, modified by off-axis lens losses):

$$E_i(x,y) = E_{ic} \cdot m(x,y) + a(x,y). \tag{8}$$

For every pair of irradiance values $E_i(x_1,y_1)$, $E_i(x_2,y_2)$ obtained from one and the same object imaged in the overlapping region on two adjacent photographs one observation equation of the form

$$E_i(x_1,y_1) + v = \frac{E_i(x_2,y_2) - a(x_2,y_2)}{m(x_2,y_2)} \cdot m(x_1,y_1) + a(x_1,y_1) \tag{9}$$

is obtained. Substituting $a(x,y)$ according to equ. (5) and

$$m(x,y) = 1 + m_1 x + m_2 x^2 + m_3 y^2, \tag{10}$$

the unknown coefficients $a_1, a_2, a_3, m_1, m_2, m_3$ can be obtained by adjustment of observation equations.

ab) Nonuniform photographic development conditions:
This case can be treated in analogy to aab), if the photographic nonuniformities (functions $\gamma(x,y)$ and $K(x,y)$) are known. This case has also been dealt with in detail by Sievers [6].

b) Nonlinear relationship between D and log $(E \cdot t)$:

Inspection of typical characteristic curves of infrared colour films (fig. 2) [9] reveals that the postulate of a linear relationship between D and log $(E \cdot t)$ often is not valid in practice. As an example, on the aerial photographs used for this investigation the average sun-lit scene has densities corresponding to exposure $E_1 \cdot t$ as shown in fig. 2, while the average shadowed scene has densities corresponding to exposure $E_2 \cdot t$. Taking into account that, especially on forest aerial photographs, the fraction of sun-lit portions of one and the same homogeneous sample area may, depending on the view angle, vary between almost 0 % and almost 100 %, it becomes clear that a nonlinear relationship D - log$(E \cdot t)$ must be assumed.

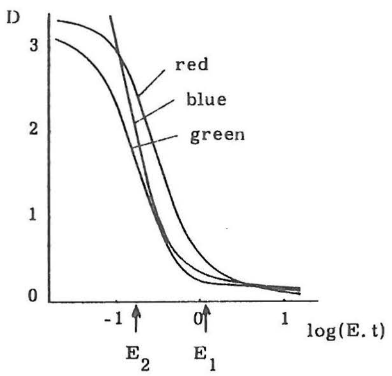

Fig. 2 : Characteristic curves of infrared colour film [9]

In this case, a purely empirical function

$$D_i(x,y) = D_{io} \cdot m(x,y) + a(x,y) \tag{11}$$

with polynomials $a(x,y)$ and $m(x,y)$ according to equs. (5) and (10) may be postulated. The coefficients of these polynomials can be obtained by adjustment of observations in complete analogy to aab).

3. Examples of spatial variations of colour densities on forest aerial photographs

The photographs used for this investigation were taken on Aerochrome Infrared film 2443 with a Wild RC-10 camera equipped with an Aviotar f = 30 cm lens, from a height of approximately 2100 m above ground. Approximately 200 homogeneous sample areas of beech, spruce and pine stands were localized in the field and on the photographs. On the average, every sample area could be identified on three neighbouring photographs. Colour density measurements at the resulting 600 positions on the photographs were performed using a densitometer Macbeth TD 504 with measuring apertures varying between 1 mm and 3 mm, depending on the size of the homogeneous sample areas .

Image coordinates of the sample areas were determined and transformed to a coordinate system oriented relative to the direction of incident sunlight according to fig. 1.

The spatial variations of the colour densities of the different tree species were computed according to the methods described above. As an example, functions $m(x,y)$ and $a(x,y)$ of equ. (11) are reproduced in fig. 3 for colour channel blue and tree species beech and spruce. The "standardized" density values $D_{io}^{(j)}$ of individual sample areas, calculated with the aid of these functions from density measurements $D_i^{(j)}(x,y)$ at different positions on the photographs, have standard deviations as low as 0˙02, 0˙03 and 0˙04, depending on colour channel and tree species. It must be stressed that, despite of this excellent degree of "standardization", deviations between density values of different sample areas within one category are not reduced. The full information content of the data with respect to further differentiation of samples within one category therefore is maintained.

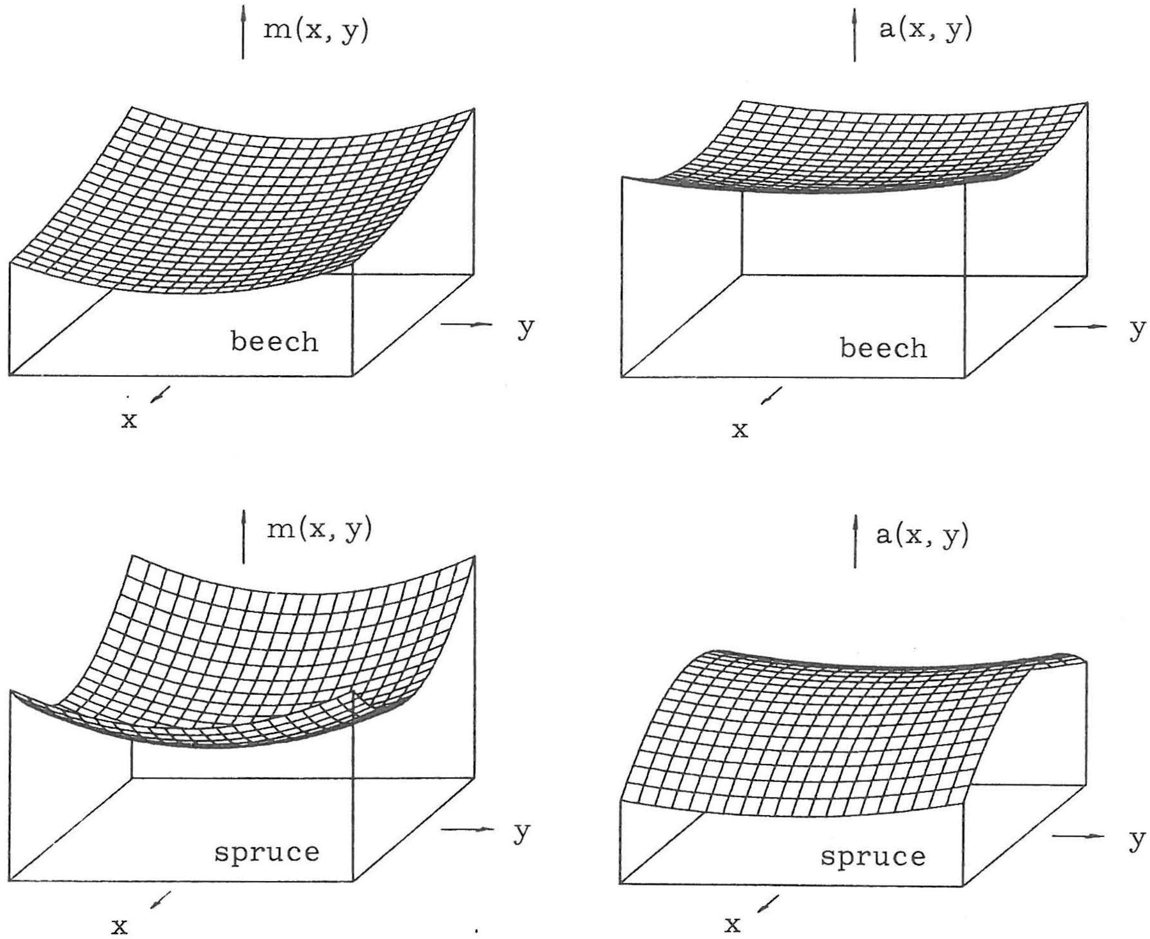

Fig. 3: Multiplicative and additive density variation functions for colour channel "blue"

4. Improvements in classification accuracy by compensating spatial density variations

Compensation of spatial variations of densities is a useful preprocessing method in order to improve the selectivity of a subsequent classification process. Strictly speaking, the "standardization" of density values according to the methods described above can be performed only for one category of objects (e.g. tree species). If, however, a standardization algorithm for object category A is applied to an entire image, the overlap between object category A and the other categories in density space is nevertheless reduced.

In order to demonstrate this, plots of the one-σ-boundaries of clusters of 3 tree species in "standardized" colour density spaces are reproduced in fig. 4 . For comparison, a plot of clusters obtained after preprocessing by ratioing [10] is included.

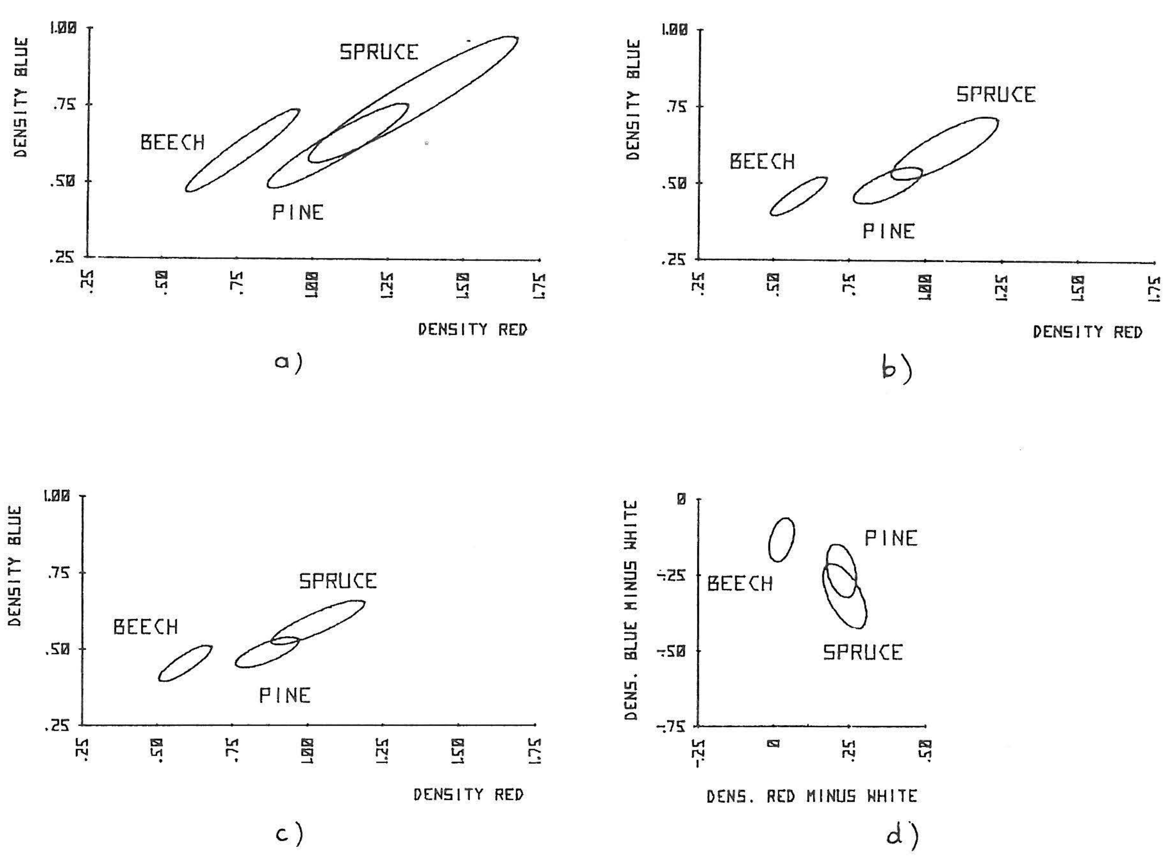

Fig. 4: One-σ-boundaries of clusters in colour density spaces: a) original densities, b) densities corrected according to equ. (11) for beech, c) densities corrected according to equ. (11) for spruce, d) differences of densities (corresponding to ratios of irradiances).

5. Classification based on object-specific spatial variations of signatures

Sample areas in the overlapping region of neighbouring photographs can be classified on the basis of differences in the spatial variation of densities, provided that density values from at least two different photographs are available for every sample area:

Every density value $D_i(x,y)$ of a sample area of unknown category is converted to "standardized" density values D_{io} under the assumptions that the sample area belongs to categories A, B, C etc. The sample area is then assigned to the category with the minimum standard deviation of the values of D_{io} calculated from the various (at least two) values of $D_i(x,y)$.

This method has been tested using pairs of density measurements made with white light on neighbouring photographs. In fig. 5, the frequency distributions of the quantity

$$\Delta = |D_{i1S} - D_{i2S}| - |D_{i1B} - D_{i2B}| \tag{12}$$

are shown for sample areas of beech and of spruce. In equ. (12), D_{i1B} and D_{i2B} (D_{i1S} and D_{i2S}) are the "standardized" density values calculated from density values of the same sample area measured on neighbouring photographs at positions 1 and 2, respectively, under the assumption that the sample belongs to category beech (spruce). It can be seen from fig. 5 that approximately 75 % of all samples could be classified correctly.

No spectral information is used for this classification. The discrimination between the two categories is possible because of the different form of canopy surfaces of beech and spruce stands, which influences the view-angle-dependent ratio of sunlit and shadowed areas.

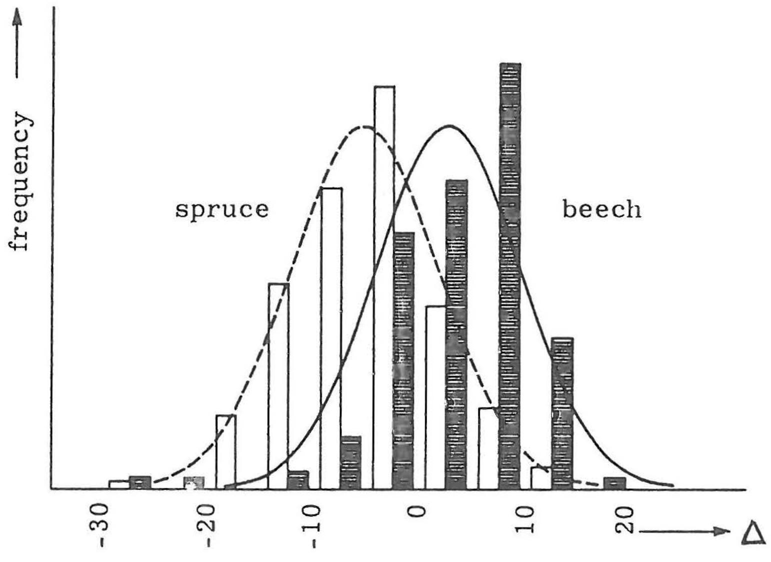

Fig. 5: Classification according to spatial density variation features

6. Conclusions

Methods for determining the spatial distributions of colour density on aerial photographs from density measurements on sample areas imaged at least twice on neighbouring photographs have been described. No assumptions are necessary concerning the distribution of sample areas on the photographs.

It has been demonstrated that information on spatial distributions of colour densities thus obtained is important

a) for the compensation of disturbing density variations prior to automatic photointerpretation.

b) for classification methods making deliberate use of object-specific spatial variations.

Further investigations mainly on the problem of the optimum degree of the polynomials used in the adjustment computations are necessary.

References

[1] Hildebrandt, G.: Die spektralen Reflexionseigenschaften der Vegetation. Remote Sensing in Forestry. Proc. of the Symp. held during the XVI. IUFRO World Congress, Oslo, June 1976, p 9 - 22.

[2] Richardson, A.J., et al.: Plant, Soil, and Shadow Reflectance Components of Row Crops. Phot. Eng. and Rem. Sens., 41 (1975), p 1401 - 7.

[3] Hoffer, R.M., Holmes, R.A., Shay, J.R.: Vegetative, Soil, and Photographic Factors Affecting Tone in Agricultural Remote Multispectral Sensing. Proc. 4th Int. Symp. on Remote Sensing of Environm., 1966, p 115-34.

[4] Turner, R.E., Malila, W.A., Nalepka, R.F.: Importance of Atmospheric Scattering in Remote Sensing (or Everything You Always Wanted to Know About Atmospheric Scattering But Were Afraid to Ask). Proc. 7th Int.Symp. on Remote Sensing of Environm., 1971, p 1651 - 97.

[5] Bähr, H.-P.: Analytische Bestimmung und digitale Korrektur des Lichtabfalls in Bildern eines Hochleistungsobjektivs. BuL 47 (1979) p 81-7.

[6] Sievers, J.: Density Corrections and Directional Reflectances of Terrain Objects from Black-and-White Aerial Photos. Photogrammetria 33 (1977) p 95-112.

[7] Steiner, D., Haefner, H.: Tone Distortions for Automated Interpretation. Phot. Eng. 31 (1965) p 269-8.

[8] Nalepka, R.F., Morgenstern, J.P.: Signature Extension Techniques Applied to Multispectral Scanner Data. Proc. 8th Int. Symp. on Remote Sensing of Environm., 1972, p 881-93.

[9] Kodak Data for Aerial Photography. Kodak Publication No. M-29.

[10] Quiel, F.: Zur Vorverarbeitung multispektraler Daten. BuL 44 (1976) p 42-44.