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Study of Sealed Surfaces and Diurnal Temperature Variations in Urban Environments with Airborne Scanner Data

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ABSTRACT

The composition of surfaces in urban areas has a strong influence on urban climate and therefore on the quality of life. In general sealed surfaces will cause a stronger daytime heating in comparison to vegetated areas. Using remotely sensed data it is possible to monitor the extent of surface sealing and its effect on surface temperature.
Furthermore, the determination of thermal behaviour with regard to solar heating can be used to discriminate between different surface types. In this study we investigate the usefulness of remotely sensed temperatures of a part of the diurnal brightness temperature curve for unsupervised classification purposes in an urban environment, in particular for sealed and unsealed surfaces. Thermal image data were taken with the thermal IR channel of the Daedalus AADS 1268 scanner at four different times (4:30, 8:30, 11:30, 12:30 MET). We propose a straightforward method to classify a scene into vegetated and non vegetated regions based solely on thermal data. No spectral bands in the frequency range of reflected sunlight were used, accepting worse classification accuracies for the benefit of a more accurate interpretation of the results.

1 INTRODUCTION

Thermal infrared measurements of vegetation surface temperatures are widely used to calculate heatfluxes (Gash 1987) and to determine surface conditions and heating properties (e.g. urban heat island, (Kim 1992)). On the other hand thermal data has been used for classification purposes in only very few investigations (e.g. (Leak & Venugopal 1990), (Lambin & Strahler 1994)), requiring a deeper understanding (Price 1981). This is due to the fact that the surface temperature is not a material property like albedo but results from the balance between incoming and outgoing energy fluxes. Since many passive remote sensing systems acting in the frequency range of reflected sunlight have also the ability to measure thermal infrared radiation, a useful source of information is wasted by not using this data.

In order to calculate material properties from thermal measurements we have to examine the thermal response of a substance with regard to time-varying incoming power. This response which is mainly determined by the thermal inertia of the substance. So temperature measurements at different times of a day provide an appropriate basis for classification purposes. To illustrate this idea we have calculated part of the diurnal temperature curves of two substances having different values of thermal inertia (Figure 1). The underlying model is described in (Price 1977). Note the distinguishability of the two curves, particularly based upon different morning slopes and noon temperatures.

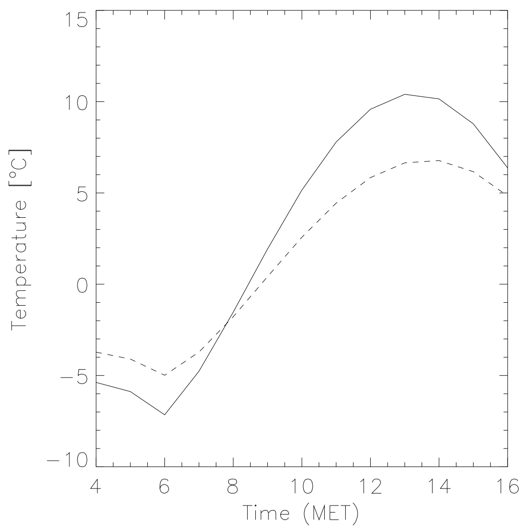

Figure 1: Modeled surface temperature curves of two surface types under solar irradiation (daily mean temperatures cannot be calculated with this model). All parameters but thermal inertia P are arbitrary chosen and equal for both surface types (dashed line: P= $0.1\ cal/cm^2 s^{1/2}$ °C, solid line: P= $0.05\ cal/cm^2 s^{1/2}$C).

If some regions of interest have already been defined (in the so called *training* of the data set or by an initial unsupervised classification) it may be useful to take the distribition of temperature values into account for classification purposes (Holbe & Luvall 1989). We will show one possibility to use this source of information.

We derive characteristic features of vegetational and non-vegetational surface types from remotely sensed temperature data which allow a grouping of the thermal image data into these two categories. In order to assess classification accuracy we compare our results with NDVI based vegetation detection.

2 DATA SET

The analyzed imagery was recorded by a DAEDALUS AADS 1268 line scanner on board a Dornier Do 228 aircraft yielding a multispectral data set consisting of ten reflective bands and one band in the thermal infrared. The experiment took place at the 26 August, 1997, in late summer. We chose parts of the city of Nuremberg, Germany, as test site. The flight altitudes of 300 m and 900 m yielded geometric ground resolutions of about one and three meters, respectively. The data was recorded at 4:30, 8:30, 11:30 and 12:30 (MET), in order to measure a characteristic part of the diurnal temperature curve.

Atmospheric corrections were performed by using the SENSAT/MODTRAN code (Richter 1992) relying on standard atmospheric parameters supplemented by ground measurements of meteorological data. In this paper we only use brightness temperatures, because no correction for emissivities is possible (and required) to perform an unsupervised classification. Having this simplification in mind, we use the notion of temperature for abbreviation purpose. From the data set a small scene showing the airport of Nuremberg was extracted for every overflight. The early morning image was taken as reference on which the images were registered using Akima local quintic polynomial interpolation (Wiemker 1996). This scene is well suited for our work because it contains different types of concrete and roofs, dense and light grass areas and trees. The four-dimensional temperature data set resulting from the four overflights provides the basis for the investigations described below.

3 THERMAL PROPERTIES OF DIFFERENT SURFACE TYPES

In this section we briefly describe two kinds of information contained in the data set that was used for classification.

3.1 TEMPERATURE CURVES

To take a first look at the data set described in Section 2 we defined several regions of interest from aerial photographs representing different surface types. The corresponding averaged temperatures of each region are plotted in Figure 2. Grassland and concrete are represented by two curves each to describe a brighter and darker region in the aerial photographs respectively (corresponding to a brighter resp. darker colored concrete and a thicker resp. more sparsely vegetated grassland). For illustration purpose the two-dimensional his-

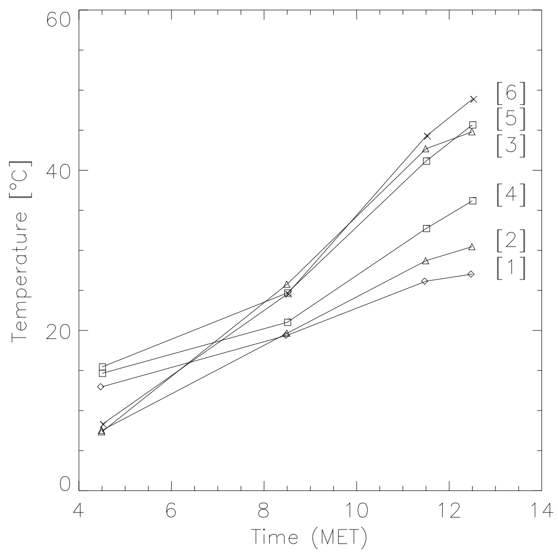

Figure 2: Temperature curves averaged over the regions of various surface types ([1]: trees, [2]: grass (dense), [3]: grass (sparse), [4]: concrete (bright), [5]: concrete (dark), [6]: various roofs)

tograms of early morning and noon temperatures of the same regions are shown in Figure 3.

With regard to a classification application based solely upon the temperature data Figure 2 shows some remarkable features:

- as expected from model runs trees and thick vegetated grassland have flatter temperature curves with relatively low noon values corresponding to high thermal inertia values. It should be easy to separate these substances from other materials,
- roofs have the steepest curve and highest noon temperatures,
- bright concrete and sparse grassland have nearly the same heating behaviour and are expected to be hardly distinguishable.

So temperature curves alone will not provide enough information for a proper separation of surface types.

3.2 TEMPERATURE DISTRIBUTIONS

A second source of information based on thermal measurements are the temperature distributions of various surface types. On the right side of Figure 2 some examples corresponding to the temperature curves on the left are shown. It can be seen that roofs have temperature values of about 20° to 80° (of course several roofs were put together in this region of interest) and so have the broadest temperature histograms while concrete surfaces have the smallest.

To draw surface specific information from thermal infrared images (Holbe & Luvall 1989) have modeled surface temperature distributions of forest landscapes using a two-dimensional beta probability distribution. For our purposes the standard

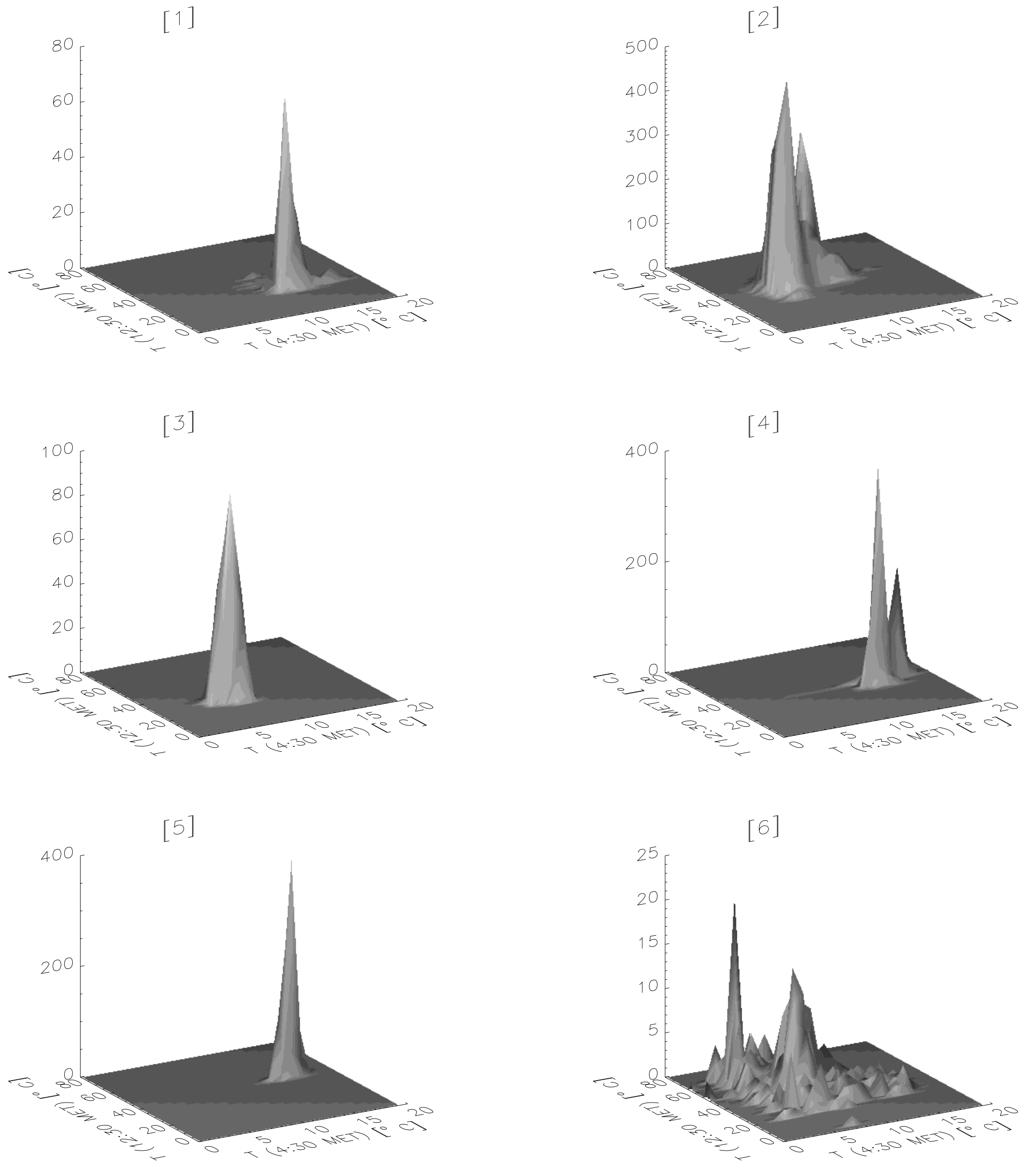

Figure 3: Two-dimensional histograms of temperatures recorded at 4:30 MET (x-axis) and 12:30 MET (y-axis). Note that the axes have different ranges. For the definition of the regions see Figure 2.

Gaussian distribution leads to similar good modeling results providing a much easier computability (see Section 4).

4 CLASSIFICATION METHOD

To separate the pixels of the underlying scene in appropriate classes we used unsupervised k-means-classification (Duda & Hart 1973) which provides a well known algorithm for remote sensing applications. As data set we used four-dimensional temperature vectors described in Section 2.

A striking disadvantage of unsupervised classification techniques is the unknown number of classes which should be used for an appropriate separation of the underlying scene. Therefore the user must preestimate the distinguishability of surface types with regard to their spectral properties. The latter are in general unknown. Furthermore, surface types with similar spectral behaviour will probably not be separated into different classes. In some cases this could be avoided by providing appropriate starting parameters to the unsupervised classification algorithm, the so called *seeds*, instead of using random values. Again a preestimation is required.

To guarantee a high degree of independence from human assessment we apply the following method (see Figure 4):

1. start the classification with an arbitrary number of classes (6 is an appropriate choice for a first guess classification in most scenes)
2. compute the cross correlation of the histograms of early morning and noon temperatures of each resulting class and the Gaussian density function defined by the cor-

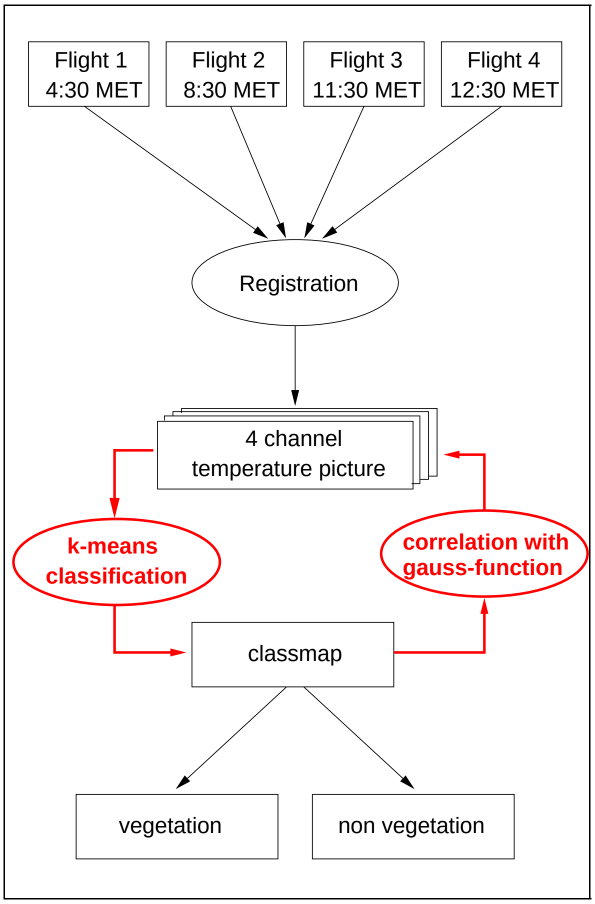

Figure 4: Algorithm used to calculate vegetation maps by using remotely sensed thermal data recorded at different times

responding calculated mean value and standard deviation; if the correlation values are smaller than certain thresholds (we found the values of 0.8 for morning and 0.95 for noon temperature histograms to be appropriate), divide this data subset by a new unsupervised classification into two subsets, if the number of pixels in each subset exceeds a certain threshold (e.g. 1 percent of whole image size)
(The cross correlation C_{XY} between two sample populations X and Y is defined as:

$$C_{XY} = \frac{\sum_{j=1}^{N} (x_j - \bar{x})(y_j - \bar{y})}{\sqrt{\left[\sum_{j=1}^{N} (x_j - \bar{x})^2\right]\left[\sum_{j=1}^{N} (y_j - \bar{y})^2\right]}}$$

with N: number of samples, x_j: j-th element of X, y_j: j-th element of Y.)

3. repeat step 2 until the classmap is constant (a maximum number of iterations should be provided, because man-made surfaces cannot be assumed to have a Gaussian distribution; in our examinations 3 iteration steps yielded sufficiently good results)

In all cases the initial seeds are calculated as random numbers.

Of course correlation of a histogram with a Gaussian density function is not an adequate test for the hypothesis of normality, but for our purposes it provides an appropriate measure of similarity and a feasible deduction of the required thresholds.

The resulting classmap represents a division of the underlying scene in small subsets (10 to 20 classes in our test scene, depending on starting parameters), which can be assumed to have very similar heating behaviour. To separate the found classes into vegetation and non vegetation we took into account the correlation value described above and the noon temperature's standard deviation of the underlying regions. For all classes representing vegetational regions the following observations hold:

- the correlation value calculated from noon temperatures is greater than 0.9
- the noon temperature's standard deviation lies between $2.0°$C and $3.5°$C

Through the correlation value threshold we can exclude classes consisting of small artificial areas with slightly different heating behaviour which have too few pixels to form a class of them own (as it is always the case for several roofs). The histogram of noon temperatures of such a class consists of several peaks representing the areas and therefore yields small correlation values.

The second observation concerns the inhomogeneity of vegetational surfaces. Man-made surfaces tend to have very small temperature ranges because of their homogeneity. Vegetational surfaces have much broader temperature distributions because of shadow and the contribution of the underlying surface (bare soil in most cases), which can be related to the Leaf Area Index (LAI) (Smith & Choudhury 1991). Standard deviations greater than $3.5°$C indicate a class representing various small man-made surfaces.

We found that for classes representing non-vegetational areas either one or both of these observations do not hold, providing us with a method to calculate a vegetation map of the underlying scene.

5 RESULTS

A one-time classification of the described scene does not yield a separation into appropriate classes. E.g. in many attempts light concrete and sparsely vegetated grassland fall into one class (as one would expect from the temperature curves shown in Figure 2). Here a subdivision of the resulting classmap according to the method described above always yields a more sophisticated classification of the underlying scene.

The effect of subdivision is shown in Figure 5. After an initial unsupervised classification with six classes, trees and a metal roof where mixed up in one class. Because of the correlation values being less than the threshold value a second unsupervised classification was performed that provided the division of vegetation and the metal roof.

To test the robustness of the algorithm we classified the airport scene a hundred times using random seeds and performed a pixel-by-pixel comparison of the resulting vegetation maps

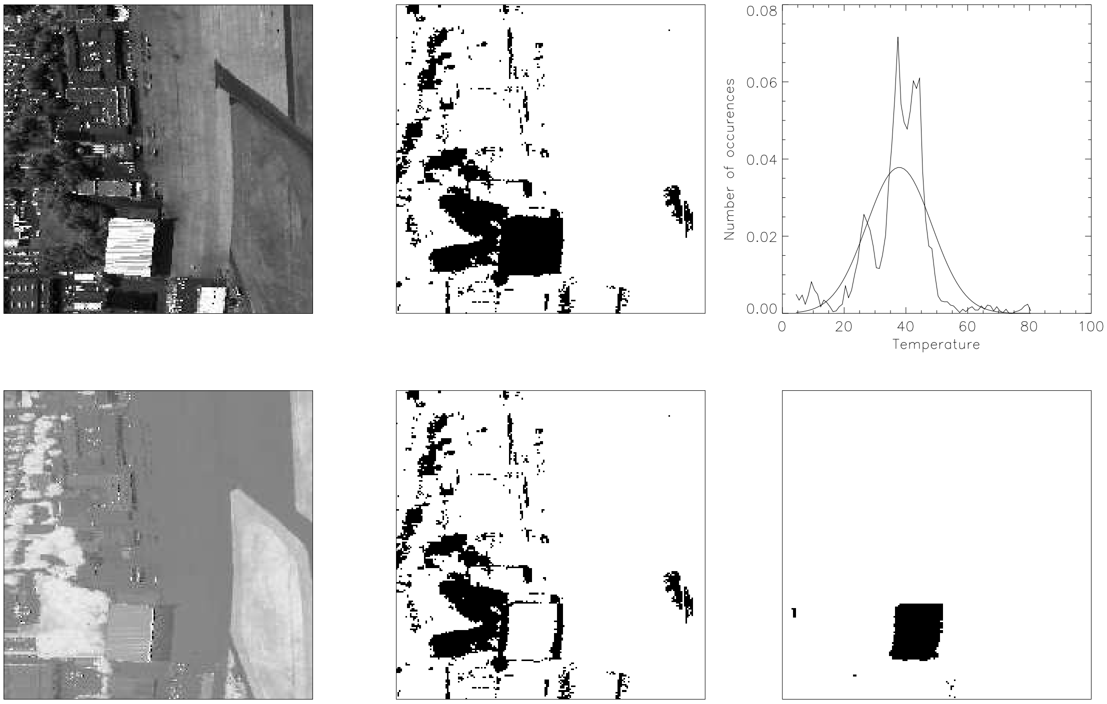

Figure 5: Top: Daedalus channel six image ($0.695 - 0.750\ \mu m$, recorded at 12:30 MET, flight altitude: 300 m), original class (black pixels) and the corresponding histogram of noon temperatures together with the appropriate Gaussian density curve (correlation coefficient: 0.85); below: NDVI-image (recorded at 12:30 MET) and the resulting two images after applying subdivision (step 2). A rectangular metal roof was isolated by this subdivision.

with the ones based on NDVI methods (see figure 7).

$$\boldsymbol{agreement(ndvi > 0.5) = (75 \pm 4)\%}$$
$$\boldsymbol{agreement(ndvi > 0.3) = (79 \pm 8)\%}$$

The errors represent the standard deviation of the agreement values. In Figure 6 two resulting vegetation maps are shown. It can be seen that the maps differ slightly from each other (for the reason of different initial seeds), but even in the worse case shown on the right the agreements with the NDVI-based maps are satisfying.

6 DISCUSSION

The subdividing of the classmap through the correlation mechanism always provides a better separation of the underlying scene in comparison to a one-time unsupervised classification. An inherent disadvantage of this method is the separation of data subsets which the user probably wants to see in one class. But this is inevitable, since man-made surface types cannot be assumed to have Gaussian distributed temperatures.

Another source of misclassification is the necessary assumption that there is no change of the scene contents from one overflight to another. If this is not valid, the concerned objects are probably misclassified because different parts of the corresponding temperature curves belong to different substances. This effect can be seen in Figure 6, where aeroplanes which were only present in the early morning scene are part of the vegetation maps. Areas which are shaded at noon show the same effect.

Registration inaccuracies yield misclassification essentially at the borders of different surface types. Even by using many so called passpoints (corresponding points in different images, up to thirty in our case) it is not possible to get a registration accuracy better than one pixel. Objects with a specific height cannot be registered exactly if the corresponding viewing angles are different.

The proposed algorithm is sensitive to the choice of the initial parameters for the first classification, as expected from the similar heating behaviour of many substances (see Figure 2). On the other hand the subsequent unsupervised classifications providing the subdividing of the "first guess classmap" are robust against the choice of its initial seeds. So the final vegetation map essentially depends on a one time choice of parameters. Providing some adequate temperature values as initial seeds (e.g. from regions of interest or model runs) one can avoid this problem.

At one point the proposed algorithm surpasses the NDVI-based method: with a threshold of 0.3 the latter one classified the metal roof as vegetation (Figure 7), the first one succeeded at this point (Figure 6). This is one example for the statement that by using thermal data one can improve classification results based on other methods.

To illustrate the usefulness of histogram data the temperature curves of all resulting classes for a typical classification

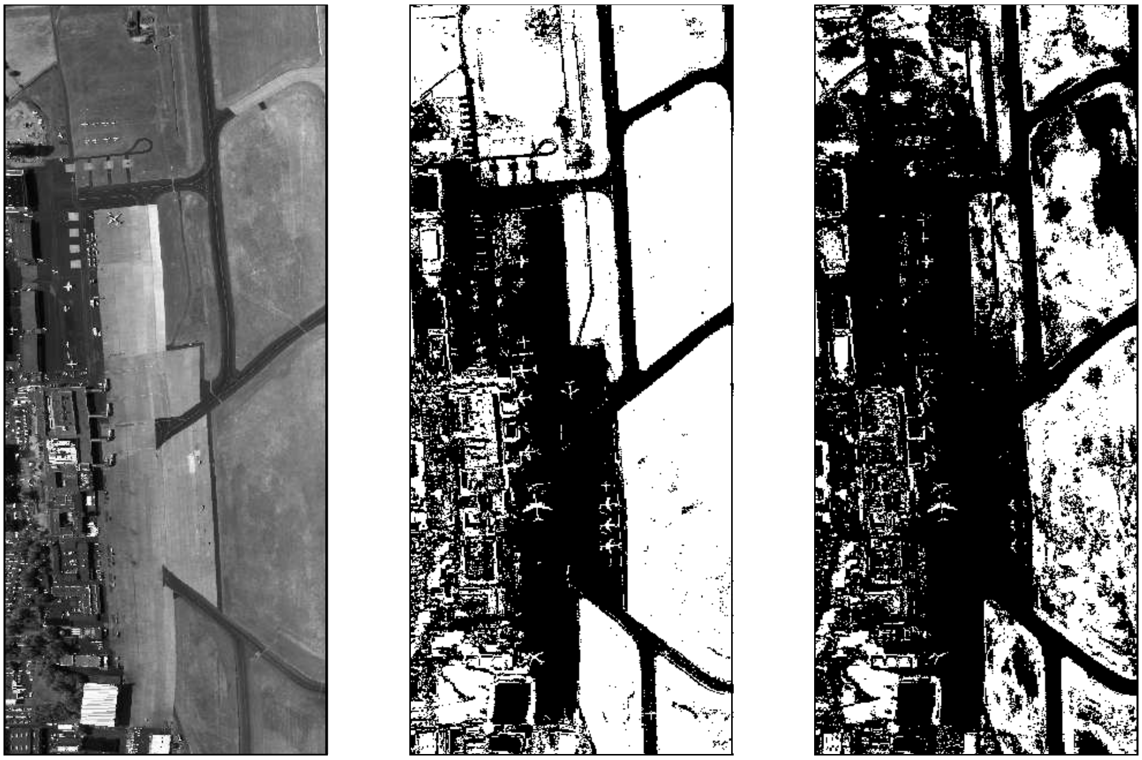

Figure 6: Daedalus channel six image ($0.695 - 0.750\ \mu m$, recorded at 12:30 MET, flight altitude: 300 m) (left) and two vegetation maps calculated with the algorithm described above with different initial seeds. Areas which are classified as vegetation are shown in white.

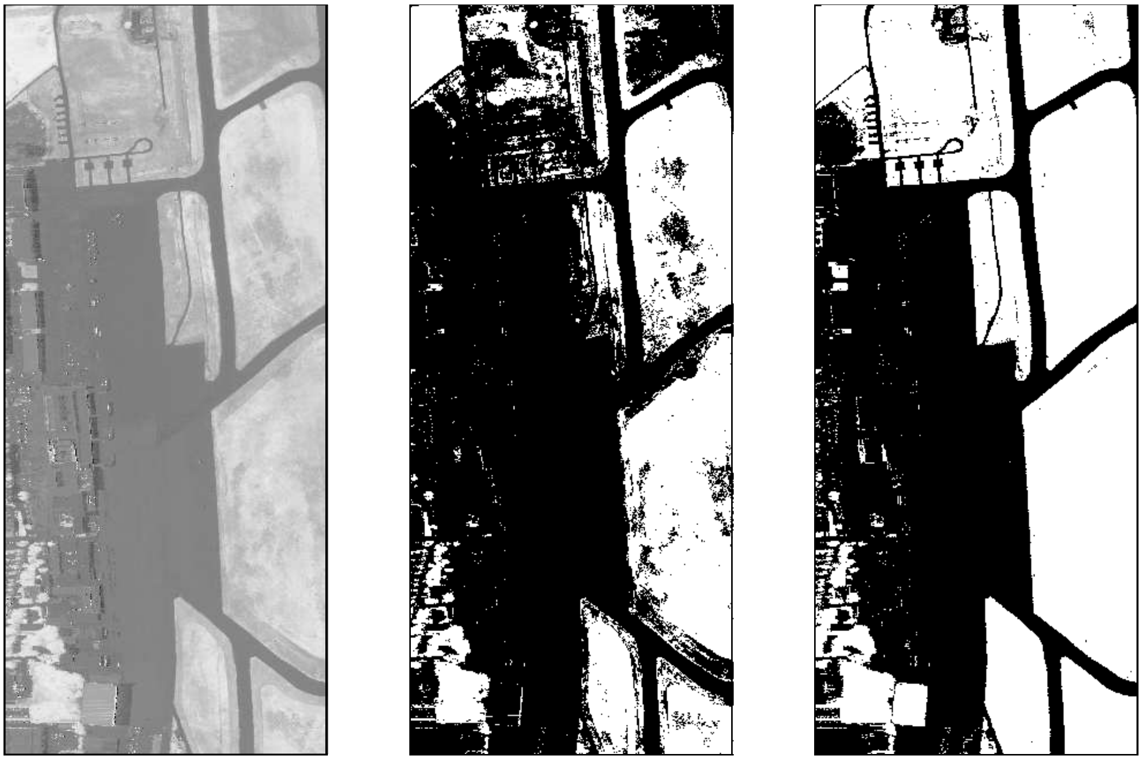

Figure 7: NDVI-image (recorded at 12:30 MET) (left) and vegetation maps resulting from applying certain thresholds on NDVI data; middle: pixels having NDVI-values greater 0.5 are assigned to the vegetation class, right: same method using a threshold of 0.3

following the described method are plotted in Figure 8. The concentration of curves in the mid-temperature regions clearly shows the unseparability of the related classes by using this feature alone (compare Figure 2).

We did not consider here the surface slopes which affect the incident solar flux and hence also the surface temperature. Surface slopes lead to misclassification in almost all albedo based classification applications too (Wiemker 1995), (Wiemker 1998).

7 CONCLUSIONS

An algorithm has been proposed which separates a given scene into vegetational and non vegetational regions. It solely relies on remotely sensed measurements of a part of the diurnal temperature curve without using any spectral bands in the frequency range of reflected sunlight.

As mentioned above the used algorithm cannot compete with methods based on reflected sunlight such as the NDVI. But the results clearly recommend the use of thermal data as a complement to albedo data for classification purposes.

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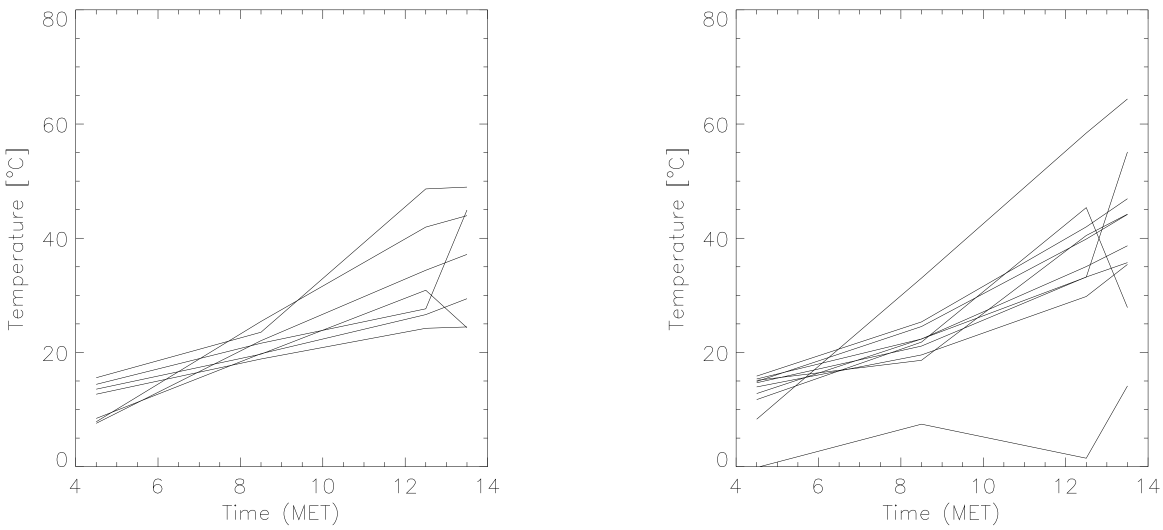

Figure 8: Temperature curves of classes determined to represent vegetational (left) and non vegetational substances (right)