A methodology to support environmental degradation monitoring and analysis using AVHRR data

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Abstract. This work proposes a particular approach to assess information about soil degradation from NOAA/AVHRR data. As erosive processes change physical and chemical properties of the soil, altering, consequently, the superficial color, monitoring the change in color over time can help to identify and analyze those processes. A methodology for the determination of soil color from NOAA/AVHRR data was devised, based on a theoretical model that establishes the relationship among the soil color, described in the Munsell color system, vegetation indices, surface temperature and emissivity. The test area of the methodology was the Upper Taquari Basin, in the central region of Brazil, where the lack of land use planning and soil conservation practices have been causing severe erosion and siltation of the water bodies, increasing the spatial and temporal significance of flood events over the Brazilian Pantanal region. The tests showed that the methodology was efficient in determining soil color using the NDVI, MSAVI and PAVI vegetation indices. Best results were obtained for the hue color component. To further test the methodology, the calculated digital color models were compared with the characteristic color of soil classes of that region.

Key words: remote sensing; soil color; erosion; vegetation index; surface temperature; emissivity; ecology; sensoreamento remoto; cor do solo; erosão; índice de vegetação; temperatura da superfície; emissividade; ecologia.

1. Introduction

The Taquari River is a major contributor to hydrological system of the Brazilian Pantanal, a Biosphere Reserve (UNESCO). Its watershed covers approximately 80,000 km2, being approximately one third located in the highlands of the Paraguay River basin.

The topography and characteristics of most of the soils in the region make them highly or very highly susceptible to erosion, potential erosion rates may vary from 600 to 950 mt/ha/year.

The occupation of the highlands in the center-west region of Brazil in the last 30 years, characterized by the lack of planning of land use, lack of soil conservation practices, and destruction of river bank vegetation, has amplified degradation of soil and water resources, to a point that it is considered the principal menace to the Pantanal biome integrity. Currently the Taquari river carries a sediment load of 491 mg/l. Deposition in the Pantanal lowlands occur at rates higher than 100mt/ha/year, resulting in flood events that, every year, increase their spatial and temporal significance.

The present work describes a methodology conceived to assist land use management of the Upper Taquari Basin. The methodology was developed as a component of the ECOAIR Project, a Scientific International Cooperation Project for the development of models and automated routines to identify environmental parameters associated to erosive processes and degradation using satellite images (automatic monitoring of land/use, land cover change).

In order to unravel the complexity of the Taquari issue we adopted a problem-oriented approach in which, we have considered to predict erosion process by satellite data, where soil color is considered as a key factor indicator for monitoring erosion processes.

2. Soil Color

Soil is a complex matrix containing mineral, water, air and organic matter at various levels. The easiest soil properties to assess are the morphological ones, expressions of the appearance of soil according to macroscopic characteristics promptly perceptible, such as color, texture and structure.

Often the morphological characteristics of soils are determinant for its classification, what indicates its strong correlation with the physical, mineralogical and chemical properties. In fact it is possible to extract a lot of information about a particular soil based on its morphology.

According the U.S. Soil Survey Staff (1981) color is one of the most useful properties for soil identification and appraisal. Qualitative and quantitative information can be gained on parameters such as organic matter content (Schultz, 1993), mineralogy (Schulze, 1993), moisture and drainage (Richardson, 1993), pH-Eh (Fanning, 1993), and soil horizon delineation (Soil Survey Staff, 1999).

Dark soils are usually richer in organic matter. The red color can indicate high amount iron oxides. Carbonate and calcium sulphate give soil a lighter color, whereas moisture lowers the intensity of soil color.

Generally, eroded soils have higher color values, as a consequence of the removal of the top layers of soil and the subsequent decrease in organic matter. When the top layers are totally removed, soil material with color significantly different from that of the non-eroded soils will be exposed.

The standard method for specifying the color of soil is based on a comparison of soil samples of color chips contained in a Munsell color chart (*Munsel*, 1994). The Munsell color designation makes use of a characterization scheme that describes color in terms of three variables: hue, value and chroma. The hue notation of a color indicates its relation to red, yellow, green, blue and purple, according to Munsell (1907) hue is "the quality by which we distinguish one color from another". Value is a neutral axis that refers to the gray level of the color, it is "the quality by which we distinguish a light color from a dark one". Chroma is the quality that distinguishes the difference from a pure hue to a gray shade.

3. Theoretical Model

The proposed approach aims at assessing soil color from NOAA/AVHRR data. It starts from establishing the correlation models between soil color, collected in situ by pedologists, and Vegetation Indices and Emissivity, calculated from the NOAA images. The next step is the inversion of the models so that soil color can be determined directly from the NOAA data.

It is a semi-empirical approach. The determination of the correlation models between vegetation indices and emissivity and soil color/moisture starts from the definition of the physical significance of the vegetation indices and emissivity.

Vegetation Indices have been used extensively for the derivation of the biophysical properties of vegetation and soil. In this work a few types of vegetation indices were used, in order to determine witch is more useful for the assessment of color:

- Normalized Adjusted Vegetation Index (NDVI);

$$NDVI = (\rho_{nir} - \rho_{red}) / (\rho_{nir} - \rho_{red}) \quad (1)$$

- Modified Soil Adjusted Vegetation Index (MSAVI) (Qi, 1994);

$$MSAVI = ((2\rho_{nir} + 1) - ((2\rho_{nir} + 1)^2 - 8(\rho_{nir} - \rho_{red}))^{0.5}) / 2 \quad (2)$$

- Global Environment Monitoring Index (GEMI) (Pinty, 1992);

$$GEMI = \xi(1 - 0.25\xi) - (\rho_{red} - 0.125) / (1 - \rho_{red}) \quad (3)$$

$$\xi = (2(\rho_{nir}^2 - \rho_{red}^2) + 1.5\rho_{nir} + 0.5\rho_{red}) / (\rho_{nir} + \rho_{red} + 0.5)$$

- Purified Adjusted Vegetation Index (PAVI) (Singh, 2004).

$$PAVI = (\rho_{nir}^2 - \rho_{red}^2) / (\rho_{nir}^2 - \rho_{red}^2) \quad (4)$$

Surface Emissivity is a measure of the inherent efficiency of the surface in converting heat energy into radiant energy above the surface. It depends upon the composition, roughness and moisture content of the surface and on the observation conditions (i.e. wavelength, pixel resolution and observation angle). Surface emissivity variation, consequently, have a direct relationship with surface composition change (Sobrino, 2000).

The channel emissivity difference and mean channel emissivity can be calculated directly from AVHRR/NOAA data using NDVI Threshold Method - $NDVI^{THM}$ (Sobrino, 2000).

Vegetation indices and surface emissivity can be considered as a function of the ecosystem investigated, climate, terrain, soil and hydrology variables. Conceptually the vegetation indices and emissivity can be modeled using those environmental variables:

$$VI / Emissivity = f(Cl, Ve, Ph, S) + K \quad (5)$$

The sub-models may in turn be represented as a function of their major components: climate (*Cl*), Vegetation/Ecosystem (*Ve*), Physiography (*Ph*), Soil/Hydrology (*S*). Where K, is the modeling errors caused by environmental variables and potential inaccurate measurements. The model could evidently be more complex, however, not all environmental variables are completely independent, what makes it possible to obtain theoretical VI/Emissivity with a limited number of environmental variables.

Vegetation indexes are influenced by variations of vegetation and soil. They can be considered as the sum of two components:

$$VI = VI_{soil} + Vi_{vegetation} \tag{6}$$

The same can be said about surface emissivity:

$$\varepsilon = \varepsilon_{soil} + \varepsilon_{vegetation} \tag{7}$$

In this work we segmented the images and investigated only the locations where the influence of soil in the indices are greater than that of the vegetation. So, we restricted the application of the model to the space of vegetation indices where the influence of the component $VI_{vegetation}$ is small (NDVI between 0 e 0.2).

Furthermore, for a specific geographic location, the vegetation/ecosystem and phisiography sub models become relatively less time variant. Therefore, NDVI for a specific time (*t*) at a specific geographic location becomes primarily a function of climate variables and soil moisture/color.

$$\text{VI(t)} = \text{f [soil color/moisture]} + \text{f [climate variables]} + \text{K1} \tag{8}$$

To simplify the models:

$$\text{VI} = \text{f [soil color]} + \text{f [temperature)]} + \text{K2} \tag{9}$$

$$\text{Emissivity} = \text{f [soil color]} + \text{K3} \tag{10}$$

Surface temperature was calculated through one of the split window algorithms (Ulivieri, 1992);

$$Ts = T4 + 1.8\ (T4 - T5) + 48(1 - \varepsilon) - 75\ \Delta\varepsilon \tag{11}$$

Where *Ts* is the surface temperature, *T4* is the brightness temperature from band 4 of AVHRR and *T5* is the brightness temperature from band 5.

4. Materials and Methods

The ground truth data consisted of 60 color profiles (in Munsell notation) of the soil top layer collected in the years of 1995, 1996 and 1999, from different sites in the Upper Taquari basin.

Local Area Coverage (LAC) AVHRR/NOAA images were acquired from the Satellite Active Archive from the NOAA Administration (<www.saa.noaa.gov>) for the dates the soil samples were collected.

After geometric correction and atmospheric calibration, the Vegetation Indices (NDVI, GEMI, MSAVI and PAVI) and Emissivity (mean and difference) were calculated. Then, VIs and Emissivities were calculated for the ground truth sites

Different kinds of regression analysis were tested to determine the best correlation models among the VIs and Emissivities and the soil color.

Data were separated into two sets, data from 1995 and 1996 (22 samples), and data from 1999 (37 samples). Regression coefficients were calculated using data from 1999 and the regression model was tested against 1995 data.

5. Results

The calculations made taken all data into consideration shown that the best correlations were obtained by linear regression for all the vegetation indices and surface emissivity. The best correlation coefficients were obtained by linear/multiple regression:

VI	*r (H)*	*r^2 (H)*	*r (V)*	*r^2 (V)*	*r (C)*	*r^2 (C)*
NDVI	0,69	0,47	0,46	0,21	0,36	0,13
MSAVI	0,69	0,48	0,48	0,23	0,36	0,13
GEMI	0,32	0,10	0,27	0,07	0,31	0,10
PAVI	0,68	0,46	0,46	0,21	0,37	0,14

Table 1. Values of correlation coefficient (r) and coefficient of determinations (r^2) for Hue, Value and Chroma respectively (from left to right) with various vegetation indices by equation Hue/Value/Chroma = b0 + b1 (VI) + b2 (Surface Temperature)

E	*r (H)*	*r^2 (H)*	*r (V)*	*r^2 (V)*	*r (C)*	*r^2 (C)*
ε	0,45	0,20	0,18	0,03	-0,25	0,06
$\Delta\varepsilon$	0,49	0,24	0,15	0,02	-0,29	0,08

Table 2. Values of r and r^2 for Hue, Value and Chroma respectively (from left to right) with channel and difference emissivity (E) by equation Hue/Value/Chroma = b0 + b1 (E)

When testing the 1995-1996 data against the color (hue, value and chroma) grids calculated from the NOAA images, using the regression models determined from the 1999 data, the following results we obtained:

VI/E	*r (H)*	*r^2 (H)*	*r (V)*	*r^2 (V)*	*r (C)*	*r^2 (C)*
NDVI	0,86	0,75	0,71	0,51	0,48	0,23
MSAVI	0,86	0,74	0,73	0,54	0,47	0,22
GEMI	-0,52	0,27	0,60	0,36	0,38	0,14
PAVI	0,86	0,74	0,70	0,49	0,49	0,24
ε	-0,62	0,39	-0,42	0,18	0,39	0,15
$\Delta\varepsilon$	-0,71	0,51	-0,43	0,18	0,44	0,19

Table 3. Values of correlation coefficient (r) and coefficient of determinations (r^2) for Hue, Value and Chroma respectively (from left to right) with observed and calculated values of Hue, Value and Chroma using various vegetation indices, channel and difference emissivity.

6. Soil Class Matching

To evaluate the precision of color calculation trough the methodology an application was devised to confirm the soil classification of the Upper Taquari Basin, produced earlier by EMBRAPA (Brasil, 1997).

For the application, we selected the Neossolos Quartzarênicos Órticos soil class, which covers an area of 13.450 km2, corresponding to 47% of the Basin area.

Each pixel of the digital color model calculated, situated inside the areas associated to the selected class and in locations where the NDVI values ranged from 0 and 0.2, was tested.

The color interval for the Neossolos Quartzarênicos Órticos soil class was determined from a set of morphological descriptions of soil profiles collected in the High Paraguai River Basin.

From the color records provided by EMBRAPA, the color component intervals for the selected class are: 2.5YR a 10YR for Hue; 3 a 4 for Value; and 2 a 5 for Chroma.

Four AVHRR images from different years were tested. The digital soil color models were calculated using both NDVI and MSAVI vegetation indices.

Considering only the hue component, the comparison gave the following results:

Image Date	*Hit Rate (MSAVI)*	*Hit Rate (NDVI)*
19/8/1995	99.93 %	99.91 %
29/11/1995	99.84 %	99.51 %
24/11/1996	99.95 %	99.91 %
15/10/1999	96.69 %	96.07 %

Table 4. Percentage of pixels for which the calculated hue lies inside the characteristic color interval for the selected class.

Considering all the three color components (hue, value and chroma) at the same time, the comparison gave the following results:

Image Date	*Hit Rate (MSAVI)*	*Hit Rate (NDVI)*
19/8/1995	92.76 %	93.52 %
29/11/1995	93.52 %	90.5 %
24/11/1996	89.92 %	85.56 %
15/10/1999	90.44 %	89.77 %

Table 5. Percentage of pixels for which the calculated color (hue, value and chroma) lies inside the characteristic color interval for the selected class.

It must be noted that the color interval considered for the selected class is considered large, with respect to hue it varies from 2.5YR to 10YR.

In a future application we intend to investigate classes characterized by smaller color intervals, such as the Latossolos Vermelhos or Latossolos Vermelho-Amarelo.

7. Conclusions

The results show a good correlation between NDVI, PAVI and MSAVI (in that order) and Hue. They also show that Hue can be predicted with a good level of accuracy directly from the NOAA images

The low correlation between the color components and emissivity indicates that unaccounted characteristics of soil have a larger influence on emissivity than color. As emissivity has been linked with the structure of soils, maybe other factors, such as texture, roughness or chemical composition can be better correlated to emissivity.

A fair correlation has been established between Value and Vegetation Indices (specially MSAVI, NDVI and PAVI, in that order), and a low correlation between Chroma and Vegetation Indices. That can be partially explained by the higher influence moisture has on Value and Chroma than on Hue. The investigation of soil profile records obtained from EMBRAPA (from the same Central-West Region of Brazil), shows that a wet soil sample has usually the same Hue, but lower Value and Chroma values than a dry sample.

Further tests are currently being made to evaluate the capacity of prediction of soil degradation processes of the proposed approach. In the future moisture information should be added to the models, what we believe will improve the results obtained by the approach.

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