GULLY EROSION MAPPING WITH HIGH RESOLUTION IMAGERY AND ALS DATA BY USING TREE DECISION, HIERARCHICAL CLASSIFICATION AND OBIA

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ABSTRACT:

The gully erosion presents spectral and spatial heterogeneity and altimetry variation. It is not a land use class, but an object and it can be mapped as a subclass, using OBIA. This study presents a methodology for delimitation of gullies in rural environments, based on image classification procedures. For such, two study areas were selected: one located in Minas Gerais, Brazil and another one located in Queensland, Australia. There were used high resolution images and ALS data. The objects were generated by multiresolution segmentation method. The most important attributes in the definition of gullies were selected using decision tree induction algorithms, being these attributes spectral, altimetry and texture. Classifications hierarchical and by decision trees were carried out. Using decision tree the classification is performed only by a factor of scale, not allowing the identification of all the constituent features of the gully system. In hierarchical classification, the procedure is performed at different scales and allowing to use of fuzzy logic. The classification obtained with hierarchical classification showed results more reliable with the field of reality, by allowing the use of different scales, fuzzy logic and integration of knowledge (the established rule base) compared to the automatic classification by decision tree. As different gullies erosion are similar when presents the same evolution stage and soil type, it is not possible to select attributes to classify all gully systems, being necessary to investigate attributes for each gully erosion, based on available data and existing land use classes in the area.

1. INTRODUCTION

The gullies are the biggest erosive processes and, consequentely, responsible for ambiental, social and financial damages. Corrective and preventive measures need mapping and monitoring, which can be made by local measurements or by remote sensing.

Local measurements can be done by staking (Hessel e Van Asch, 2003; Morgan, 2005), by topographic surveys, by GNSS receivers, or using TLS (Terrestrial LASER Scanning) (Perroy et al., 2010). However, these methods needs traversal and equipment installation on edges and inside the gullies, which can aggravate erosive processes and it can be a risk for surveyours.

Remote sensing monitoring has been carried out by using aerophotos (Marzolff; Poesen, 2009), or multiespectral images (King et al., 2005; Vrieling; Rodrigues; Sterk, 2005), or DTM (Digital Terrain Model) (Martínez-Casasnovas; Ramos; Poesen, 2004), or ALS (Airborne LASER Scanning) data (James; Watson; Hanse, 2007; Eustace; Pringle; Witte, 2009). Recently, researches have used OBIA for detection, mapping, monitoring, volume calculation and predictive models of erosion risk.

In relation to the remote sensing, the gully erosion presents spectral heterogeneity (soil, vegetation, shade and water mix), spatial heterogeneity (existence of features as head, canals and digits with irregular forms and variable dimensions) and altimetry variation (with high declivity on the edges). Due to spectral heterogeneity, it is not enough use only spectral data, being necessary auxiliary data, as altimetry and texture data. Using auxiliary data is recommended to use data mining.

In this context, this study proposed a methodology for delimitation of gullies on image classification procedures based on OBIA (Object Based Image Analysis), identifying attributes to establish a decision rule base. For such, there were used an Ikonos image, an orthophoto and ALS altimetry and intensity data of an area located in Uberlandia - Minas Gerais – Brasil and of an area located in Queensland - Australia. The objects were generated by multiresolution segmentation (FNEA-Fractal Net Evolution Approach method). The most important attributes in the gullies mapping were selected by decision tree, being these attributes spectral, altimetry and texture, and a classification by tree decision was carried out. The hierarchical classification was carried out and presented satisfactory results, by allowing the use of different scale factors, uncertainty insert (by fuzzy logic) and integration of knowledge (the established rule base) compared to the automatic classification by decision tree.

2. METHODS

2.1 Data

For the Brazilian study area, there were used a 1 meter spatial resolution and 11 bits radiometric resolution Ikonos image, illustrated by Figure 1 (presented in a coloured composition R=3, G=4, B=1, with coordinates related to WGS84 - UTM zone 51ºW), and ALS data from ALTM 2025 Optech (1 meter spatial resolution rasterized).

For the Australian study area, there were used a 0,5 meter spatial resolution and 8 bits radiometric resolution orthophoto, illustrated by Figure 2 (with coordinates related to GDA94 – MGA 1994 zone 55), and ALS data from Riegl LMS-Q560 (0,5 meter spatial resolution rasterized).

The procedures were carried out by using ENVI (The Environment for Visualizing Images) 4.7, ALDPAT (Airborne LiDAR Data Processing and Analysis Tools) and eCognition Developer 8.8.

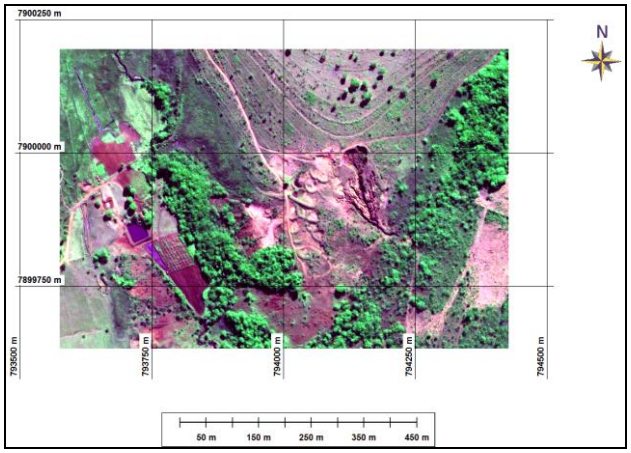

Figure 1. Study area in Minas Gerais, Brazil

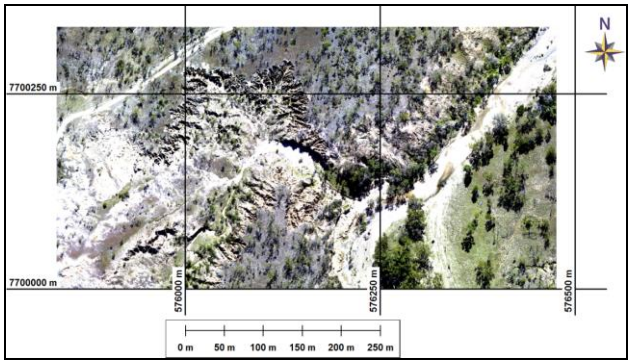

Figure 2. Study area in Queensland, Australia

2.2 Methods

2.2.1 Spectral and altimetry data processing

From the ALS data, there were generated the DSM (Digital Surface Model) and intensity image for both study areas, by linear interpolation. From the DSM, there were generated the DTM, the nDSM (Normalised Digital Surface Model) and the slope map.

The NDVI (Normalised Difference Vegetation Index) was generated by Ikonos Image. For the Australian study area, as the infrared image is not available, we propose a new index based on intensity image. The Intensity Based Contrast Index – IBCI, can be obtained from:

$$IBCI = (Red - Intensity) / (Red + Intensity) \qquad (1)$$

Unlike NDVI, the IBCI highlights the ground and not the vegetation. There is obviously a need for spectral and altimetry data and it has been acquired at the same time and therefore are georeferenced and correspond to the same date.

2.2.2 Generating objects

The objects were obtained by using multiresolution segmentation applied to spectral data (because there are not a perfect coincidence between edges in the image and in the ALS data), ranging the scale factor between 5 and 100, with multiple range of 5. The composition of homogeneity criterion was shape = 0.1 and compactness = 0.5.

2.2.3 Classification

For the Brazilian study area, there were identified these land use classes: tree vegetation, ground vegetation, shadow, water, bare soil and gully erosion. For the Australian study area, there were identified these land use classes: vegetation, shadow, bare soil and gully erosion.

The spectral, geometric, texture and context attributes available in eCognition software were processed using CART (Classification And Regression Trees) algorithm, and a decision tree was obtained for each study area, for objects generated with a scale factor (SF) = 50. A classification was carried out applying this decision tree.

Refining the attributes and ranges obtained from the decision tree and inserting the expertise knowledge, a hierarchical classification was carried out.

A hierarchical classification evaluation, for both study areas, was performed by confusion matrix, selecting verifying samples.

3. RESULTS

3.1 Spectral and altimetry data processing

The Figure 3 shows the DTM and the Figure 4 shows the slope map obtained for Brazilian study area. Figures 5 and 6 showed the same for the Australian study area. It is possible to verify that altimetry data is an important auxiliary data in gully erosion mapping. In the slope map the gully system edge is evidenced because of its high declivity.

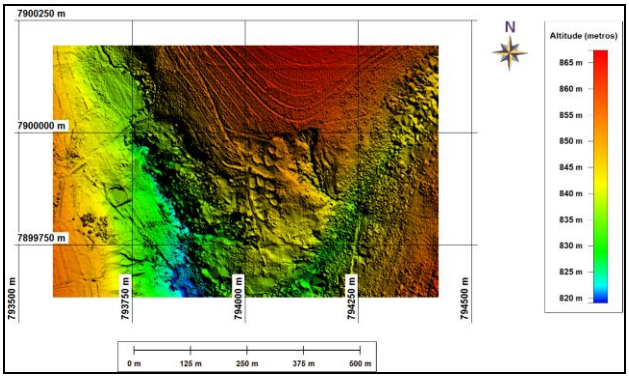

Figure 3. DTM - Brazilian study area

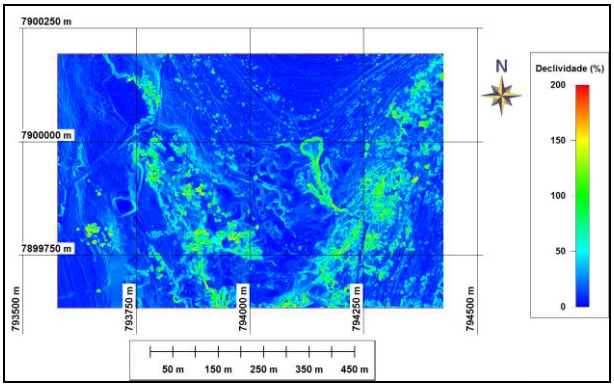

Figure 4. Slope map - Brazilian study area

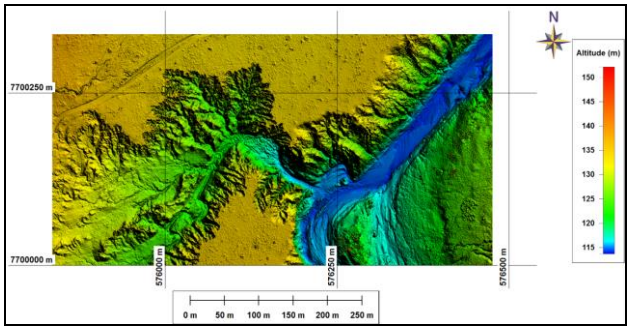

Figure 5. DTM - Australian study area

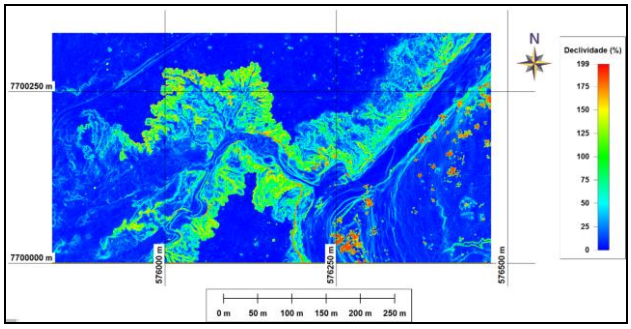

Figure 6. Slope map - Australian study area

The Figure 7 shows NDVI image for the Brazilian study area. The vegetated and not vegetated areas can be discriminated, as well tree vegetation and ground vegetation areas. The IBCI image was generated for the Australian study area, as shown in the Figure 8. The areas with soil are evidenced. The Figure 9 shows the IBCI image for the Brazilian study area. Comparing to Figure 7, it is evident the featured in the soil areas.

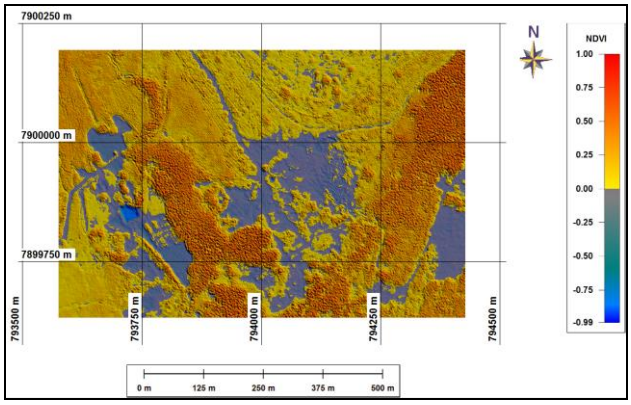

Figure 7. NDVI image - Brazilian study area

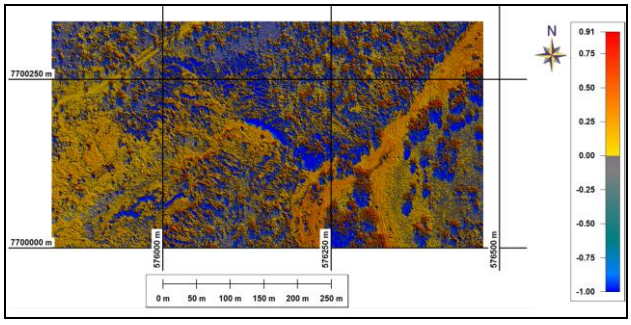

Figure 8. IBCI image - Australian study area

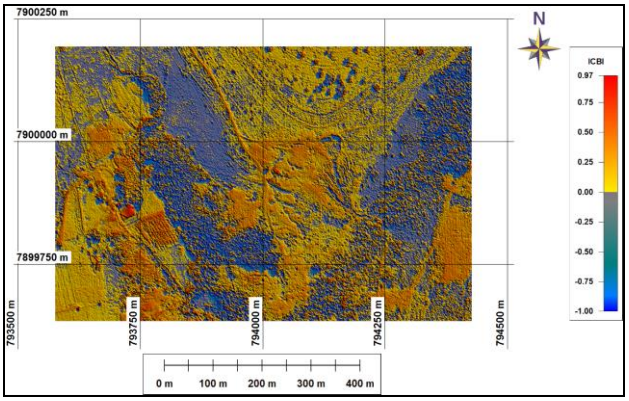

Figure 9. IBCI image - Brazilian study area

3.2 Classification

3.2.1 Classification using tree decision

The data mining carried out by CART algorithm resulted in the decision trees showed in the Figures 10 and 11 (Brazilian and Australian areas, respectively). For the Brazilian study area, in a first node, using circular mean applied to nDSM, the samples were divided in an intermediate node 1 and in a leaf of the Tree Vegetation class. In the node 1, using circular mean applied to NDVI, the samples were divided in a leaf of the Water class and in the intermediate node 2. In the node 2, using NDVI, the samples were divided in intermediate nodes 3 and 4. In node 3, using circular mean applied to slope map, the samples were classified in Soil class or in Gully erosion class. In node 4, using Brightness, the samples were classified in Shadow or Ground Vegetation classes. For this data set, the major attribute for gully classification was the slope.

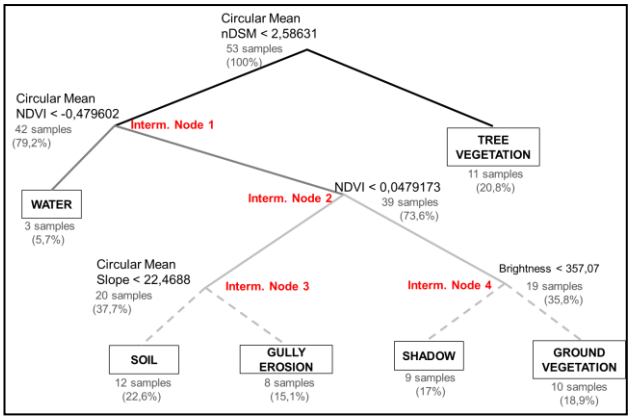

Figure 10. Decision tree - Brazilian study area

For the Australian study area, in a first node, using Texture after Haralick (GLDV entropy), applied to slope map, the samples were divided in an intermediate node 1 and in a leaf of the Gully Erosion class. In the node 1, using Green band, the samples were divided in a leaf of the Shadow class and in the intermediate node 2. In the node 2, using Blue band, the samples were divided in a leaf of the Vegetation class and in the intermediate node 3. In the node 3, using Texture after Haralick (GLDV entropy) applied to slope map, the samples were classified in Soil class or in Vegetation class.

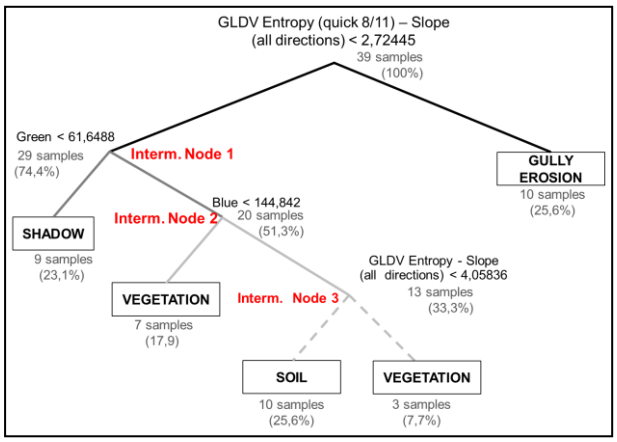

Figure 11. Decision tree - Australian study area

The Figure 12 shows the Brazilian's study area classification by decision tree. It is possible verify that occurred confusion between gully erosion and vegetation classes, in the edges of the tree vegetation due to the high declivity in these areas (height difference between ground level and tree tops). Even with the similarity between soil and gully erosion classes there was few confusion areas due to the use of the declivity attribute to separate these classes. The gully system neighbourhood was incorporated to the gully class because it was used the circular mean of the slope map attribute which expanded gully erosion area to the soil area. There was confusion between tree and ground vegetation and the shadows areas were evidenced.

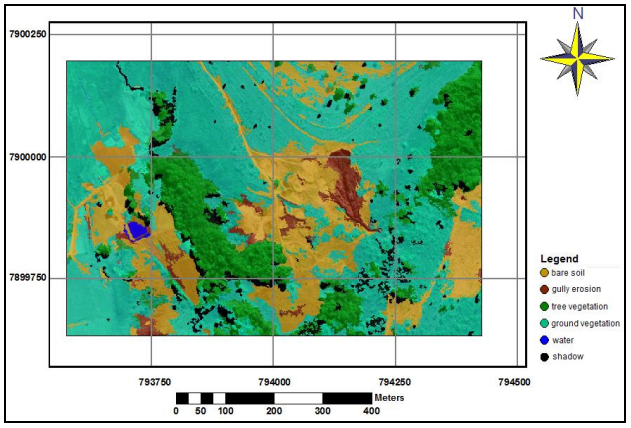

Figure 12. Classification by decision tree - Brazilian study area

The Figure 13 shows the Australian's study area classification by decision tree. There was confusion between gully erosion and vegetation classes, due to the high declivity between ground level and tree tops. The shadows areas were evidenced.

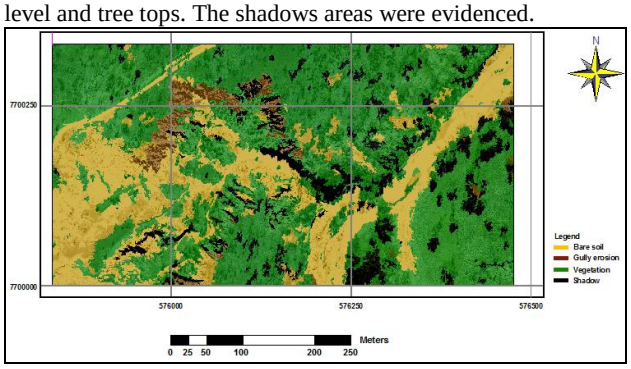

Figure 13. Classification by decision tree - Australian study area

3.2.2 Hierarchical Classification

Based on the attributes selected by CART algorithm and in the expertise knowledge, were selected attributes, fuzzy membership functions and scale factors (SF) to discriminate each class. The Figure 14 and 15 shows the hierarchical rule bases for Brazilian and Australian study areas respectively.
* note: NN = nearest neighbour algorithm; SF = scale factor

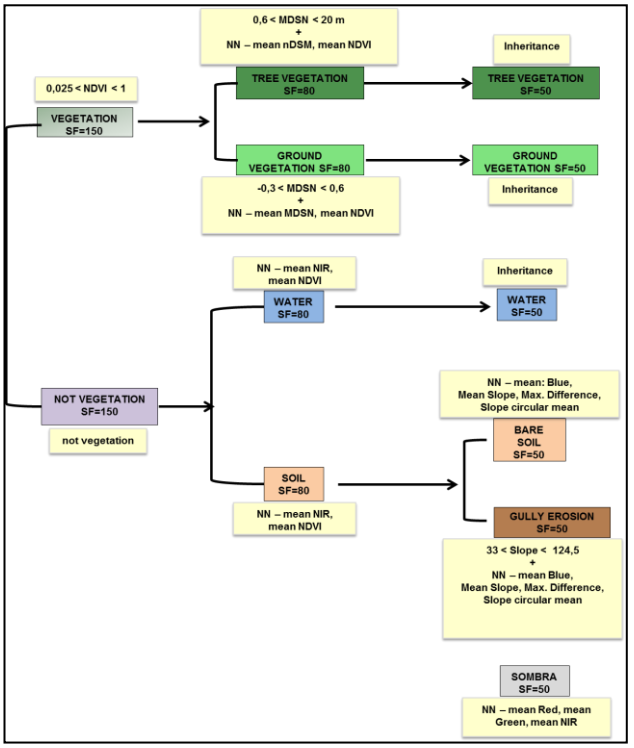

Figure 14. Hierarchical rule base - Brazilian study area

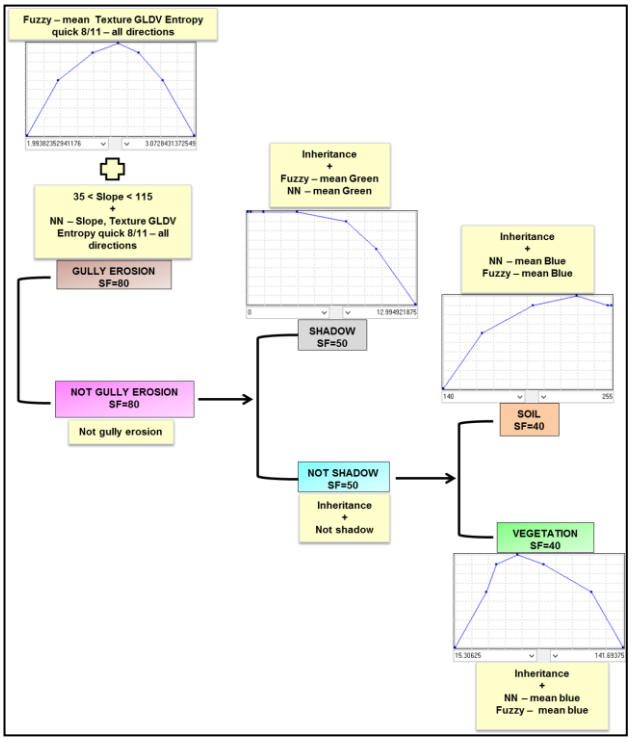

Figure 15. Hierarchical rule base - Australian study area

The Figure 16 shows the Brazilian's study area hierarchical classification. The gully system edge was better mapped than by tree decision classification. The inside areas of the gully system were classified in Soil class due to the use of slope attribute. (the declivity is low inside the gully). The water body and vegetated areas were better mapped in this classification.

In the Brazilian study area image there are 2394 image objects and 217 samples were selected, with 95% confidence interval (error = 6.35%), yielding kappa index = 0.75 and overall accuracy = 82%. 3 of 14 gully samples were classified as bare soil and 1 as ground vegetation, 3 of 42 bare soil samples were classified as gully.

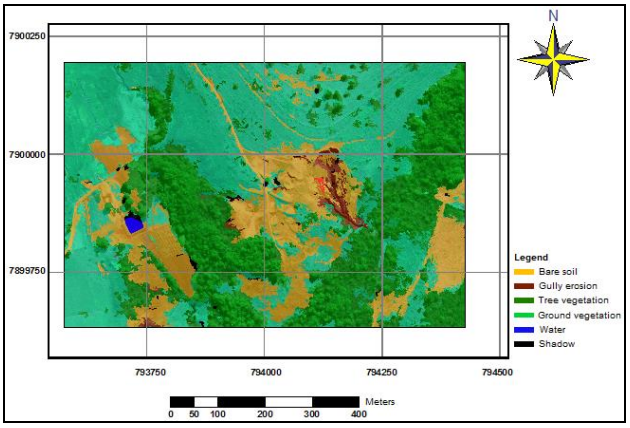

Figure 16. Hierarchical classification – Brazilian study area

The Figure 17 shows the Australian's study area hierarchical classification. The gully system was better classified than in the classification by tree decision. The mainly attributes selected for gully erosion classification were slope and texture. As vegetated areas have high declivity and texture too, there was confusion between gully an vegetation classes.

In the Australian study area image there are 2265 image objects and 865 samples were selected, with 99% confidence interval (error = 5%), yielding kappa index = 0.46 and overall accuracy = 64.05%. 3 of 102 gully samples were classified as vegetation, 29 as bare soil and 1 as shadow. 61 of 127 vegetation samples were classified as gully, 27 of 309 of bare soil samples were classified as gully and 11 of 16 shadow samples were classified as gully.

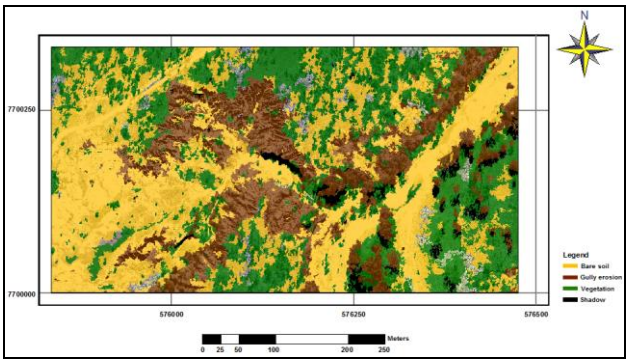

Figure 17. Hierarchical classification – Australian study area

4. CONCLUSIONS

As the gully systems are composed of features with highly variable shapes and sizes, the gullies could be mapped from high resolution imagery, with auxiliary altimetry data and by OBIA. Using hierarchical classification, it is possible to select different scale factors appropriated for gully features with variable sizes. For both data sets the scale factor equals to 50 was enough to map gullies.

As the gully systems have higher similarities when they correspond to the same stage of evolution and soil type, for example, there is no way to select attributes that are appropriate to the classification of all systems, requiring the investigation of discriminant attributes for each gully system, including on the basis of available data and existing land use classes in the scene.

Data mining by decision tree allowed rapid analysis and the best attributes selection, subsidizing the decision making process, replacing empiricism, providing a preliminary decision rule base, which can be adjusted according to the expert knowledge to realization of hierarchical classification. A disadvantage of the classification by decision trees is that you can only do it at one level of segmentation.

For data sets available and the specificities of the two study areas, the attributes that were more relevant to the discrimination of the gully class were the slope and texture. Regarding the data set, it is emphasized that the use of spectral data, high spatial resolution, coupled with the use of altimetry data allows the classification of gullies.

As the gully is an object and not a land use class, only using object-oriented classification procedures is that it can be defined.

Note also that the index proposed IBCI allowed the enhancement of the soil, being an alternative in case of unavailability of the infrared band, but the availability of ALS intensity band.

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