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Gully Features Extraction Using Remote Sensing Techniques

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Abstract

Gullies are large and deep erosion depressions or channels normally occurring in drainage ways. They are spectrally heterogeneous, making them difficult to map using pixel based classification technique. The advancement of remote sensing in terms of Geographic Object Based Image Analysis (GEOBIA) provides new possibilities to extract gullies with relative ease. This study investigates and tests a GEOBIA technique called Imagine Objective for gully features extraction in the Capricorn District Municipality of Limpopo Province. IO extracts gullies by firstly group the pixel information and then subjects them to raster and vector conversion and refinement algorithms. For the purpose of assessing the accuracy of the IO created gullies, reference data were created by manual digitising gullies from SPOT 5 satellite imagery on the background. The error matrix was computed and the results indicated a user's accuracy of 98.67% and 54% for non-gully and gully class respectively; a producer's accuracy of 68.20% and 97.59% for non-gully and gully class respectively; a overall classification accuracy of 76.33% and a kappa statistic of 0.95, 0.36 and 0.52 for non-gully class, gully class and total kappa statistic respectively. Although the accuracy levels are considered moderately acceptable, it is recommended that much higher spatial resolution imagery such as Quickbird be used in future and other functionalities of IO be tested.

1. Introduction

Gullies are deep depressions, channels or ravines in a landscape caused by water action. Gullies occur when runoff water is channelled into grooves and deepen over time forming a distinct head with steep sides that may collapse by water seepage or undermined by water flow within the gully (Stocking & Murnaghan, 2000). Gullies mainly occur in drainage ways at lower slope positions (SARCCUS, 1981) and most obvious erosion features in the landscape ranging from 30cm to 30m deep (Bergsma *et al*., 1996). Gullies may be classified as continuous or discrete, with the former having many branches whilst the latter are independent with no distinct connection with the main gully or stream channel (Geyik, 1986). Gullies cause extensive damage to infrastructure and vulnerable agricultural lands, and pollute water by removal and deposition of soil particles and chemicals from fertilisers (Torkashvand & Alipour, 2009). In South Africa (SA), gullies are widespread, especially in former homelands such as Ciskei in the Eastern Cape (EC) Province (Kakembo & Rowntree, 2003). In the central Kwazulu Natal

(KZN) Province, gullies are a characteristic feature of hilly topography, posing severe limitations to agricultural land use due to the inaccessibility of farms (Rienks *et al*., 2000). A recent study by Mararakanye & Le Roux, (2011) highlights severe gullies in other parts of SA such as the Northern Cape (NC), Free State (FS), Limpopo (LP), Mpumalanga (MP), Western Cape (WC) and North West (NW) Provinces. According to Gibson (2006 cited the National Botanical Institute, 1999), most types of soils in the LP Province are highly susceptible to soil erosion and gullies are prevalent in numerous croplands and grazing lands.

In the past, comprehensive analysis of gullies has often been neglected by the scientific community. For example, a review by Casali *et al* (2009) shows that less than 10% of soil erosion studies around the world address gullies directly. However, in order to develop strategies to control, prevent and rehabilitate gullies, the spatial extent of the problem has to be established and monitored (Le Roux *et al*., 2007; Kakembo *et al*., 2009). Geographic Information Systems (GIS) and Remote Sensing (RS) technologies have been frequently used to assess soil erosion features. However, in SA there has been lack of information regarding the spatial extent of gullies at national scale until recently. The recent study mapped gullies by means of manual digitising with SPOT 5 imagery on the background (Mararakanye & Le Roux, 2011). Although higher accuracy is achieved by manual digitising, it is extremely laborious and time consuming with lots of subjectivity during gully interpretations. Such a study will be expensive to repeat for the whole SA for monitoring purposes. It is therefore necessary to develop new methodologies that will be less expensive to repeat.

The advancement in remote sensing technology in terms of high spatial resolution satellite imagery and Geographic Object Based Image Analysis (GEOBIA) (Blaschke, 2010; Fourie, 2011), offers a potential to map gullies with less effort, time and at an acceptable level of accuracy. Previous studies have shown that supervised classification technique such as Maximum Likelihood Classification (MLC) algorithm could not express water erosion features at an acceptable level of accuracy due to the spectral similarities with other non erosion features (Solaimani & Hadian Amri, 2008; Pirie, 2009; Torkashvand & Alipour, 2009). However, the use of object based gullies extraction techniques has proven to be more effective than the conventional supervised and unsupervised classification techniques. For example, Jetten *et al* (2011) used eCognition to extract gullies in Morocco, using slope, catchment area and NDVI as threshold and the accuracy indicated a negligible over estimation. In SA, the use of eCognition for gully extraction was tested in tertiary catchment T35 in Eastern Cape Province by deriving vector segments assumed to represent homogenous landscape and by creating a bare soil mask (Mararakanye & Le Roux, 2011). However, it was decided not to continue with segmentation as it would require large amount of pre-processing especially when applied to a provincial scale. Taruvinga (2008) used the Support Vector Machine (SVM) to extract gullies in KZN tertiary catchment and the accuracy of the results was considered acceptable. According to Lillesand *et al* (2008) the advantages of using object oriented classification is that it uses both spectral and spatial patterns when classifying the image.

In context of the above, the aim of this study was to identify a GEOBIA technique and test its capability for extracting gullies in the Capricorn District, Limpopo Province. The extraction of other erosion features such as sheet and rills were beyond the scope of this study. The main objectives of this study were therefore to:

a) Test Imagine Objective (IO) technique for gullies extraction;
b) Create a reference data by manual digitising gullies; and
c) Assess the accuracy of IO created gullies by comparing it with the reference data.

2. Description of the study area

The study area is located between longitude 28°59'58" and 29°14'59" and latitude 23°4'52" and 24°0'4" as shown in Figure 1. It is in the former homeland of Lebowa, and includes Moletsi, Matlala, Mashashane and Maraba villages. A majority of the area falls under the Capricorn District Municipality in the Limpopo Province of SA. This area was chosen because it is severely affected by gullies ranging from small (discontinuous) to large (continuous) gullies within a well-differentiated and diverse land use patterns (mostly residential and subsistence cultivation). The total size of the study area is approximately 73,665ha.

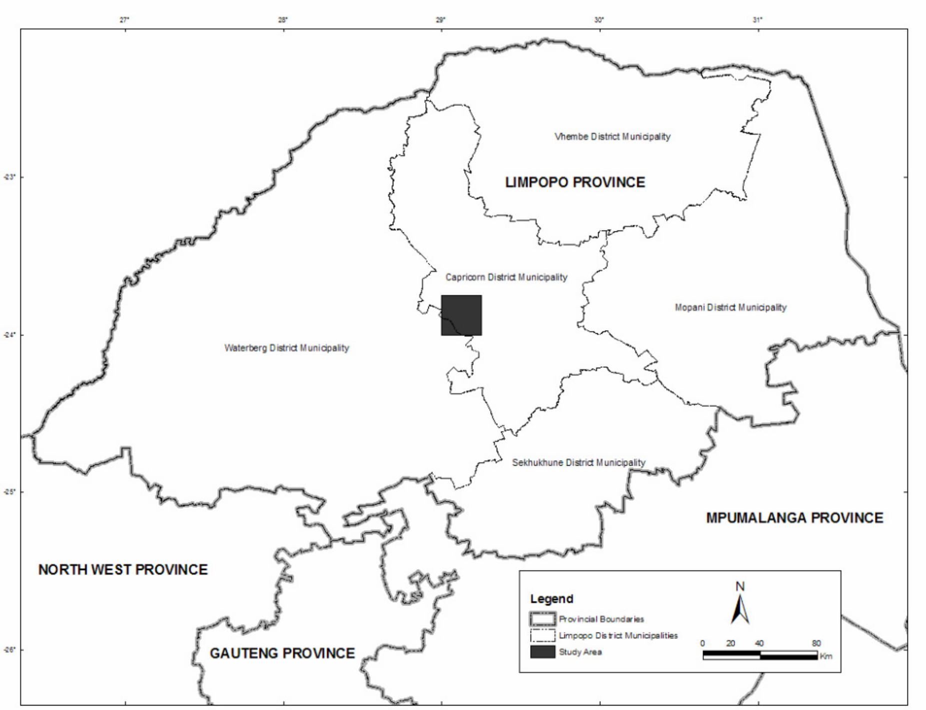

Figure 1. Location of the study area

3. Materials and methods

3.1 Materials used

This study used SPOT 5 2009 multispectral bands imagery obtained from the Department of Agriculture, Forestry and Fisheries (DAFF). This imagery was chosen because it was already purchased by government agencies and available for the whole of SA. The imagery was subset to the study area in order to save the computer processing time. Other pre-processing procedures had already been undertaken when the imagery was obtained. The SPOT 5 multispectral imagery consists of four spectral bands (Green, Red, Near Infrared, and Shortwave Infrared) and has a spatial resolution of 10m.

3.2 Extraction of gullies using IO technique

Imagine Objective is an object based feature extraction and refinement (vector or raster) framework that incorporates many image processing techniques such as image segmentation, Threshold and Clump (TAC) etc. (Phan *et al*., 2009) and offers great potential to extract gullies. IO feature extraction technique is subjected to the pixel classification, pixel groupings and then objects creation. Figure 2 summarises the algorithms used in IO gullies extraction model.

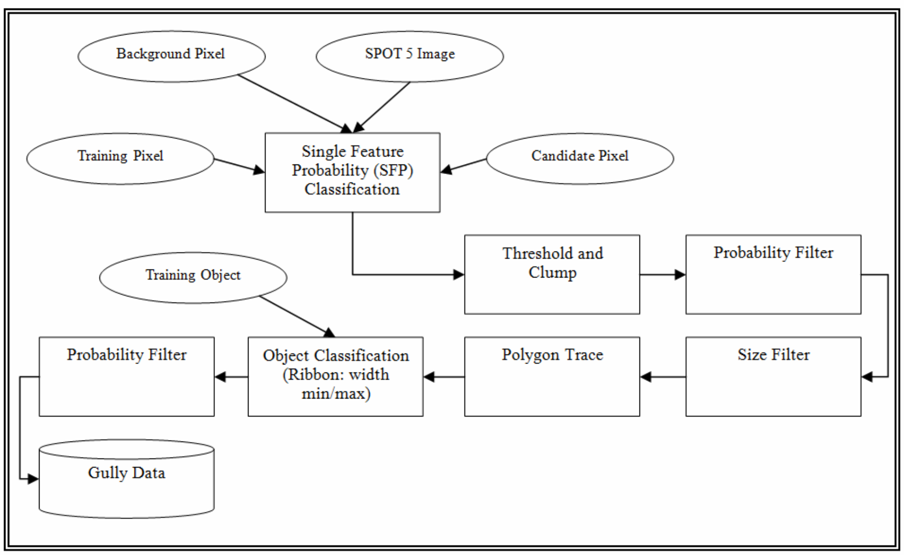

Figure 2. IO gullies extraction model

Foremost, 5 training samples were collected from known gullied sites identified by means of visual interpretation of SPOT 5 satellite imagery. Additionally, 5 samples were collected from non-gullied or background sites as required in IO workstation. The SFP was used to compute a probability metric for each pixel in a subset image. The probability metric measures how closely the candidate pixels resemble the training samples. After pixel classification, this study used TAC to group pixels together in order to form raster objects. The raster objects were refined using the probability and size filter in order to remove objects that are unlikely to be gullies. After some tests, probability values were specified and those objects that are relatively small or large were removed. For example, objects with a probability value of 0.95 to 1.0 were classified as possible gullies and objects of less than 100 and greater than 10, 000 pixels were removed. Raster objects were converted to vector objects using polygon trace tool for further object based processing. Pixel classification creates unnecessary small islands when more or less similar pixels are grouped together. It is therefore necessary to remove these islands and in this case an island filter of $100m^2$ pixels was used. Finally, 5 training samples of representative gullies were collected to compute object metric. The candidate objects that closely resemble the training samples were classified using ribbon: width minimum and maximum tool. This functionality was chosen because gullies resemble a ribbon feature rather than linear feature. The final IO gullies map was computed by assigning a probability filter value of 0.69.

3.3 Manual digitising of gullies

Manual digitising of gullies in this study involved delineating the outer boundary of a gully banks from the background SPOT 5 satellite multispectral imagery at a scale of 1: 10 000. Gullies were identified visually by means of their drainage pattern, shape, size, colour and tone. Gullies with no vegetation appear bright in red and Infra-Red (IR) bands. They normally follow a drainage patterns such as dendritic, parallel, radial, centrifugal, centripetal, distributaries, angular, trellis and annular (Stocking & Murnaghan, 2000; Taruvinga, 2008). In order to ascertain that the mapped gullies exist on the field, 47 observation points were selected based on their accessibility using the road. Gullies were located in the field in all but one observation points selected and subsequently the inaccurate gully was deleted.

3.4 Accuracy assessment

Assessing classification accuracy quantitatively requires the comparison of two maps i.e. classification derived map and the reference map (Lillesand *et al*., 2008). This study assessed the accuracy of IO derived gullies by comparing it with manually digitised gullies in an error matrix. The error matrix is the most common method of assessing the degree of accuracy (Mather, 2004) and has been widely used in gully classification accuracy assessment (e.g. Taruvinga, 2008; Pirie, 2009). Error matrix is a square, containing rows and columns equal to the number of categories whose classification accuracy is being assessed (Lillesand *et al*., 2008). A total of 300 equalised random sample points (150 for gully class and 150 for non-gully class) were generated using ERDAS Imagine® accuracy assessment tool. The results of the error matrix were interpreted using the producer’s accuracy, user’s accuracy, overall classification accuracy and the kappa coefficient statistics. The overall classification accuracy summarises the producer's and the user's accuracy and is the ratio between the numbers of samples that are correctly classified and the total number of test samples. The user's accuracy measures the errors of commission and producer's accuracy measures the errors of omission. The Kappa coefficient of accuracy is the difference between the actual agreement in the error matrix and the chance agreement (Persello & Bruzzone, 2010).

4. Results and discussion

4.1 IO extraction results

The map shown in Figure 3 illustrates the results of IO gullies extraction with SPOT 5 satellite imagery on the background. Both the small and large gullies, 181 in numbers and ranging from 1 to 90 hectares (calculation of gullies size not shown here) are illustrated on the map. It is very clear in the map that some gullies, particularly very small were omitted, especially in the south eastern parts of the study area.

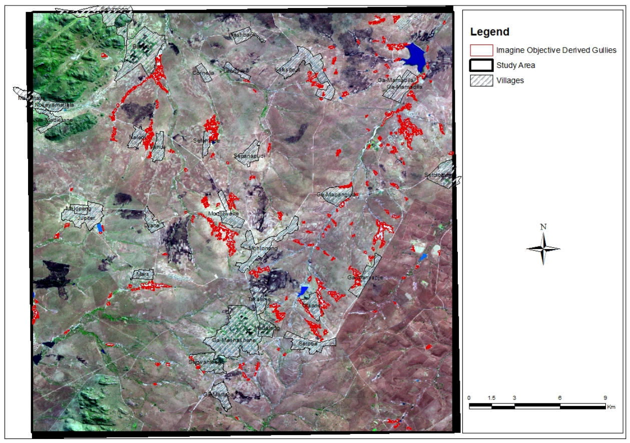

Figure 3. Gullies extracted using IO technique

4.2 Manual digitising results

Figure 4 illustrate the manually digitised gullies with SPOT 5 satellite imagery on the background. They range from small to large gullies of 0.1 to 96 hectares in size and are 672 in total number (calculation not shown here). Using manual digitising technique, very small gullies are easily detected visually and mapped thus providing the most accurate results that can be utilised as reference data to test the accuracy of a classification technique.

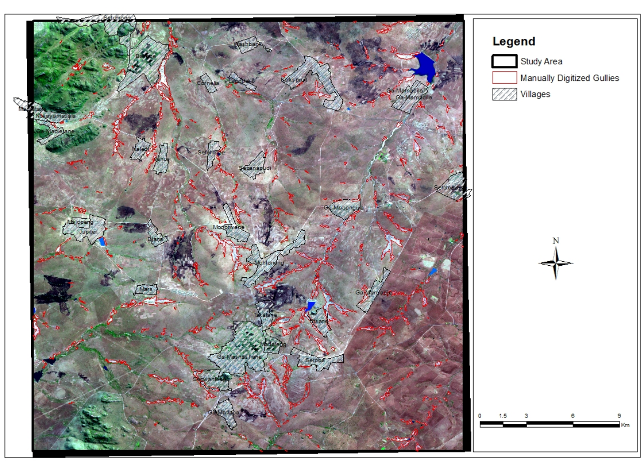

Figure 4. Manually digitised gullies map

4.3 Accuracy results

Table 1 quantitatively summarises the accuracy statistics of IO derived gullies map in comparison with manually digitised gullies. The IO gullies map has the overall classification accuracy of 76.33% and the total kappa coefficient of 0.52. The non-gully class has the user's accuracy of 98.67%, the producer's accuracy of 68.20% and the kappa coefficient of 0.95. The gully class has the user's, producer's and kappa coefficient of accuracy of 54% , 97.59% and 0.36 respectively.

Table 1. Summary of accuracy statistics

Accuracy report	**Non-gully class**	**Gully class**	**Total or Overall accuracy**
Users accuracy	98.67%	54.00%	76.33%
Producers accuracy	68.20%	97.59%	
Kappa accuracy	0.95	0.36	0.52

Figure 5 illustrate the qualitative indication of the accuracy of IO derived gullies map compared with the manually digitised gullies map. The gullies that are omitted and the features that were incorrectly mapped as gullies using IO can be identified on the map.

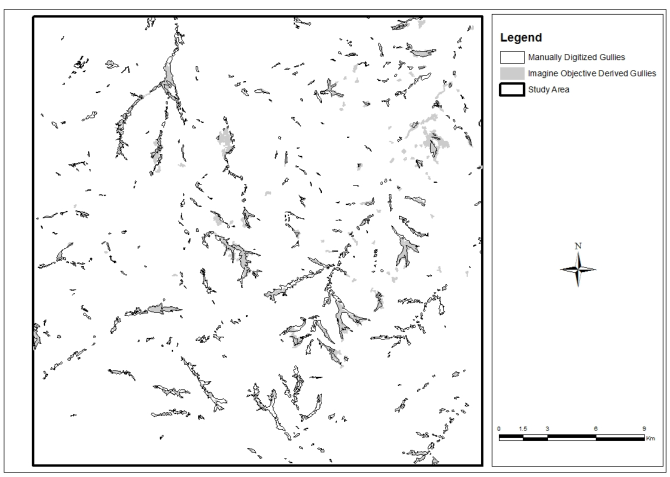

Figure 5: Comparison of manually digitised and IO derived gullies

4.4 Discussions

The overall classification accuracy of 76.33% and the kappa statistic of 0.52 indicate a good correlation between the IO gullies data and the reference manually digitised gullies data as indicated in Mather (2004). However, the above accuracies can also be misleading, because it does not indicate the performance of the IO technique per individual class i.e. gullies and non-gullies class. The user's and the producer's accuracy specifically indicates the performance of IO technique for gullies and non-gullies extraction. A 54% of user's accuracy in gully class indicates that the technique committed 46% of over mapping errors. However, in non-gully class, the user's accuracy indicates that low over mapping errors were committed. This indicates that IO technique failed to distinguish non-gully features with gullies. A 97.59% of producer's accuracy in gully class indicates a good performance of IO technique in detecting gullies. Contrary to this, the kappa accuracy in gully class indicates a less capability of the IO technique in detecting gullies. Kappa is the most commonly used indicator of classification accuracy (Taruvinga, 2008; Persello & Bruzzone, 2010), hence a kappa value of 0.36 in gully class is of great concerns.

The accuracy of IO gullies map was largely influenced by the spectral complexity of gullies and its distinction with the surrounding. According to Taruvinga, (2008), the spectral signature of gullies varies because some gullies may contain vegetation and some may be un-vegetated. Additionally, the spectral signature of bare soil (un-vegetated gully) is dependent on the moisture content, organic matter content, texture, structure and iron oxide content (Aggarwal, 2004). Spectral characteristics of vegetation vary with wavelength and the plant pigment leaves strongly absorb red and blue wavelengths but reflect green wavelengths. The spectral characteristics of bare soil and vegetation are completely different and need to be dealt with separately when selecting training areas. The heterogeneous nature of gullies makes it complex to distinguish with the surroundings, thereby posing a challenge to the classification technique. For example, the study of Torkashvand & Alipour (2009) used supervised classification in plain physiography of Iran and found out that the accuracy decreases where there are other land uses such as cultivation due to similarity in spectral characteristics. On the contrary, manual digitising technique takes full advantage of visual interpretation and delineation of gullies boundary individually by hand to circumvent the challenges of gullies classification techniques.

Compared to other recent gullies extraction studies in SA, the results of this study show a significant improvement in terms of the accuracy. For example, the study of Taruvinga (2008) produced a kappa accuracy of 0.40 for the SVM gullies extraction results and this was considered moderately accurate. The study of Pirie (2009) produced a very low kappa accuracy of less than 0.1 in all supervised classification algorithm such as Maximum Likelihood Classifier (MLC), Mahalanobis Distance Classifier (MDC) and Minimum Distance Classifier (MidDC).

5. Conclusion and recommendations

This study investigated the possibilities of extracting gullies from SPOT 5 satellite imagery using IO feature extraction technique. The accuracy levels produced by the IO technique are regarded as acceptable for gullies extraction and the technique is recommended for future studies. Although much higher accuracy associated with manual digitising of gullies is appreciated, mapping across the entire country like SA in this manner is exceedingly laborious and time consuming (Mararakanye & Le Roux, 2011). Therefore, IO technique will be particularly useful as a preliminary mapping technique to identify gullies affected areas requiring a detailed further investigation.

Although the accuracy of IO technique is acceptable, the results can be greatly improved through the use of much higher spatial resolution imagery. Spatial resolution is a limit on how an object on the earth surface can be represented by a single pixel in an image (Lillesand *et al*., 2008). The spatial resolution of SPOT 5 multispectral imagery limits the capability of IO techniques in detecting smaller gullies. Satellites with relatively higher spatial resolution than SPOT 5 allow the classification technique to detect the smaller features. Although SPOT 5 is considered one of the higher spatial resolution satellite imagery, a 10m x 10m is not enough to detect small gullies of less than 10m. For example, Pirie (2009) indicated that gullies smaller than 10m cannot be detected using SPOT 5 imagery because they become embedded with the pixels. It is therefore recommended that IO technique be tested with much higher spatial resolution imagery such as the Quickbird, TerraSAR-X and IKONOS. Additionally, it was not practical to investigate and test all the functionalities of IO technique. Therefore, it is recommended that other functionalities be tested especially with the much higher spatial resolution imagery.

6. Acknowledgements

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