CHANGE DETECTION ANALYSIS OF GULLY EROSION IN THE TSITSA RIVER CATCHMENT, SOUTH AFRICA, USING ECOGNITION SOFTWARE

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ABSTRACT

The Department of Water and Sanitation is planning to construct a dam on the Mzimvubu River, South Africa. The proposed dam site falls within the catchment area of the Tsitsa River which is a tributary of the Mzimvubu River. Previous studies conducted in the catchment highlighted the erosive nature of the soils which have resulted in widespread gully erosion. Sediment produced from this erosion will reduce the capacity and life span of the dam which is a major concern for the managers of the dam project. Thus, it is important to determine the extent of gully erosion in order to mitigate its effects. Previous studies have mapped gully erosion using manual digitising techniques. This was time-consuming and contained human error and bias. This study aimed to explore the use of object based image analysis to classify gully erosion at a catchment scale. Using SPOT 5 images in eCognition, a ruleset was developed using object brightness, texture and their relationship to neighbouring objects. The gullies classified in eCognition were used to create a gully location map of the dam catchment area. The use of eCognition removed the human error component and proved to be considerably less laborious. Results of the eCognition analysis were compared with results from the manual digitisation which produced an overall accuracy of 98% with a user's and producer's accuracy of 23% and 28% respectively. The study could be improved by using higher resolution imagery such as aerial photographs or Quickbird as well as the use of complementary data such as LiDAR data.

INTRODUCTION

The Department of Water and Sanitation is planning a water resource development in the Mzimvubu River Catchment, Eastern Cape, South Africa. The Mzimvubu River is on record as the only large river network in South Africa without a dam. The proposed dam site falls within the Tsitsa quaternary catchment which was once part of the former Transkei homeland. Although the homeland policy was abolished in 1994 the people remain impoverished, relying on subsistence farming and social grants. Thus, the proposed dam is aimed at improving domestic water supply and irrigation for agriculture [1]. Previous studies conducted in the catchment highlighted the erosive nature of the soils which have resulted in widespread soil erosion and gully formation [2], [3]. Gully erosion is an important source of sediment in the catchment and this will ultimately reduce the capacity and life span of the dam [4]. This is a major concern for planners and managers of the Mzimvubu dam project. Identifying and mapping gullies throughout the catchment is thus crucial in order to determine the effects of gully erosion on sediment production and will help mitigate its effects and improve the dam design [3].

Studies conducted in 2007 mapped gully erosion across South Africa using manual digitising techniques in a GIS environment [5]. Due to the extremely time consuming task of manually digitizing the individual gullies, along with the induced human error and bias it is preferable to automate the task of gully detection [6], [7], [8]. Object-based classification has proven to be useful in image classification as it partitions an image into separate polygons or objects each with their own unique spatial, temporal and spectral characteristics. The relationship between neighbour objects is also considered in the segmentation process thus allowing the image to be characterized by topologic information [9].

Studies using OBIA to identify gullies have previously been conducted by [10], [11], [6], [12]. More particularly, studies on the use of eCognition for the identification of gullies have been conducted by [13], [14], [15], [16] and [7] on various catchments with various accuracies. The use of eCognition to identify gullies was tested in the T35 catchment in Eastern Cape Province by [5]. However, they discontinued the study due to the large amount of pre-processing needed especially when applied at a provincial scale. Geographic Information Systems and remote sensing technologies have been frequently used to assess soil erosion features in Europe, Australia and the Americas. In South Africa, there has been lack of information regarding the spatial extent of gullies at national scale. A manually digitised 1:10 000 gully location map of South Africa using remote sensing and GIS on SPOT 5 images was produced by [5]. This was the first study of its kind conducted in South Africa. The study highlighted the need for automatic, accurate gully mapping techniques based on high resolution satellite imagery with global coverage which are applicable over large areas, in order to reduce the time spent by researchers in manually digitizing gullies [5].

This study aimed to determine the use of eCognition and SPOT 5 imagery to accurately identify and classify gullies in the Tsitsa River Catchment. This was achieved through the following objectives (1) to create a ruleset in eCognition to identify gullies based on the spectral (brightness), and textural properties, as well as to (2) determine the accuracy of the results by conducting an accuracy assessment using previously digitised gullies.

Study Site

The study was conducted in the Tsitsa River Catchment in the Eastern Cape Province of South Africa. The catchment varies considerably in altitude from its source in the Drakensberg mountains over 3000m a.s.l., to its outlet at Ntabalenga which is roughly 1200m a.s.l. At its source the average annual rainfall is over 1400mm per annum whereas lower down in the catchment it averages 625mm per annum, the climate is defined as sub-humid and average temperatures range between 6.6 and 20.3 ºC [3]. Land use is dominated by rural subsistence farming, however, there are a number of larger commercial farms and plantations in the catchment. The vegetation mostly falls within the Grassland biome, with narrow bands of Eastern Valley Bushveld and Afromontane Forests found along drainage lines or ravines [3]. Sedimentary layers of the Quaternary age dominate the geology in the area, which include mudstones of the Tarkastad, Molteno and Elliot Formations along with fine-grained sandstone and siltstone of the Clarens Formation. These layers are capped by basalt of the Drakensberg Formation. There are also numerous injections appearing as sills, sheets and dykes of hard Karoo dolerite [17]. The varied geology, climate and relief in the Ntabalenga catchment has dominated pedogenesis and gives rise to a diverse range of soil types. Due to the highly siliceous lithology from which the soils develop the soils of the catchment are very acidic [18]. Soils in the catchment are highly erosive and dispersive, this along with the presence of duplex soils causes the catchment to be extremely susceptible to gully erosion [2], [3].

METHODS

The study was conducted on SPOT 5 images from 2012 due to their generally good spatial resolution. SPOT 5 images were also easily available as they were acquired by government agencies for a 6 year period for the whole South Africa. eCognition Developer was used for image analysis and post processing of the image objects was done in ArcMap. SPOT 5 imagery was chosen as the only input data for this study in order to develop a classification approach and ruleset which will be applicable to other SPOT 5 images. This can be beneficial for comparing different areas, upscaling the ruleset to the larger catchment or used for multi-temporal analysis, as the classification approach is not location dependent [16]

A combination of eCognition generated gully objects and manually digitised gullies were used. Manually digitised gullies were captured by [5] in 2007 and updated in 2014 by [3]. In eCognition the SPOT 5 image was segmented in order to create objects for further classification. The initial segmentation settings were adjusted to be optimal for gullies; the values for shape and compactness were set to 0.3 and 0.8, respectively. In order to give spectral properties, a strong influence on the objects a low value of 0.3 for shape was set. Setting the value for compactness to 0.8 aimed at delineating more compact objects such as plantations, croplands and large areas of bare soil. As gully-affected areas contain a low degree of compactness, due to their heterogeneous appearance, they were over-segmented which allowed for differentiation against homogeneous arable areas surrounding the gullies [16].

Using the eCognition's custom algorithm function the normalized difference vegetation index (NDVI) was calculated using the red and near infra-red bands of the SPOT 5 image at the image object level [19]. A separate calculation was used to calculate the modified normalized difference water index (MNDWI) using the green and short-wave infra-red bands of the image [20]. The threshold for NDVI was set to zero in the first step and the MNDWI threshold was set to 0.25. These two indices were used to remove water and vegetation cover in the first step of the classification process. This allowed for a large portion of the image to be removed from the rest of the classification process, helping to streamline the results.

The segmentation process broke the gullied areas up between areas of soil and areas of dark soil or shadows. A series of rules were written based on soil brightness to establish areas of bare soil, sparsely vegetated soil, light shadows and very dark shadows. All these spectral properties can be found in a single gully, which makes a single classification algorithm difficult. Thus, a series of rules based on size and brightness were written to merge areas of bare soil and shadow to create the gully outline.

This method also classified tilled croplands in gully classes. In order to remove these errors the texture of the gullies were taken into account. Gullies contain areas of light and dark patches in random arrays depending on the angle of the sun or objects creating shadows. In contrast, tilled land creates shadows of continuous straight lines along the areas of tillage. Thus the texture after Haralick algorithm was used [21]. A grey level co ordinance matrix of contrast at all angles across band one was calculated to get the texture values. A threshold of 1.2 was used to separate gullies from tilled land. This was all done in eCognition using the inbuilt texture algorithm. A series of rules were then written to merge the areas classified as soils and shadows in order to create unified gully objects. Houses were also classified as gullies using these earlier rules and the separation of gullies from houses was achieved in this step. Houses are generally small, square objects less than 150 pixels in size, thus, areas classified as gullies smaller than 150 pixels were removed as houses. The relational border algorithm was then used to incorporate small gullied areas mis-classified in the previous step all objects which shared a border of more than two pixels with gullies were classified then as gullies. The results were then exported as a shapefile to ArcMap for further processing.

Another error in the classification was road lines that were incorrectly classified as gullies. The majority of the roads in the catchment are unpaved. In ArcMap, road lines at a scale of 1:50 000 were used to create a buffer of roughly 40 m, as the error threshold of the dataset is 40 m. The buffer was then used to erase the exported polygons falling along these lines.

The final challenge was to separate rock outcrops from the gullied areas. The texture algorithm after [21] was used because of challenges encountered with the similarities between the brightness values of the rock outcrops and gullied areas. Rock outcrops tended to have a higher vegetation to rock ratio than the gullies and their homogeneity texture was thus different. A grey level co ordinance matrix of homogeneity at all angles across band one was calculated to get the texture values. A threshold of 0.08 was used to distinguish rocks from gullies. The results were then exported as a shapefile to ArcMap for further processing.

An accuracy was then conducted to determine the correctness of the results. This was done by conducting a simple raster calculation between the digitized gullies and the gullies extracted in eCongition which was done in ArcMap. Both data sets were converted to raster files as follows: no data values (i.e. areas where no gullies were found) were given a value of zero, while areas where gullies had been identified were given a value of one for the eCognition data set and ten and twenty for the digitized data set. Ten represented an area of no gullies while twenty represented a gullied area. The two data sets were then added which gave four classes namely ten, eleven, twenty and twenty one. These classes represented the various combinations of gullies and no gullies between the two data sets, as shown in table 1. The results of the error matrix were interpreted using the producer's accuracy, user's accuracy, overall classification accuracy.

Table 1: showing the four classes of the basic accuracy assessment

VALUE	
10	Neither dataset found gullies
11	The digitised gullies showed no gullies yet eCognition found gullies
20	The digitised dataset found gullies where eCognition found no gullies
21	Both datasets identified gullies

RESULTS

Visual assessment of the classified gullies shows an acceptable accuracy. It also shows some benefits over the manually digitized gullies. The classified gullies formed more accurate boundaries around the gullies, "hugging" the edges more closely than that of the manually digitized gully boundaries. They were also able to distinguish between the inter gully and the gully area more accurately than manual interpretation. From visual interpretation it was also noted that errors were made by both the manual interpreter and eCognition classification.

Results of the basic raster calculation accuracy assessment gave an overall accuracy of 98%. The users and producers accuracy was less correct; 23%, 28% respectively. The manually classified gullies had an accuracy of 93% [3].

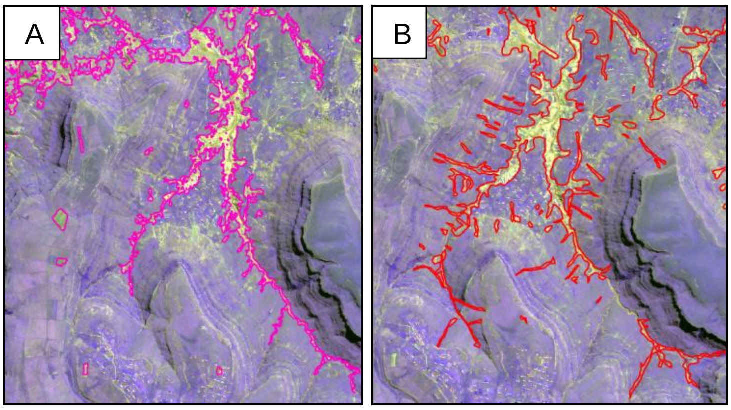

Figure1: Gully outlines created by eCognition in pink and by manual interpretation in red. Highlighting the comparison between the results of the gullies classified in eCognition [A], and those that were manually digitized [B]

Results from the accuracy assessment show a good overall accuracy, however, a poor user and producer's accuracy. This can be attributed to a number a reasons. As mentioned by [22], the accuracy assessment relies on the accuracy of the reference data which in this case was the manually digitised gullies with a user's accuracy of 93%. Human error and bias is inherent in all tasks such as manually digitising and it is accepted that the data set used in this study had some errors. eCognition did make errors and falsely classified some rock outcrops, sedimented areas of the river and tilled land which was most likely the largest contribution to the low user and producer accuracies. Another cause can be due to the eCognition gullies having a more distinct borders around the gullies whereas the manually digitised gullies were rougher and included vegetated areas. The rivers in the catchment were badly silted and the MNDWI index was unable to distinguish parts of the rivers as water. This was mainly around the river bends where the water velocity is slowed and sediment falls out of suspension. This can be corrected using an average MNDWI from numerous years to extract the river or using a river map. In some areas of the catchment, manual digitizing was found to produce similar errors to that of eCognition, for example where digitizers were unable to distinguish certain rock outcrops from gullies. It was also noted that the operators digitized gullies which were densely vegetated. eCognition was unable to distinguish these from normal grasslands. This is not necessarily a problem since highly vegetated gullies are considered inactive or contribute negligible sediment to the catchment outlet.

The study aimed to create a ruleset which was transferable to the entire catchment and with some adjustments would be transferable to other images in order to conduct a time series analysis. Thus it was important that the ruleset was not location dependent. This made it difficult to separate rock outcrops from the gully classes as they have similar spectral properties. The tilled land posed a similar problem. These problems can be corrected by using an up to date land cover map.

CONCLUSIONS

Object based image classification has developed into a powerful tool for land cover mapping. Allowing for faster processing times and more objective classification results. This study aimed to classify gullies at a catchment scale using a ruleset which would be transferable to allow for time series analysis of gully erosion in the area. The results produced a good overall accuracy at 98% yet poorer users and producers accuracies. These results compare similarly with that of [16] who used eCognition to extract gullies in Morrocco with a producers and users accuraacy of 16% and 38% respectively. They concluded that the resolution of the image as well as the diversity of the gullies over their study area were the causes for the low users and producers accuracy overall yet they were satisfied with their reults. When taking into account the diversity of gully erosion in the catchment as well as the potential for noise and the resolution of the images used, the accuracies obtained in the study are acceptable. The results were satisfactory for gully analysis over the catchment and the final analysis took just over four hours for the two SPOT 5 images which were processed, considerably less time than manually digitizing these images. It was also found that eCognition produced more accurate boundaries along the gully edges as well as producing more objective results than manual digitizing, [8] also concluded this from their study in Morrocco.

There are, however, numerous techniques which could be used to improve this study. Light Detection and Ranging (LiDAR) techniques have been used quite extensively and with good accuracy in numerous studies [23], [24], [25] and [26]. As gullies are usually defined by their depth, LiDAR data will greatly facilitate in the distinction between gullies and other forms of erosion as well as facilitate in the separation of roads and rock outcrops from gullies. The study could also be improved by using higher resolution imagery with a greater spectral resolution to allow for the use of other indices such as the bare soil index which may also aid in creating more accurate classification results.

The results of this study can be useful for time series analysis to determine the sediment generated from the gullies over a certain time period as well as for the mapping of gully erosion for conservation projects. It is envisaged that with some modification of the ruleset, it can be transferred to other catchments in South Africa as well as other satellite images such as Ikonos or QuickBird. Further studies should consider the use of LiDAR data as a complementary dataset to aid the classification of gullies and separate them from other noises such as rock outcrops or tilled land.

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