OBJECT-BASED MONITORING OF GULLY EXTENT AND VOLUME IN NORTH AUSTRALIA USING LIDAR DATA

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ABSTRACT:

Gully erosion is a major cause of sediment movement to water courses and can cause significant environmental problems such as soil fertility loss, sediment and nutrient discharge, and deterioration of water quality within a catchment. In northern Queensland, Australia the discharge of sediments and nutrients into the Great Barrier Reef lagoon may impact on vital marine ecosystems with associated consequences for tourism. The volume of sediments discharged from gully erosion in northern Queensland is unknown. Therefore, the objectives of this research were to: (1) develop an object-based approach for monitoring gully extent and gully volume based on multi-temporal LiDAR data acquired in 2007 and 2010; and (2) assess changes in extent and volume of gullies for three selected study sites in northern Queensland. The rule set developed in eCognition 8 could successfully be used for all three study sites in the Fitzroy catchment, Queensland to map gully extent and volume. However, the assessment of the results indicated that an accurate ground point classification of the LiDAR data will improve the results of mapping gully extent. Although widening of gullies was identified in some areas, the main expansion of gully extent occurred near gully heads and meander bends. Deepening of gullies resulted in the majority of soil loss.

1. INTRODUCTION

Gully erosion processes significantly degrade land condition and have detrimental effects on water quality and sediment discharge in a catchment (Poesen et al., 2003). Recent sediment tracing work has shown that gullies are a significant contributor of sediment loads in the catchments of the World Heritage listed Great Barrier Reef in Queensland, Australia. Locating and quantifying gullied areas and volumes within a catchment is a major challenge for the monitoring and reduction of sediment movement to reduce sediment and nutrient discharge into the Great Barrier Reef lagoon (McKergow et al., 2005).

Gully erosion can be defined as a process causing removal of soil through concentrated surface runoff characterised by incised channels greater than 30 cm and generally restricted to streams $\leq 3^{rd}$ order (Peasley and Taylor, 2009). Some of the major causes of gullying are triggered by inappropriate cultivation and irrigation, overgrazing, logging, road construction and urbanization. While gullies have been mapped through conventional field surveying, it is labour intensive and expensive. Identifying the edges of large gullies is difficult, even from in-situ observations. Accurate and spatially extensive information on gully location and extent at an appropriate spatial scale is essential to reduce sediment movement (Poesen et al., 2003). Remote sensing may provide suitable means for delineating gully extent. Some studies have successfully mapped gully extent using remote sensing, but to derive detailed spatial information on gully volume and geomorphic characteristics, LiDAR data are required (James et al., 2007). Despite the ability to include shape and contextual information, object-based image analysis has only been used in very few studies for mapping gully extent (Eustace et al., 2009). This research builds on that study, but expands the object-based processing routine to include the volume estimation and assessment of multi-temporal change.

Information on land condition is essential for sustainable management of natural resources in rangelands and quantification of gully erosion is invaluable for grazing land managers and policy makers responsible for sediment loads from reef catchments draining into the Great Barrier Reef lagoon. Therefore, the objectives of this research were to: (1) develop an object-based approach for monitoring gully extent and gully volume based on multi-temporal LiDAR data; and (2) assess changes in extent and volume of gullies for three selected study sites in northern Queensland, Australia. eCognition 8 was used for the object-based classification of gully extent and volume. Changes occurring in gully extent and volume were assessed based on LiDAR data captured in 2007 and 2010 of the three study sites. Challenges related to object-based multi-temporal analysis of gully extent and volume using LiDAR data will also be identified and discussed. The derived results will be used to support calibration and validation of gully extent and volume at the catchment scale using optical and ancillary spatial data to map and model the probability of gully erosion.

2. STUDY AREA

The study area was located within the northern parts of the Fitzroy catchment, Queensland, Australia and consisted of three sites each covering two LiDAR transects that were 5.5 km long and 0.4 km wide (Figure 1). The three study sites covered an area of approximately 4 km^2 each and were selected because of extensive gully erosion occurring within them (Figure 2). Within the study area extensive clearing of woody vegetation has occurred in the past and transformed large areas into open woodland converted into pastures for beef cattle. However, patches of remnant woodland vegetation remain and regrowth is common. The major land use is grazing with some agriculture also occurring. The soils vary considerably and include extensive areas of fairly erodible red duplex soils and large areas of poorly structured sand. The area receives on average 600-700 mm of rain mainly between October and March. As most, but not all, gullies are connected to streams, the sediments from gully erosion are often washed into the streams.

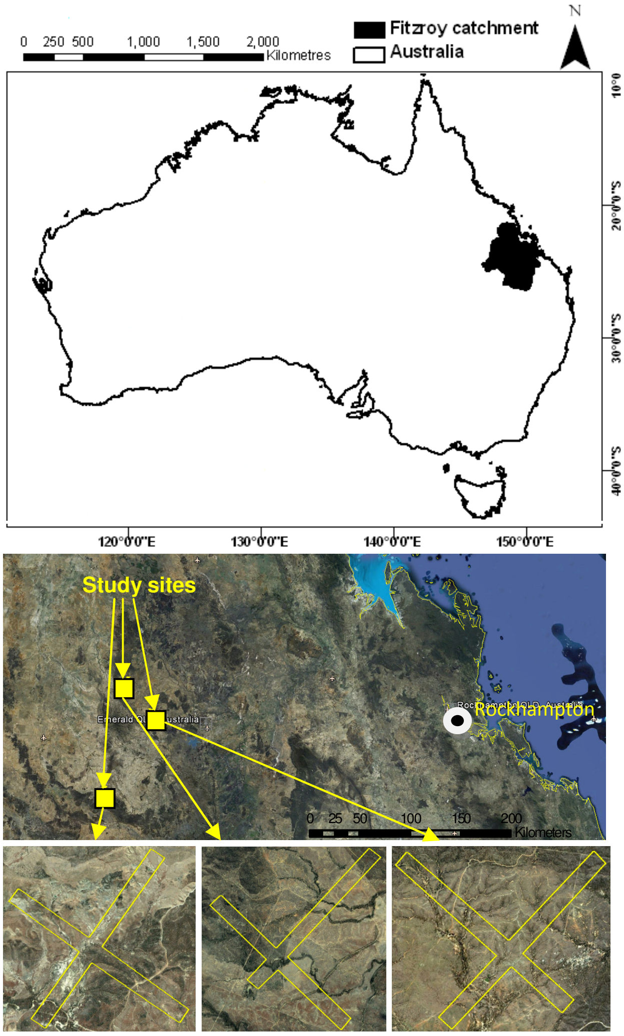

Figure 1. Location of study sites within the Fitzroy catchment in Queensland and the area covered by LiDAR data in 2007 and 2010 within the three study sites.

Figure 2. Photos of different gully types within the study area.

3. DATA AND METHODS

3.1 Image and Field Data

LiDAR data were used to assess changes in gully extent and volume and to generate calibration and validation data for catchment scale mapping and monitoring. LiDAR data were captured for three selected sites in the Fitzroy catchment in February 2007 with the discrete return Optech ALTM3100EA sensor and in June 2010 using the full waveform Reigl-680 sensor. The point spacing of the LiDAR data was 0.5 m along track and across track. The cloud points were classified into ground and non-ground returns by the data providers using proprietary software. Substantial research was invested in pre-processing the LiDAR data sets to understand the effects of using different LiDAR sensors and data acquisition specifications. Based on this initial LiDAR pre-processing research, a suitable spatial scale of mapping was selected to account for uncertainties associated with the data.

Field observations of gully location were carried out between the 13 and 17 November 2009, including, but not limited to, the three study sites. A laptop connected to a GPS receiver was used to display pan-sharpened SPOT-5 images with 2.5 m pixels in ArcGIS 9.3 while driving along roads. The routes were selected based on access and visual identification of potential gullies from the pan-sharpened SPOT-5 image data and areas with high spatial resolution image data coverage in Google Earth. The majority of gullies were identified from the roads and immediately marked on the pan-sharpened SPOT-5 image in ArcGIS while driving and additional remarks were added where appropriate. Other features that had image based appearance similar to gullies, such as scalded ground, quarries, gravel pits and sandy streambeds were also identified and marked on the image. While this allowed classification of gullies versus non-gullies, high spatial resolution orthophotos of 13 cm pixels captured coincidently with the 2010 LiDAR data were used to assess and validate the mapping of gully extent.

3.2 Image Processing Methodology

3.2.1 Data Preparation: To monitor gully extent and volume LiDAR derived digital terrain models (DTMs) and terrain slope layers were produced from each data set at a spatial resolution of 0.5 m. The DTM was produced by natural neighbour interpolation of returns classified as ground hits. From the DTM, a raster surface representing terrain slope, i.e. rate of elevation change in horizontal and vertical directions from the center pixel of a 3 x 3 moving window was calculated using ArcMap 10. Layers of plant projective cover and a canopy height model were also produced as outlined in Johansen et al. (Johansen et al., 2011).

3.2.2 Mapping Gully Extent: As gullies were defined as incised channels greater than 30 cm and restricted to streams ≤ 3rd order, a stream order shapefile provided by the Queensland Department of Environment and Resource Management was used to eliminate stream banks belonging to streams > 3rd order to prevent them from being classified as gullies. This was done using the object-based approach described by Johansen et al. (2011) to map streambed and riparian zone extent. The subsequent classification of gullies was based on the DTM and slope layers (Figure 3a,b). To identify edges of gullies, a pixel min/max filter using the difference of brightest to darkest pixel mode with a 2D kernel size of 5 x 5 pixels based on the DTM was applied to produce a new layer (Figure 3c).

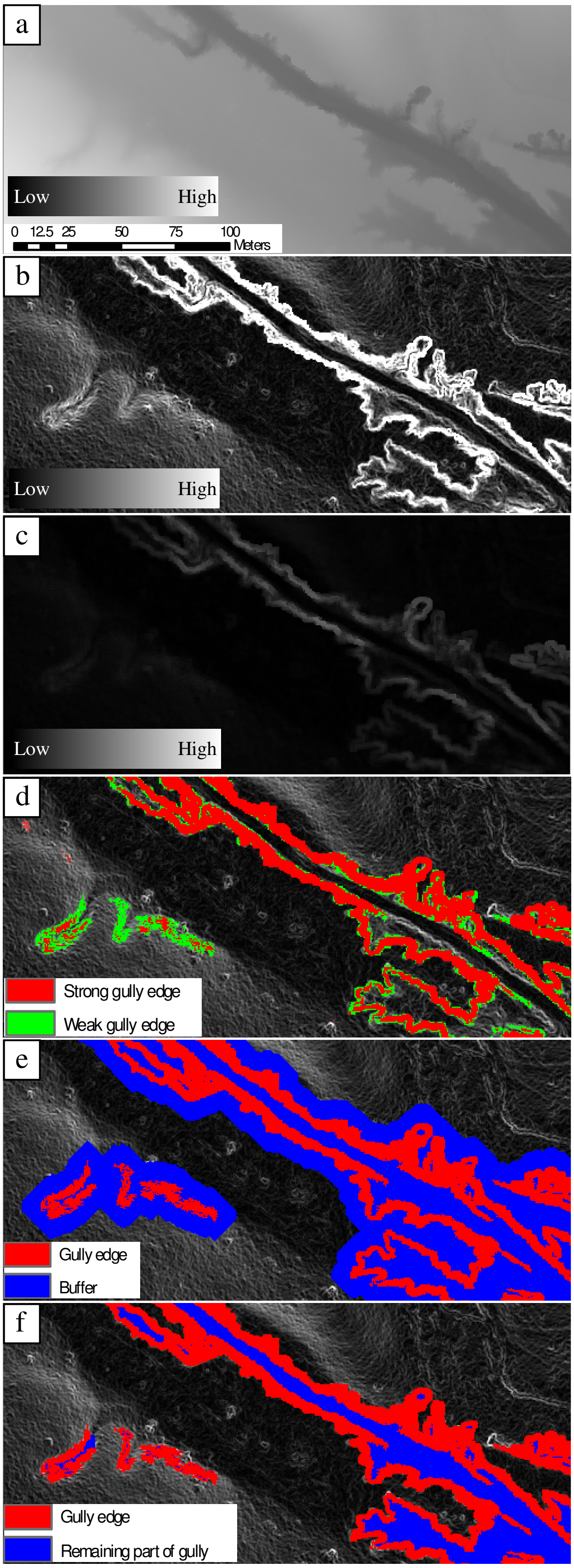

Figure 3. Steps in the rule set used to map gully extent. (a) DTM; (b) slope; (c) filtered layer; (d) strong and weak gully edges; (e) buffered gully edges; and (f) final gully classification.

The new layer produced using the filter was used to classify strong and weak edges of gullies by setting a threshold of 0.6 and 0.45, respectively. Weak edges having a relative border of less than 10% with strong edges were unclassified to avoid classifying sloping land as gullies (Figure 3d). This provided an outline of most gully edges within all three study sites. Subsequently, strong and weak edges were merged and remaining small objects of less than 100 pixels were unclassified. The pixel-based object resizing algorithm and the coating mode was then used to create a 25 pixel wide buffer around objects classified as gully edges (Figure 3e). This process was applied to fill out the centre of the gullies with flat or limited sloping surfaces generally found at lower elevation than the classified gully edges. A chessboard segmentation (object size = 5) followed by a multiresolution segmentation (scale parameter = 9, shape = 0.1, compactness = 0.5) was applied based on the DTM and slope layers to create objects on both the outside and inside of the gullies. Those newly created objects within the buffer that bordered unclassified objects were unclassified. A number of steps then followed to eliminate those remaining buffer objects that did not belong to the gullies, assuming that buffer objects belonging to a gully would have a large relative border to gully edge objects, a small relative border to unclassified objects and a lower DTM value than adjacent gully edges (Figure 3f). As the buffer did not cover the centre sections of large gullies, additional processes were added to the rule set to expand these gullies (Figure 4a,b).

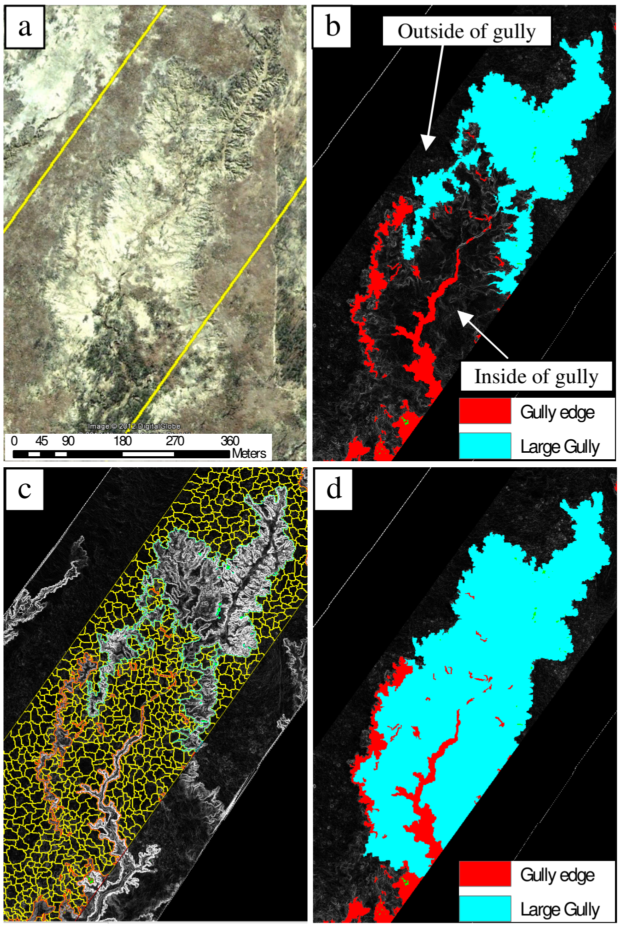

Figure 4. Mapping of large gullies. (a) Google Earth image of gully extent; (b) initial classification of large gully; (c) segmentation of remaining unclassified parts of the large gully; and (d) final classification of the large gully.

Those parts of large gullies already classified were reclassified as large gullies based on their large area, their compactness and density relative to other classified gullies (Figure 4b). A chessboard and multiresolution segmentation (scale parameter = 10, shape = 0.1, compactness = 0.5) based on the DTM layer was applied (Figure 4c). The obtained objects, as opposed to using single pixels and the pixel-based object resizing algorithm, were required, as the external edge of the large gullies did not form a continuous classified edge, but occurred with some minor gaps due to sections with limited slope. Using pixels or small objects, the growing of the large gullies outside the extent of the actual gully occurred due to local elevation decreases. The use of larger objects ensured that objects on the inside of the gully edges had lower mean DTM values than the gully edges and those objects on the outside of the gully edges not forming a part of the actual gully. Based on these elevation characteristics, the image object fusion algorithm was used to grow the large gully objects into non-classified objects of the remaining unclassified parts of the large gullies (Figure 4d).

3.2.3 Mapping Gully Volume: To calculate the volume of the extent classified as gullies, the outer layer of pixels classified as gully edges were initially identified using the pixel-based object resizing algorithm and the shrinking mode to classify this line of pixels (Figure 5a). The volume per pixel within the gullied areas was calculated using a number of Update Variable algorithms developed. First the mean elevation difference between edge pixels and the adjoining gully pixels were calculated. This layer of joining pixels was then classified as edge pixels, i.e. two layers of edge pixels were produced. A loop was then introduced where the following four steps were progressively repeated to calculate the elevation difference between the gully pixels and the edge pixels within the closest Euclidean distance: (1) For pixels adjoining the new layer of edge pixels, the accumulated elevation difference of the adjoining edge was calculated; (2) Next the difference in elevation between the edge pixel and adjoining pixels was calculated; (3) An updated accumulated elevation difference measure was calculated by adding the accumulated elevation from (1) with the elevation difference from (2); and (4) The pixels adjoining the edge pixels were classified to become the new edge pixels (Figure 5b). This loop was then repeated for the next adjoining layer of pixels until all pixels classified as gully were processed. This means that each single pixel classified as gully consisted of a calculated volume in relation of the nearest gully edge (Figure 5c).

3.2.4 Multi-Temporal Analysis of Gully Extent and Volume: Visual interpretation of the mapping results revealed that some areas with sloping land had incorrectly been classified as gullies. To ensure a more appropriate interpretation of changes in gully extent and volume, the classified gullies or sections of gullies within each of the study areas were subset to exclude areas with sloping land. This produced 10, 5 and 4 subsets within the three study sites, respectively. For the selected gully subsets, a change detection map of gully extent was produced. In addition, the overall extent and volume of the gullies in 2007 and 2010 were calculated. A comparison of the extent and volume assessed within 1 m depth intervals was conducted for the gullies mapped by the LiDAR data from 2007 and 2010.

3.2.5 Accuracy Assessment: Only gully extent mapped from the 2010 LiDAR data was validated based on the high spatial resolution orthophotos captured coincidently with the 2010 LiDAR data. A total of 50 validation points within each study site using the subset gullies were selected from the orthophotos as well as another 50 validation points within areas classified as gullies using the object-based approach. This produced a total of 300 validation points for the three study areas. User's and producer's accuracies were calculated for gully extent.

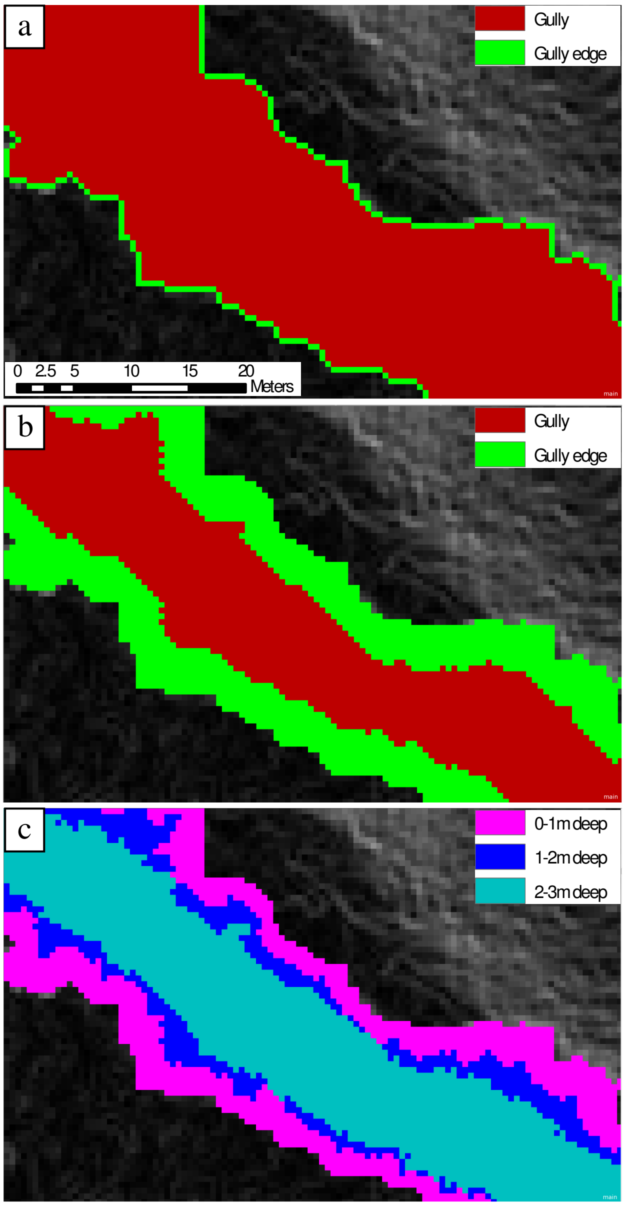

Figure 5. Mapping gully volume. (a) Classification of gully edge; (b) calculation of gully volume for each pixel based on elevation difference to the gully edge; and (c) final gully volume classification.

4. RESULTS AND DISCUSSION

4.1 Object-Based Image Classification

The results of the object-based classification of the three LiDAR study sites revealed that the same rule set could be used for both the 2007 and 2010 LiDAR data and for the three sites for mapping gully extent. The only part of the rule set that required minor adjustment, was the step that eliminated remaining buffer objects not belonging to the gullies (Figures 3e,f). The calculation of the gully volume worked in all cases, but relied on the accurate mapping of the gully extent. However, it is recognised that the proposed method for mapping gully volume is only one of several approaches. The approach used in this project may produce a disjointed appearance of gully volume in the centre of the gully, as the volume is calculated in relation of the edge elevation within the closest Euclidean distance. However, the calculation of the gully volume performed in this research was not affected by rugged gully edges of different elevation and the volume calculation was based on a direct measure of elevation difference to the gully edge as opposed to interpolating the landscape surface within gullies and then estimating the height difference between the interpolated surface and the elevation of the gully floor (Eustace et al., 2009). Future work should focus on comparing different approaches and related results of estimating gully volume.

Based on the 300 validation points, and overall accuracy of mapped gully extent was 92.3% for the LiDAR data from 2010. The main contributing factor to classification error was areas of sloping land, especially when located next to gullies, which in some cases resulted in errors of commission. All classification errors occurred close to the gully edges. The user's and producer's accuracies were 93.9% and 98.2%, respectively, indicating the difficulty of discriminating between gully edges and adjacent sloping land in the classification process.

4.2 Change Detection Results

The comparison of gully extent between 2007 and 2010 showed that the extent had increased by 4639 m^2 for site 1, but decreased by 1235 m^2 and 1023 m^2 for sites 2 and 3, respectively. From visual assessment of the mapping results, it was apparent that the gully extent was overestimated in the classification of the 2007 data, because the point cloud classification of ground and non-ground points were less accurate for the 2007 data than the 2010 data. Some areas with trees and shrub cover appeared with minor increases (0.1 – 1.0 m) in elevation in the 2007 data, whereas these elevation increases were not detected in the 2010 data (Figure 6a). In many cases where trees or shrubs occurred along the edge of gullies, these areas were incorrectly included as part of the gully edge in the 2007 data because of the incorrect elevation differences producing steep slopes similar to those of gully edges. However, in those situations where the trees and shrubs were not adjacent to the gully edges, they were not mapped as gullies because of their small areal extent.

Several cases of gully expansion were identified in the change detection between the gully extent classifications based on the 2007 and 2010 LiDAR data. Figure 6 provides an example of a 14 m expansion of a gully head. While many gullies did widen, the majority of change occurred at the gully head and in meander bends. Gully head expansion up to 23 m between 2007 and 2010 was detected. When assessing the change in gully extent at different gully depth intervals, the extent of depth intervals of 1-2 m, 2-3 m, 3-4 m, 4-5 m, 5-6 m, 6-7 m, and >7 m increased for the 19 gullies assessed in 88-100% of cases. When assessing all gullies for each of the three sites, it can be seen that all, but the 0-1 m gully depth interval, showed an increase in extent (Figure 7). Study site 1 had significantly deeper gullies than the other two study sites. For study site 1, the 3-4 m depth interval had the highest levels of soil loss (Figure 8). The largest amount of soil loss within gullies for study sites 2 and 3 occurred in the gully depth interval of 1-2 m. Figure 9 provides an example of a gully that expanded and deepened between 2007 and 2010 within study site 1. Because of some misclassifications of gully edges in the 2007 data caused by the misclassification by the data provider of LiDAR ground points, the extent and volume were assessed excluding the 0-1 m depth interval. Table 1 shows that gully extent and volume increased for all three study sites when excluding the 0-1 m depth interval. When excluding the 0-1 m depth interval, an average soil loss of 0.33 m^3, 0.32 m^3, and 0.27 m^3 per m^2 of gully extent was mapped for study sites 1, 2 and 3, respectively.

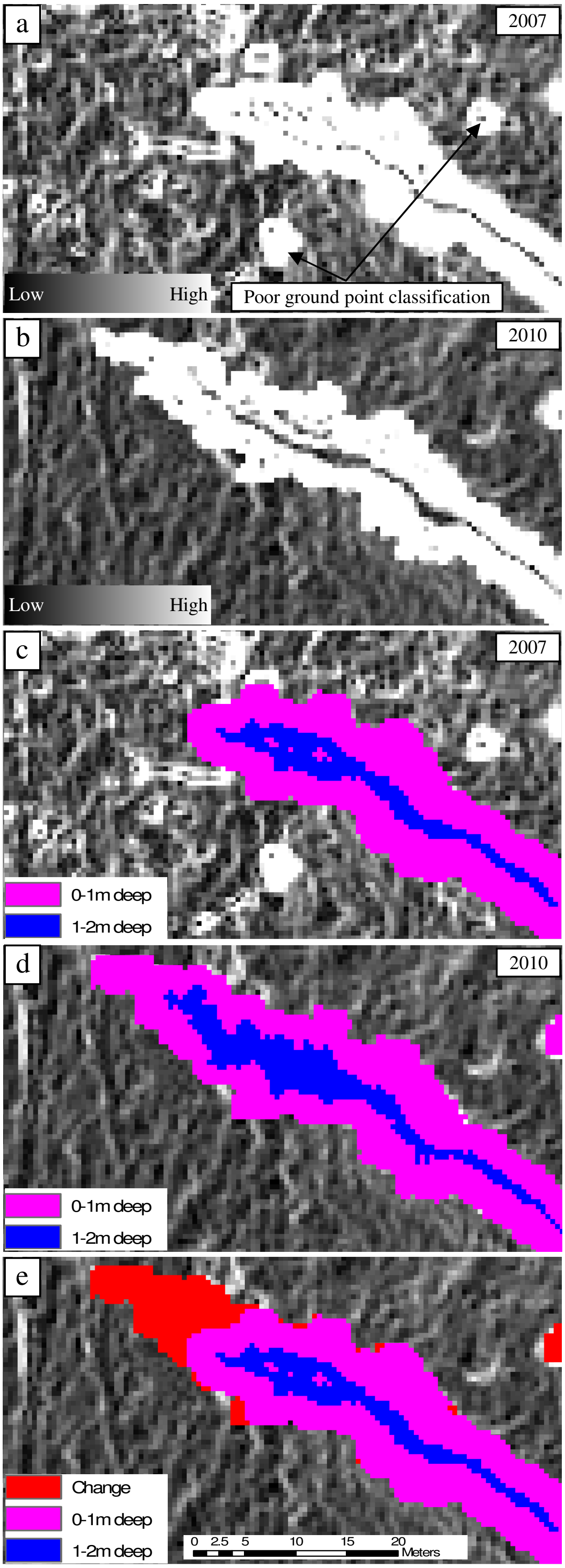

Figure 6. Change detection of gully extent. (a) Slope layer from 2007; (b) slope layer from 2010; (c) gully volume based on 2007 LiDAR data; (d) gully volume based on 2010 LiDAR data; and (e) change in gully extent between 2007 and 2010.

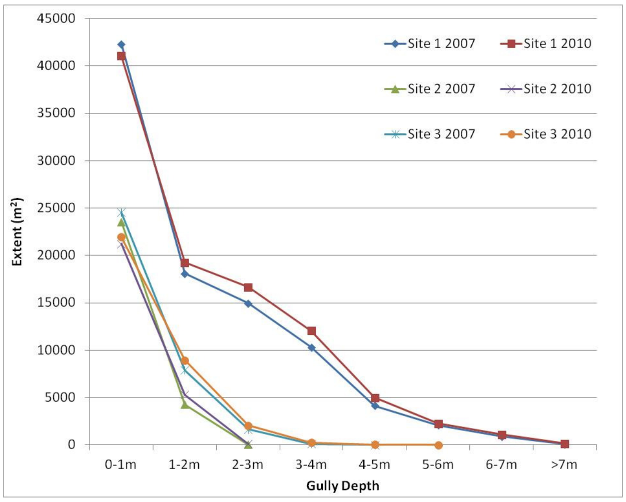

Figure 7. Gully extent in 2007 and 2010 within different gully depth intervals.

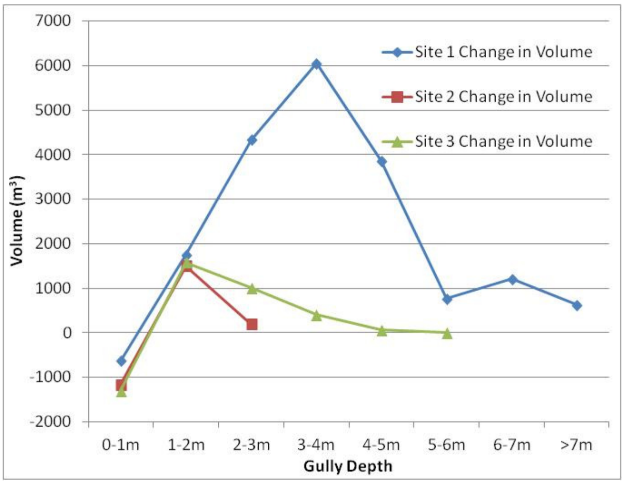

Figure 8. Positive values in volume indicate a loss of soil within gullies between 2007 and 2010, whereas the negative values for the 0-1 m depth interval were caused by incorrectly gully edge mapping of the 2007 LiDAR data.

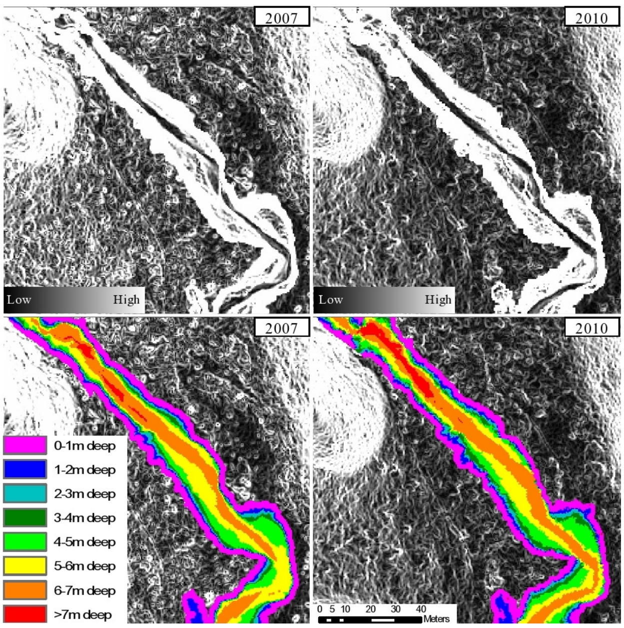

Figure 9. Slope layers and associated classification of gully volume of a subset of the 2007 and 2010 LiDAR data.

Table 1. Gully extent of the subset gullies within each study site with and without the 0-1 m depth interval included.

Site no and year	Extent (m^2)	Extent excl. 0-1 m deep gullied areas (m^2)	Volume (m^3)	Volume excl. 0-1 m deep gullied areas (m^3)
1/2007	92843	50536	158207	137053
1/2010	97483	56429	176169	155643
2/2007	27836	4296	18239	6469
2/2010	26601	5378	17963	8171
3/2007	34172	9630	28592	16321
3/2010	33148	11218	30346	19381

5. CONCLUSIONS

This work focussed on the development of a rule set for mapping the extent and volume of gullies occurring within three study sites. The developed rule set could be used for all three study sites to map gully extent and volume. However, an overestimation of gully extent mapped from the 2007 LiDAR data was caused by poor LiDAR ground point classification in areas with trees and shrub cover. The majority of gully expansion occurred at gully heads and meander bends. When excluding the 0-1 m gully depth interval, both gully extent and volume increased for the three study sites between 2007 and 2010. The expansion and deepening of gullies within the three study sites indicate that erosive processes are active in the landscape and may over time lead to significant soil loss, which will require management activities to focus on reducing sediment discharges from reef catchments into the Great Barrier Reef lagoon.

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