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Large-Area, High-Resolution Remote Sensing Based Mapping of Alluvial Gully Erosion in Australia’s Tropical Rivers

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Abstract

Alluvial gully erosion is a dominant sediment source of many large rivers draining into the Gulf of Carpentaria. Recent field reconnaissance and aerial survey has highlighted that gullies have a considerable impact on the landscape. In order to understand alluvial gully erosion it is essential that a detailed survey of the nature and extent of alluvial gully erosion be undertaken. Remote sensing is the only practical approach for undertaking this assessment due to the extent and nature of gully erosion in Australia’s tropical rivers.

In this paper a two level method for mapping gully erosion in Australia’s tropical rivers is reported that uses Aster (Advanced Spaceborne Thermal Emission and Reflection Radiometer) satellite image data as the regional level data source. The first level is a data centred remote sensing overview and the second level is a remote sensing image analysis method. Results of a pilot study looking at a 600km² section of the Mitchell River demonstrate feasibility of the method. The results illustrate a variable scale approach for mapping alluvial gully extent and density with potential for a range of regional scale mapping applications.

Key Words

Remote Sensing, alluvial gully erosion, framework, large-area mapping, feature mapping

Introduction

A previously unrecognised class of gullies, found exclusively within alluvium, have recently been identified in Northern Australia (see Brooks et al. this volume). These alluvial gullies are believed to be the dominant sediment source of many large rivers draining into the Gulf of Carpentaria. In particular, recent field reconnaissance and aerial survey in the Mitchell, Gilbert, Leichhardt and Nicholson-Gregory rivers has highlighted that the impact of gully erosion is considerable (see Brooks et al. this volume) despite being highly spatially variable in extent. While gully erosion may be locally common in a particular river setting, their occurrence is quite sparse at the catchment or regional scale. Alluvial gully features in tropical savannah Australia are morphologically complex (see detailed description in Brooks et al. this volume) with considerable variation in size, (from < 100m² to > 1km²), shape (ranging from linear to circular), placement with in landscape (immediately adjacent to streamlines or spatially separated), and orientation (parallel to or perpendicular to a streamline). However, no catchment wide assessment of alluvial gully erosion has been undertaken in the remote tropical savannah rivers, and existing sediment budget models, such as SEDNET, do not distinguish between alluvial and non-alluvial gullies.

The objective of this research was to undertake a remote sensing baseline assessment of alluvial gully erosion extent and severity in Australian tropical savanna rivers. The research...
has been constrained by the scale of Australia’s tropical rivers, by remoteness and by the lack of infrastructure. For example, the Mitchell River catchment is 72,000 km² in area, with headwaters near Cairns in the east flowing more than 600 km northwest into the Gulf of Carpentaria (see Figure 1). There are few roads (most are unsealed and completely impassable in the wet) and ground access to rivers is difficult at best and generally impossible. A remote sensing based mapping approach is the only practical approach for mapping features and processes over large areas (such as catchments >10,000 km²) and when access on the ground is difficult. However there are a number of unique issues that have to be addressed when undertaking remote sensing over large areas that are not evident when mapping over small areas. For example, when dealing with relatively high resolution imagery (such as Landsat or Aster imagery) mosaic files can be very large (>10Gb), comprised of numerous (50 or more individual satellite image scenes), most of which have been acquired at different times (at different seasons and years). As a result the remote sensing process becomes more complicated and cumbersome requiring considerable processing power and data storage resources.

In this paper a method for undertaking remote sensing based mapping of alluvial gully erosion in tropical Australia is presented. The method has two levels. A data centered overview strategy and an image analysis method that facilitates processing in spatially manageable stages. Results from a pilot study are presented to illustrate the application of the method. The pilot study comprises a 600 km² study site in the Mitchell River Catchment (Figure 1) and provides a test for scaling processing up to the regional extent.

Remote Sensing Methodology

The higher level data centred remote sensing methodology (Table 1) is based Phinn (1998) with modification in Phinn et al. (2003) and McDermid et al. (2005). The modifications presented focus on selecting

Table 1: Summary of data centered remote sensing methodology after Phinn (1998).

<table>
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<tr>
<th>Remote sensing stage</th>
<th>Detailed description</th>
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<td>1. Problem definition and understanding issues</td>
<td>Tasks</td>
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<td></td>
<td>1. Feature detection (i.e. - a process of finding target features in the imagery).</td>
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<td></td>
<td>2. Delineation (i.e. - a process of describing the feature once identified).</td>
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<td>3. Regional scale mapping of gully erosion.</td>
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<td>2. Evaluation of existing remotely sensed data as a</td>
<td>Existing remotely sensed data:</td>
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| suitable solution                                       | 1. DTED2 digital elevation data (30m DEM): SRTM (Shuttle Radar Topography Mission) derived data supplied by Australian Defence Force under licence for use in this project. This data is most useful for delineating valley features at the regional scale (NASA DTED2, 2007).
|                                                          | 2. ASTER satellite imagery (NASA Aster, 2007): Aster is the preferred remote sensed data (particularly bands 1 2 & 3 with 15m pixel resolution) as it is an almost complete coverage over the study area and has the highest resolution data available to the project. 3. Landsat / Landsat ETM+: The main benefit of Landsat imagery is as a backdrop for the Aster mosaics to fill gaps in the Aster coverage. |
| 3. Identification of new remotely sensed data as a      | Acquisition of very high resolution image data for calibration and validation of classification routines to map alluvial gullies using Aster imagery. Includes: |
| suitable solution                                       | 1. Aerial photographs (~10500 photos) 12 megapixel camera (Canon EOS 1Ds) for all flight paths (0.1-0.3m resolution) to enable accurate target description and conceptual model development. |
|                                                          | 2. Lidar - Airborne Laser Scanner (ALS, Riegl Q560i) acquired over 25 sites x 10-30 sq km at approximately 0.3m resolution essential for calibrating and validating the DTED2 DEM data and detailed delineation of gully structure. |
|                                                          | 3. Tri-spectral scanner (TLS) imagery providing green, red and near infrared imagery at very high resolution (0.5-0.9m / 1.5m low/ high flying altitudes). Comparable to Aster data in bands 1,2 and 3; essential to validate Ecognition based processing (see below) of Aster imagery. |
| 4. Selection of an appropriate processing methodology and | Detection and delineation of alluvial gully extent will be undertaken using the remote sensing methodology described below (and Figure 2). The procedure relies on field surveys and high resolution ancillary data (described in the previous step) to train (calibrate) classification of gully mapping routines and test (validate) accuracy of results. |
| suitable reference data                                  | 5. Establish criteria for error assessment                                                                                                  |
|                                                          | A random split of field data will be employed to derive equal sets of field and ancillary data for calibration and validation purposes. The error assessment will be based on a confusion matrix and standard remote sensing error assessment statistics. |
appropriate remote sensing data and analytic methods for mapping alluvial gully erosion over regional extents. It comprises five steps set out in Table 1. For each step a brief description of process and/or status for each of the steps is presented.

By taking an overview approach as the top level in the methodology a wide range of data and remote sensing processing issues unique to very large area mapping of target features (alluvial gullies) that are both relatively small and relatively scarce within the context of the larger regional mapping extent have been identified and addressed. For example, an analysis of the Aster image mosaic originally supplied to the project indicated unacceptable seasonal and inter-annual variations in image acquisition that would have caused inconsistent results in subsequent processing. This issue will be addressed by reconstructing the Aster image mosaic.

A remote sensing image analysis flowchart (Figure 2) illustrates the second level of the methodology that encompasses Steps 4 and 5 in Table 1. The method is based around Definiens “Ecognition” software, incorporating image segmentation procedures and a processing workflow described by Definiens (2006, p 22). The Definiens’ Ecognition processing loop at Step 4 in the flowchart details how alluvial gully detection and delineation is to be achieved with a nine-step loop operating on approximately 24 individual image subsets. Partitioning the image data into spatial subsets is necessary due the large extent of the study and to limitations of the Ecognition software. This is because Ecognition can only process a relatively small number of image objects compared to the number that would potentially be needed to describe each catchment.

The first three image analysis steps (Figure 2) ensure that data is processed consistently prior to being subset for input into the Ecognition loop, Step 4). Step 2 involves deriving indices, such as NDVI (Normalised Difference Vegetation Index). Indices are combinations of images designed to standardise and highlight features of interest, such as NDVI. NDVI is derived from red and near infrared images to normalise for differences in sun angle of satellites across latitudinal gradients and to standardise the greenness of vegetation canopies (Rouse et al., 1973). As only one image scene was used for processing of the pilot study site Aster image NDVI was not utilised. However, use of such indices as NDVI is planned as part of future processing.

To optimise processing efficiency, partitioning imagery at Step 3 needs to be undertaken to delineate meaningful spatial extents (eg. biogeographic subregion, native pasture community or, landholder property boundaries) so as to enable efficient mapping and validation of map products. For example, landholder validation of mapping products (Step 5) requires maps that are at the property scale, not at the catchment scale. Thus, partitioning
the data at Step 3 to provide coverage over complete properties is an effective spatial partitioning rationale. It needs to be noted that properties in Australia’s tropical remote north are very large averaging around 2500km².

The bulk of processing occurs within Step 4, the Ecognition processing loop. Image segmentation (Step 4.1) is the key to the processing where imagery is segmented into groups of similar and spatially related pixels as image objects. Constructing image objects that are easily interpreted visually is what makes the Definiens Ecognition software preferable over other remote sensing software. The scale at which the segmentation is performed determines the size of the image object, and thus the homogeneity of the feature delineated. All image objects partitioned at a given scale are referred to as an image object level. When two or more image object levels are combined they form an image object hierarchy (Step 4.4) whereby image objects at a finer scale (called children objects) are wholly contained within image objects of the courser scale (called parent objects) (Definiens, 2006, p.16). In order to train a classification routine and then to determine the accuracy of the classification all available field based observation data (study sites) are randomly split into two equal subsets. The first subset is used to train or calibrate the classification (Step 4.6) and the second is used to test or validate the classification (Step 4.7). Sites used in training are not used in error assessment (Jensen, 1996, p 247-248). A Confusion Matrix (Step 4.8) is used to establish the accuracy of a classification result by comparing the classification result with field-based observation and other ancillary validation data such as aerial photographs. Also, overall accuracy, errors of omission and commission and kappa coefficient are statistics used to quantify the accuracy of the classification routine (see Jensen, 1996, 247-252).

Validation of map products at Step 5 encompassing property level detail allows for verification of gully extent and severity both at the processing level and also in terms of utility of the products to landholders. Landholders who participated in the 2006 field campaign are involved in this validation process. Once feedback from landholders (Step 5) has been taken into account, individual maps will be merged into catchment scale maps for reporting purposes.

Derivation of gully density or severity index is a work in progress, however, in this paper the simple formulation of area of gully overlaid on a grid of 250m cells was used. This resulted in a proportion of gully per cell between 0 and 1.

Results

Results from image processing are shown in Figure 3 where the series of four images illustrate key processing Steps. The series starts with an Aster subset (Figure 3A) output from Step 3 (Figure 2) and input to Step 4.1. To illustrate the process of image segmentation a set of image objects (outlined in white Figure 3B) is overlayed on to the input Aster image. Classification results (Step 4.6) are shown in Figure 3C where individual image objects have been merged into 4 classes highlighting the location and extent of alluvial gully erosion. The final image in the series (Figure 3D) derived at Step 4.9 gives an estimate of gully severity as the density of gully eroded land per 250m grid cell. Other grid cell sizes were evaluated however the 250m cell was considered the most useful at the property level of mapping.

An initial error assessment has been undertaken producing an overall accuracy of approximately 50%. Confounding of seasonally bare earth / grassland with gullies appears to be the main reason for the relatively low accuracy. It is probable the low accuracy level is due to the larger gullies being over estimated and the smaller gullies being under estimated (missed) because of the resolution of the satellite imagery used.

Discussion

The results demonstrate that the proposed remote sensing approach has merit and that with some tweaking should provide the requisite output mapping products with significantly improved accuracy. Indices that can be derived from the Aster imagery to emphasise land cover classes were not utilised in the pilot study, however, these are a significant source of improved feature discernment. In addition, the simplest image segmentation algorithm (Standard nearest neighbour) in Ecognition was used. In subsequent processing a range of more sophisticated segmentation and classifying approaches will be employed to improve class separability, such as delineating between dry grass and gully areas.
Figure 3: Stages of image processing: A) Input Aster image; B) Image segmented into Image Objects; C) Classified image highlighting gully extent; D) Gully Density Map (gully area proportion to 250m grid). Bare earth and grassland have been grouped with non-riparian areas in Figure 3C to simplify visual interpretation.
The size of the gully density mapping unit (grid cell size; Figure 3D) can be at any resolution. The size of the grid cell should be determined by considering what is meaningful from a management perspective. It should also be noted that the resolution of the grid cell has a direct influence on the maximum reported density of gullies. For example in the present study the maximum gully proportion was 0.94, where as a smaller grid cell size would report higher density values up to 1. Larger grid cells (eg. 1km) resulted in a lower gully density maximum of 0.78. Implications of grid cell size and reported gully density requires considerable investigation and is a focus of ongoing research.

Conclusion

The task of mapping alluvial gullies in Australia’s tropical rivers is a complex activity requiring attention to the problems of working at different scales to capture details of diverse features that are relatively small, spatially scarce, yet are morphologically similar within a diverse landscape setting. By utilising the remote sensing approach outlined in this paper, key issues particular to large-area mapping have been considered including assessing and selecting suitable image data, evaluating appropriate remote sensing techniques and determining acceptable information to answer the research objectives.

The pilot study undertaken has demonstrated the feasibility of mapping alluvial gullies using a remote sensing approach. Reporting of gully extent and severity has been explored and a method responsive to the scales of a range of management needs has been described.

Also, the logistics associated with large-area mapping have been explored, highlighting some of the possible ways of resolving issues of very large datasets and multitudes of variable image scenes. Any remote sensing solution hinges on available data type, resolution and extent given the available financial resources. For mapping of alluvial gullies in tropical rivers the quality and coverage of good ground validation data and quality high resolution imagery that allows accurate interpretation of moderate resolution image classification results is essential.

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