Incorporating Remote Sensing as a Tool to Assist Rehabilitation Monitoring in a Dolomite Mining Operation in South Australia

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Key words: Mine rehabilitation, Remote sensing, Spectral derivatives

SUMMARY

Monitoring for rehabilitation success in the mining industry has grown in use and relevance in recent years. Remotely sensed data are considered as a reliable alternative for the field-based monitoring methods which are usually expensive and time-consuming. This study, conducted at the Ardrossan Dolomite Operation (ADM) in South Australia, utilises a time series of freely available Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) satellite images to monitor and assess the status of permanent re-vegetation using different spectral derivatives. Four vegetation indices namely - the Simple Ratio (SR), Tasseled Cap Greenness/Brightness (TC G/B), Normalized Difference Vegetation Index (NDVI) and Inverse Band 3 (B3I) were evaluated through Landsat images. Satellite derived vegetation characteristics were compared with contemporary high-resolution Google Earth^{TM} imagery as well as prevailing ground conditions. NDVI was found more robust among the four spectral derivatives and was consequently used to analyse the time series (2000-2012) of imagery. The changes detected in the vegetation condition were further compared with ground-based photographs, historical rainfall records and the conventional monitoring data of the mine site. The remote sensing method found useful in mapping the health of re-vegetated areas where vegetation dominated the ground area of a pixel. However, the remotely sensed data were found inadequate to map the accurate ground conditions for the areas with nominal vegetation cover. This limitation was due to coarser spatial resolution (30m) of the Landsat data that contained the vegetation spectra contaminated with the soil. Furthermore, NDVI showed a strong correlation with historical rainfall records, specifically severity of the 2006 drought.

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1. INTRODUCTION

In the light of sustainable mining practices being of substantial importance, it is essential to re-evaluate the health of planted species until the re-vegetated areas are self-propagating (Raval, 2011). In modern mining operations, mine reclamation activities are undertaken gradually. Reclamation programs aim to repair and restore the disturbed land and return the land to its natural state (Erener, 2011).

Remote sensing techniques facilitate continuous quantification of the change using multispectral and multi-temporal satellite images (Kasawani and Norsaliza, 2010). Number of studies has confirmed the effectiveness of remote sensing techniques for different mining applications (Erener, 2011). For example, remotely sensed data were used for mapping the size changes of the mining area for different years (Prakash and Gupta, 1998; Townsend et al., 2009), detecting and monitoring coal fires (Cracknell and Mansor, 1992), surveillance of mining environments (Raval, 2011), monitoring environmental impact of surface coal mining (Schmidt and Glaesser, 1998) and distinguishing mined areas from undisturbed forest (Richter et al., 2008; Sen, 2011). Studies relating to mapping of mine reclamation are scarce due to difficulties in spectral discrimination of grasslands or agriculture land from reclaimed mines (Richards et al., 2004; Straker et al., 2004; Townsend et al., 2009).

The majority of studies related to mapping of mine rehabilitation involve change detection through time. Prakash and Gupta (1998) explored remote sensing techniques for identification of time-sequential changes in the land-use patterns. Townsend et al. (2009) demonstrated an approach to distinguish active mines and closed rehabilitated mine lands by using Landsat imagery. Raval et al. (2013) demonstrated the utility of high resolution (2m) data from WorldView2 satellite in monitoring progressive rehabilitation. Straker et al. (2004) identified discrete vegetation units on the reclaimed mine site by using supervised classification techniques. Sen (2011) used chronosequence of Landsat TM and ETM+ images to discriminate surface coalmines from other prevalent forest. Erener (2011) used the NDVI, Tasseled Cap (TC) and Simple Ratio (SR) indices to evaluate and monitor the progress of rehabilitation at a lignite mine in Turkey.

Key objective of this study was to investigate the monitoring process of re-vegetated areas at the Ardrossan Dolomite Operation (ADM), located in South Australia, by using remotely sensed data. The existing practice for monitoring of rehabilitated vegetation at ADM involves ground-based visual inspection procedures that can be tedious as well as limited in scope. The project was aimed to examine capabilities of freely available satellite data for indicating relative health of the vegetation across the last 13 years.

2. STUDY AREA AND DATA

The Ardrossan is home to the largest dolomite mining operation in Australia. It is located on the northern York Peninsula in South Australia where a mining company, Arrium, runs their operations. In 1950 BHP (Broken Hill Proprietary) began mining fine grade dolomite deposit located in south of Ardrossan. At present the quarry has 22 employees and produces around 1 million tonne dolomite per annum through conventional truck and shovel method of mining. The mine is situated between latitude 34°26'36.46"S to 34°27'20"S and longitude 137°53'12"E to 137°54'45.12"E.

Arrium captures photographs for its rehabilitation record database during summer because during this time of the year, it is easy to discriminate between the rehabilitated plant and the grassland (Freer, 2012). The choice of species planted randomly for rehabilitation was based on trees that are native to the region.

There are number of images acquired by the Landsat satellites over the study site from 2000 onwards. The satellite data were downloaded from the United States Geological Survey (USGS) image catalogue. The images selected for download were cloud free images for all years during the summer period (January, February and March), except for 2006, where the only available image that met the processing criteria was acquired in April. A total of 14 images were selected for processing. Table 1 indicates the detail on sensors and sun elevation angles at the time of image acquisition for each dataset. The images acquired were geometrically corrected Level 1 products.

Table 1: List of the selected Landsat images for study

Image acquisition date	Sensor	Sun elevation angle (degrees)
01/10/2000	ETM+	55.99
01/28/2001	ETM+	52.33
02/16/2002	ETM+	48.39
01/08/2003	ETM+	53.79
03/17/2004	TM	49.48
09/25/2004*	TM	43.37
01/31/2005	TM	50.84
04/24/2006	TM	52.94
03/26/2007	TM	51.76
03/12/2008	TM	49.87
01/26/2009	TM	53.24
01/29/2010	TM	49.99
03/20/2011	TM	51.76
01/27/2012	ETM+	48.71

*Data generated from this image was used for the comparison with the Google Earth™ 2004 image which was also acquired in September.

The sun elevation angle and the image acquisition time information were used to remove the atmospheric effect of the image using Landsat calibration tool of the geospatial software interpretation package ENVI 4.8.

High resolution aerial survey was conducted at ADM in 2002, however the images acquired in the visible range of the electromagnetic spectrum had limited use because an advanced vegetation analysis needs data captured at near infrared (NIR) wavelength. Google EarthTM displays a high resolution image of the Ardrossan mine acquired in September 2004. Both, the aerial photograph and the Google EarthTM image, were used for validating spectral derivative results of the respective years.

3. METHODOLOGY

Following three steps describes the methodology.

3.1 Selection of the region of interest (ROI)

In order to implement this study, first some pixels were randomly selected over the reclaimed area. 12 regions of interest (ROIs), namely r1 to r12, were identified across various reclaimed areas of the mine. Thirteenth ROI was identified outside the mine pit, 2 km north-west from the center of the pit, in the bush land to serve as a ‘baseline’ region. The vector polygons of the ROIs were superimposed on the high resolution Google Earth^{TM} image to validate its location on the ground. The selected points were then further validated through the field inspection.

(*a*) (*b*)

Figure 1. (*a*) Regions of interest pinpointed on 2004 Landsat image; (*b*) transposed ROIs including labels (yellow pins) on top of the Google Earth^{TM} 2004 aerial photograph

The 12 ROIs were combined under 5 groups based on their year of plantation for further analysis (Table 2).

Table 2: ROI Groups for Time Series Comparison

ROIs	Plantation Year (s)
r10	Late 1980s
r4 and r7	1997-1998
r1, r5 and r9	1998-1999
r2 and r11	1999-2000
r6, r8 and r12	2005-2006

3.2 Calculation of spectral derivatives

In order to investigate capabilities of Landsat data, five spectral derivatives were calculated. The combinations of red and near infrared (NIR) bands are the most common indices used for vegetation studies (Tucker, 1979).

The Normalized Difference Vegetation Index (NDVI) developed by Rouse et al. (1973) is one of the oldest, most well-known, and most frequently used VIs. The combination of its normalized difference formulation and use of the highest absorption and reflectance regions of chlorophyll make it robust over a wide range of conditions (Tucker, 1979). NDVI is preferred because it helps to compensate for changing illumination conditions, surface slope, aspect, and other extraneous factors (Lillesand et al., 2008). Theoretically NDVI values range from -1.0 to 1.0; however, the negative values are rare (Lenney et al., 1996). While the negative values determines the lower distribution of the vegetation in the reflectance of a pixel, the NDVI values which are higher than 0 and closer to 1 indicate more vegetation cover in a pixel. The common range of NDVI values for green vegetation is 0.2 to 0.8 (Sellers, 1985; Rouse et al., 1973; Tucker, 1979). In this study, according to Sobrino et al. (2004), following three categories were considered:

- NDVI < 0.2: The pixel is considered as bare soil
- $0.2 \leq$ NDVI ≤ 0.5: Pixel is composed by a mixture of bare soil and vegetation
- NDVI >0.5: Pixels with values higher than 0.5 are considered as fully vegetated

Simple Ratio (SR) index which is derived from the ratio of NIR to red reflectance is the most simplistic and common VI (Sellers, 1985; Rouse et al., 1973; Tucker, 1979). It is used for discriminating between soil and vegetation in the study area. Living green plants reflect strongly in the NIR range, while they absorb in the red spectral region (Erener, 2011) and consequently, the value of SR is higher for these cases.

The other spectral derivative calculated for this study was the inverse values of the reflectance in band 3. Sen (2011) reported the effective relationship of the inverse of Landsat band 3 (B3I) with forest disturbance, regrowth and biophysical parameters.

Finally, the tasselled cap (TC) developed by Kauth and Thomas (1976) was calculated for the Landsat images. TC transformation is often used to derive information about the development and health of vegetation of rehabilitated regions (Erener, 2011). A number of researchers have used these indices to monitor land cover changes (Cohen et al., 1995; Rogan et al., 2002; Fiorella and Ripple, 1993). The TC transformation of the spectral bands generates new axes called brightness, greenness, and wetness (Epting et al., 2005). Brightness is the first component of the TC which is the weighted sum of the six reflective TM/ETM+ bands. It is responsive to changes in total reflectance and all factors that contribute towards it. This index is extremely responsive to the differences in soil brightness but not particularly to the variation in vegetation density (Crist and Cicone, 1984). Greenness is particularly responsive to the green vegetation density since it responds to the combination of high absorption in the visible bands and high reflectance in the NIR. Along with brightness, greenness defines the 'plane of vegetation' (Sen, 2011). For this reason, the ratio of greenness to brightness (G/B) was used in this study.

3.3 Selection of suitable vegetation index

After calculating the spectral derivatives mentioned above, in order to compare the NDVI, SR, TC (G/B) and B3I values for 2004, these values were standardized (up to two decimal places) and plotted against each other (Figure 2). Three regions, namely r6, r8 and r12 were not taken into consideration because these areas were planted after 2005.

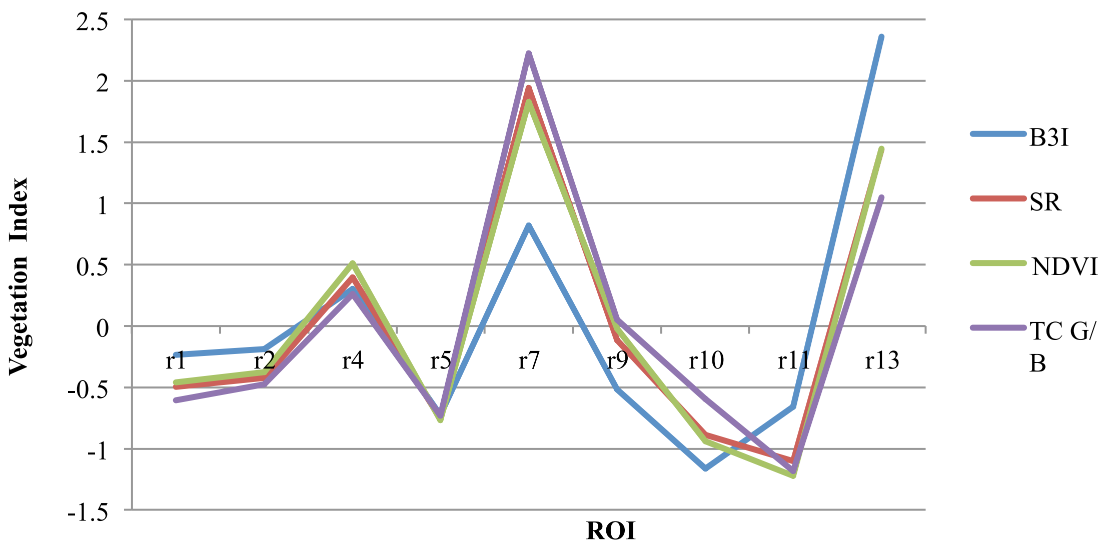

Figure 2. Comparison of normalized spectral derivatives – Summer 2004.

All spectral derivatives show increase in the earlier planted two ROIs, i.e. r4 and r7. As shown in the Figure 2, although all spectral derivatives increased for these regions, the increase of SR, NDVI and TC G/B is more significant. For the regions of r1, r5 and r9, the biomass content is supposed to be less than regions r4 and r7, and more than regions r2 and r11. The graph in Figure 2 indicates that although the B3I is more useful than the other spectral derivatives for region r1, this spectral derivative do not show a correct trend for r9 unlike the trend of B31 in the ROI r2. The performance of NDVI and SR for regions r1 and r9 is relatively better than TC G/B, and they perform similarly for r5. Although all spectral derivatives could not show correct trend for r2 compared to the regions rehabilitated earlier, the performance of NDVI, SR, and TC G/B is better than B3I for r2 and r11. Since it was shown that NDVI compensates for changing illumination conditions and surface slope (Ray, 1995), NDVI was preferred for further analysis of vegetation monitoring.

4. RESULTS AND DISCUSSION

The atmospherically corrected images were processed for the NDVI transformation. Reflectance values of each pixel in the red band (660 nm) and the NIR band (825 nm) was used to calculate NDVI. Figure 3 displays four of the 14 transformed images using ENVI's rainbow color table tool which assigned warmer colors (red) for the higher index values to cooler colors (purple) for the lower index. Locations of the ROIs were outlined in white on the image subsets (Figure 3). Results were categorized based on the year in which the ground cover by ROI was planted (see Table 2). In order to monitor and track the changes of the rehabilitated vegetation, NDVI values were then derived for the respective regions over the time series 2000- 2012. In order to avoid temporal variation in the NDVI, imagery acquired only during summer period (January, February, March) were considered.

4.1 NDVI values higher than 0.2

Figure 4 displays the results of monitoring the NDVI over the time series (2000 – 2012) for the regions r4 and r7 where the NDVI values were found higher than 0.2. These regions were planted adjacent to each other in 1997-1998. NDVI values were also compared against the total annual rainfall and the NDVI value of the baseline ROI (r13) taken from the bushland which was 2.5km far from the mining lease. The NDVI values were also compared with the annual rainfall record of each year as well as the NDVI value of the r13. Although there is an improvement in NDVI for both regions between 2001- 2002, r7 appears to respond more severely to the amount of rain that occurred in the preceding year. 2002 was the year of the 1 in 25 year drought event that had a devastating impact across South Australia's agriculture industries (Truscott, 2003), as reflected in the NDVI values derived for January 2003. There was significantly higher rainfall in years 2003-2005, resulting in a significant increase in NDVI for April 2006. 2006 was another drought year that had severe implications on the biomass of all ROIs. Since the 2006 drought, NDVI has fluctuated in the range of $0.35 \leq r7 \leq 0.4$ and $0.25 \leq r4 \leq 0.33$.

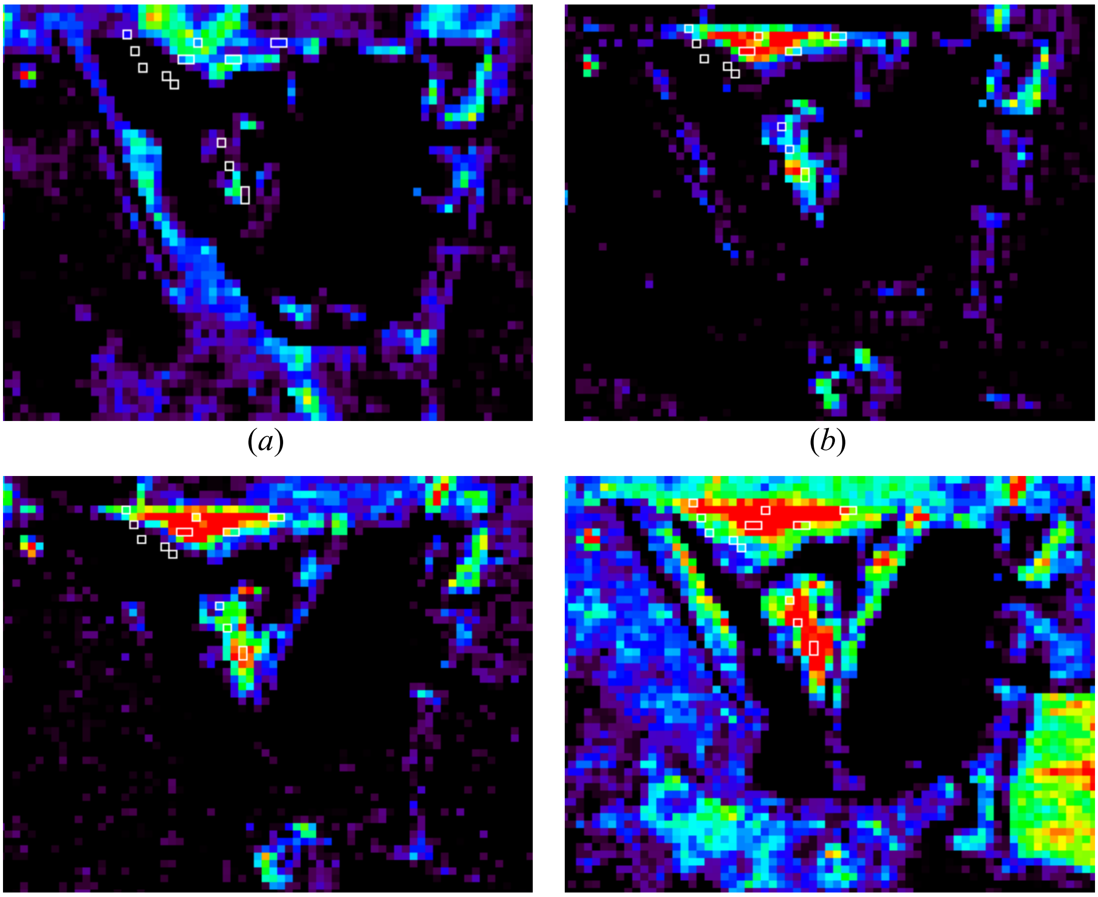

Figure 3. (*a*), (*b*), (*c*), and (*d*) show The spatial variation of NDVI values for the images acquired on 01/10/2000, 03/17/2004, 03/26/2007, and 02/20/2011, respectively.

The NDVI for r4 and r7 experienced a rapid jump when measured in summer 2006; this could be due to the mixture of native species having different growth rates. It is most likely that a certain species had accelerated growth rates and formed dense vegetation. However, the severe drought that occurred over the remainder of the year influenced all the species. The 'baseline' ROI (r13) had little reaction to the temporal or rainfall variations that occurred throughout 2000-2012. This could be the result of the asymptotic saturation that occurs in conditions of moderate to high green biomass (Sellers, 1985), or that the vegetation had run out of nutrients or a combination of these factors (Erener, 2011).

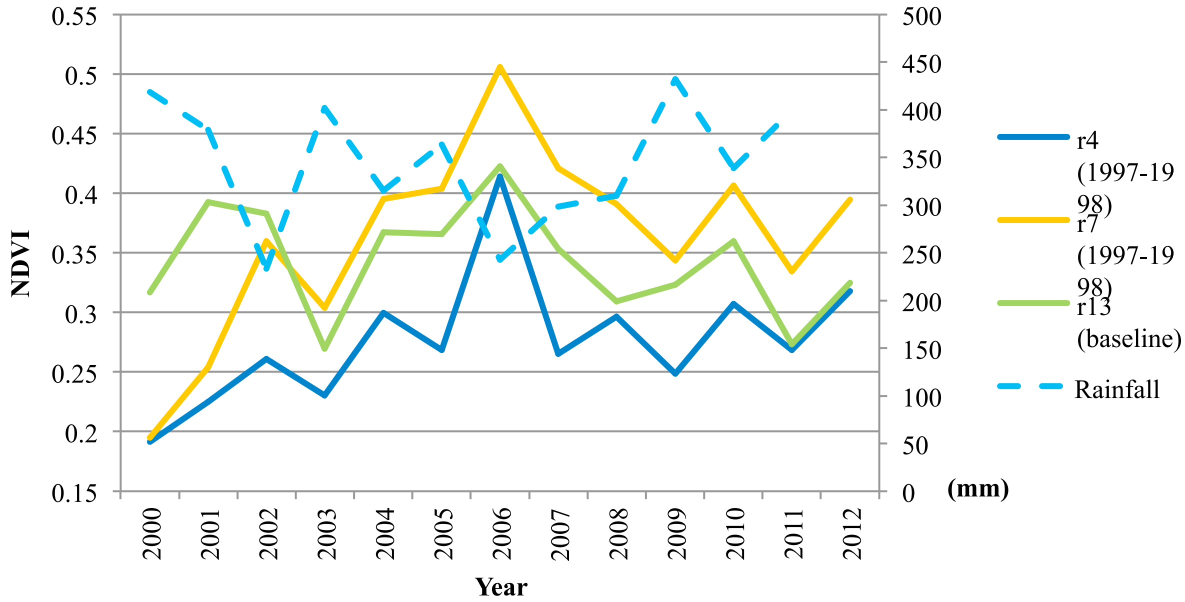

Figure 4. NDVI (primary y axis) vs. Rainfall (secondary y axis) ploted for 12 years for r4, r7 and r13.

4.2 NDVI values lower than 0.2

The NDVI values displayed in figure 5 pertain to the ROIs covering the areas which were planted after 2005. The ROI r6 is located within a region of rehabilitation that Freer (2012) considered to be performing relatively poorly since the drought of 2006. Freer (2012) highlighted that r8 and r12 made good progress since the drought relative to r6. r6, r8 and r12 have NDVIs lower than 0.2 for all years prior to 2012 which was indicative of bare soil and very little plant cover. It takes rehabilitation areas at Ardrossan around 10-13 years to become self-propagating (Freer, 2012). Although there is no correlation with NDVI and rainfall for the ROIs planted after 2005 (Figure 5), NDVI still reflected a significant variance in the density of the regions compared with r13.

It was difficult to understand the trend of behavior within these ROIs because the NDVI is not a good measure for the regions with very low vegetation densities. For example, the VI values for 2007 do not reflect the severe drought which occurred in 2006 (e.g. the VI decreases for r6 and r8 but this is not the case for r12) due to the sparse plant cover within the ROIs at this time. The r6, r8 and r12 are still developing towards producing offspring and becoming self-propagating. The rainfall average over the last 13 years is 13% less than the average taken over the period of 1969 to 2013. It is the characteristic of plants to adapt to these semi-arid conditions by reflecting less light, this also could have contributed to the lower NDVI values of these regions because they were planted during the drought of 2006. Finally, it should be mentioned that using higher resolution images with more spectral bands, e.g. WorldView-2, which provide the opportunity to calculate new vegetation indices (Shamsoddini et al., 2013) can overcome the deficiency of NDVI over these regions; however, it requires further investigation.

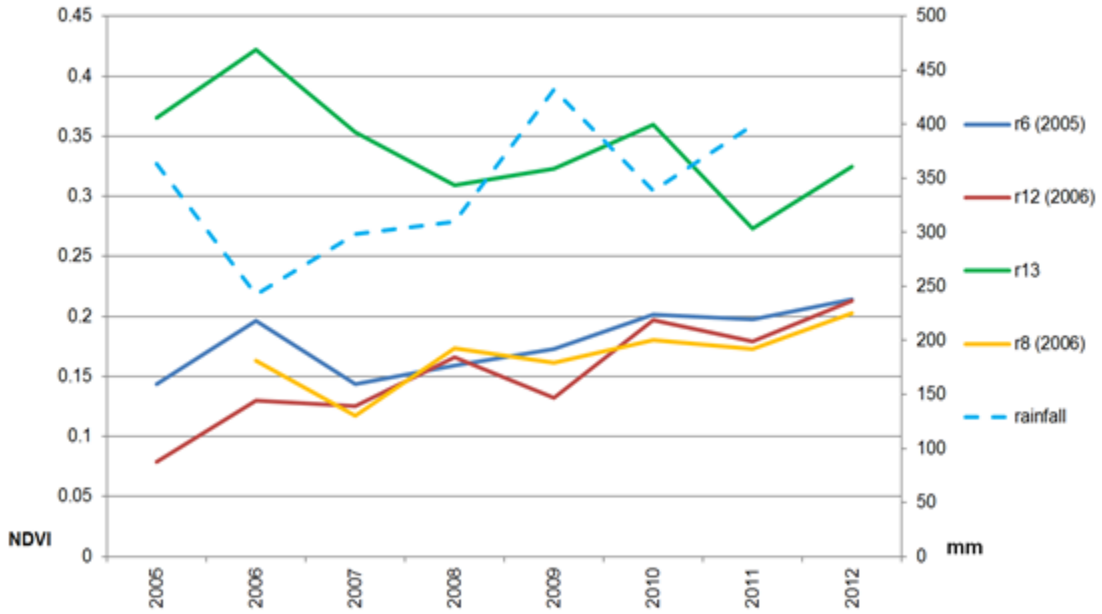

Figure 5. NDVI (primary y axis) vs. Rainfall (secondary y axis) ploted for 12 years for r6, r12, r13 and r8.

5. CONCLUSION

Open cut mining causes land-cover disturbance and vegetation degradation across large areas. It is essential to re-evaluate the health of the planted species at ADM as it is a statutory requirement to restore reclaimed areas in such a way that they develop and eventually become consistent with the typical local farming region. Current rehabilitation monitoring procedures adopted at ADM are purely ground based which depends on experiences and capabilities of the observer. This paper has concluded that with certain limitations, freely available satellite images can be used to quantify the relative health of rehabilitated regions. This study provided significant advancement to Arrium's existing ground based monitoring procedures.

The selection of regions of interest aimed to cover a wide distribution of all the rehabilitated areas of the mine site. The NDVI was successfully used for monitoring the biomass changes occurred from 200-2012 across nine rehabilitated regions. The NDVI was indicated as efficient index for evaluating the relative health of vegetation of the reclaimed areas that were planted prior to 2005. These regions also displayed correlation with the historical rainfall data. The NDVI values highlighted the impact of the two droughts that devastated the agriculture industry across South Australia in 2002 and 2006. However, the relationship between rainfall and NDVI weakened for the three newly-planted regions due to low density plant cover since the regions being in an earlier growth stage compared to the other reclaimed areas monitored. In fact, in the regions with sparse vegetation cover, the efficiency of medium spatial resolution data such as Landsat reduces because the spatial resolution of 30 m could not account for variability of the area covered by the pixel. Therefore, the overall reflectance of the low density vegetation regions is substantially influenced by the bare soil spectral properties. Finally, the research from this project concluded that the NDVI values over 0.2 generated from freely available satellite data is a good supplementary monitoring tool to assess the re-vegetation. This threshold is generally achieved within five years from the plantation date. The time series results indicated that the Landsat data were not only good indicators of the rehabilitated area progress, but also they could highlight the influence of the total annual rainfall on the vegetation cover.

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BIOGRAPHICAL NOTES

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