Identifying post-harvest soil disturbance using satellite imagery

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Abstract

Minimising the overall level of soil disturbance during forest operations is a cornerstone of sustainable forest operations. Soil disturbance assessments are generally carried out using plots or line transects that are both labour-intensive and time-consuming, and hence currently rarely done except for research purposes. The increasing availability of higher resolution satellite imagery and improved image classification tools means there may be an opportunity to efficiently estimate soil disturbance as part of a performance assessment tool.

Seven harvest sites in the South Island were used to assess the accuracy of using satellite images for measuring soil disturbance. Satellite images obtained through *PlanetScope* were collected for each site (3 x 3 m resolution). The images were processed in ArcMap using two supervised classification tools: Maximum Likelihood Equation (MLE) and Support Machine Vector (SVM). Ground-truthing was carried out creating two lines of 15 points at 10 m intervals where land cover type was determined by visual inspection (e.g. bare soil, slash or vegetation).

The accuracy assessment compared classification methods and techniques. The supervised classification techniques were able to easily identify large disturbances (such as roads and skid sites), but struggled to pick up smaller disturbances due to the effects of 'mixed' pixels, where the pixels contain more than a single land cover class. The average overall agreement for MLE and SVM with the ground-truth measures was 64% and 65%, respectively. For best case scenarios, average overall agreement for MLE and SVM was 68% and 72%, respectively, confirming that the SVM classifier outperforms the MLE.

This project highlights that it is feasible to achieve realistic measures of soil disturbance from satellite images. Higher resolution imagery from daily satellite images, or drones and fixed-wing aircraft, presents an opportunity to increase the accuracy of the classifications.

Introduction

It is well known that vegetation, and in particular trees, improve slope stability and reduce erosion (Norris et al., 2008). Tree roots reinforce soil, making it stronger, and tree canopy keeps soil drier through interception and transpiration which also increases soil strength (Phillips et al., 2015). However, after harvest the loss of canopy cover exposes the soil to direct rainfall impact, increasing the amount of fluvial erosion. Exposed soil from forestry practices (such as earth works, movement of harvesting equipment, dragging logs across slopes and mechanical land preparation) have the potential to create erosion and sedimentation issues that do not meet the National Environmental Standards for Plantation Forestry (NES-PF) regulations.

Determining soil disturbance at forestry sites has been carried out using ground-based methods, including the Point Transect (PT) method, Line Transect (LT) method and Grid Point Intercept (GPI) method (McMahon, 1995). These are tried and tested methods that are well known and provide consistent results. Firth et al. (1984) combined aerial photographs with ground reconnaissance to assess site disturbance and found this method had several advantages over the ground-based methods (such as rapidly assessing large areas for deep disturbance). However, identifying less severe disturbance (and disturbance without a distinct colour difference) was difficult.

With soil disturbance from infrastructure, Petherick (2014) looked at the amount of long-term unproductive land as a proportion of the total harvest area. This unproductive area was classed as landings and permanent forestry roads (roads used for accessing skids, not skid trails) and the unproductive area averaged 4.8% of the total harvest area. This unproductive area was determined using satellite images and ArcGIS to measure the area of the skids and lengths of roads within the harvest area. The road lengths were then multiplied by a width, depending on the type of road, to get a total sum of unproductive area for skids and roads. A similar approach was used by Allum (Personal communication, 2020) to successfully ascertain the infrastructure levels in New Zealand woodlots. However, this direct measure method was not found to be suited to measuring soil disturbance in the cut-over.

Satellite imagery is a readily available resource, with around 95% of New Zealand being mapped and accessible through Land Information New Zealand (LINZ, 2020). While platforms such as Google Earth provide free satellite imagery, more detailed imagery can be obtained using drones, fixed-wing aircraft or satellites to help provide more current and/or higher resolution images. These images have many uses (such as determining land cover type or looking at land use change over time).

Images can be processed using a range of software programs, and the image classification is a very useful tool for determining the land cover type over large areas. Three of the main types of image classification are supervised, unsupervised and object-based image analysis (OBIA). Supervised classification uses training samples to classify the image, while the unsupervised classification finds spectral classes without the analyst's intervention. OBIA groups pixels into representative shapes with size and geometry. When using low spatial resolution, supervised classification outperforms unsupervised resolution. For high spatial resolution, OBIA is considered superior to traditional pixel-based classification (GISGeography, 2014).

The goal of this project is to investigate the opportunity of identifying soil disturbance using readily available satellite imagery for post-harvest assessments, and compare its accuracy against in-field classification of land cover.

Methods

The satellite constellation used for this study was *PlanetScope*, providing a pixel size of 3 x 3 m (from Planet.com). The multispectral sensors aboard the satellites collect information from different wavelengths. Unlike digital cameras, which are limited by visible wavelengths, it detects a much broader range of wavelengths not visible to the human eye (such as infrared and thermal). Information from each wavelength is stored as a separate image, commonly called a 'band' (Horning, 2004).

PlanetScope has four bands, which include red, blue and green (RGB), and a near infrared band (NIR). These bands when viewed alone are like a black and white photograph, and a user can combine the images from different wavelengths to create the desired colour image. The combination of bands can be used to highlight certain features within an image (such as vegetation, water or soil). The following list provides information on the first four bands (from Horning, 2004) and provides a generalised wavelength range and common uses for each band:

- **Band 1 (0.45–0.52 µm, blue-green):**
  This short wavelength penetrates better and is often used for aquatic ecosystems. It is used to monitor sediment in water, mapping coral reefs, and water depth. However, short wavelength blue light is scattered more than the other bands
- **Band 2 (0.52–0.60 µm, green):**
  Has similar qualities to band 1 but not as extreme, and was selected because it matches the wavelength for the green we see when looking at vegetation
- **Band 3 (0.63–0.69 µm, red):**
  Since vegetation absorbs nearly all red light (it is

Figure 1: Location of three harvest sites near Nelson

sometimes called the chlorophyll absorption band), this band can be useful for monitoring vegetation health, but also for distinguishing between vegetation and soil

- **Band 4 (0.76–0.90 µm, near infrared):** Since water absorbs nearly all light at this wavelength, water bodies appear very dark. This contrasts with bright reflectance for soil and vegetation, so it is a good band for defining the water/land interface.

A total of seven sites were analysed for this study. Three sites were from the Golden Downs area near Nelson and are managed by OneFortyOne (Figure 1) and ranged from 71 ha to 330 ha. All had been recently harvested, with some areas having undergone mechanical site preparation. Four Canterbury sites managed by Laurie Forestry, ranging in size from 2 ha to 10 ha, were also used. These four sites have all been mechanically prepped and recently planted.

The satellite images for each site were uploaded into ArcMap 10.7.1 and projected using the WGS84 coordinate system. Using the polygon tool on ArcMap, the harvest boundary of the harvest area was outlined. This allows for only the pixels within the harvest boundary to be processed.

Each harvest area was visited to create ground-truth plots using two separate lines of 15 points at 10 m spacing. The ground-truth plots were differentially corrected using the known location of a base station, individually correcting each point at the same time that point was created. At each point a visual inspection determined the major land cover type to be either bare soil or slash/vegetation for a 3 m radius around the point (Figure 2).

Slash was further broken down into five sub-classes: 1 being Light slash cover and 5 being Heavy slash cover. Figure 3 provides an example for some of the possible land cover types, and it shows a Light and Heavy slash example (1 and 5 on the scale range, respectively), as well as a Bare soil and a Vegetation example. The Light slash, Heavy slash and Vegetation are all classified as 'Slash', while the Bare soil is the only one classified as 'Bare soil'.

Selecting appropriate training samples is the most important step in the image classification process as they are used to train the algorithms in the software. Training samples can be created for the two classes – either bare soil or slash and vegetation. This is done by zooming into sections of the image where each class can be easily identified (Figure 4). The training sample collection process is a matter of manual interpretation between the two classes where the location and size of the training sample comes down to the analyst's interpretation.

When selecting training samples, they should be evenly spread over the site, aiming to cover the entire

Figure 2: Using GPS ground-truth land cover assessment

Figure 3: Example of land cover types used in this study

Figure 4: Comparison of training sample sets

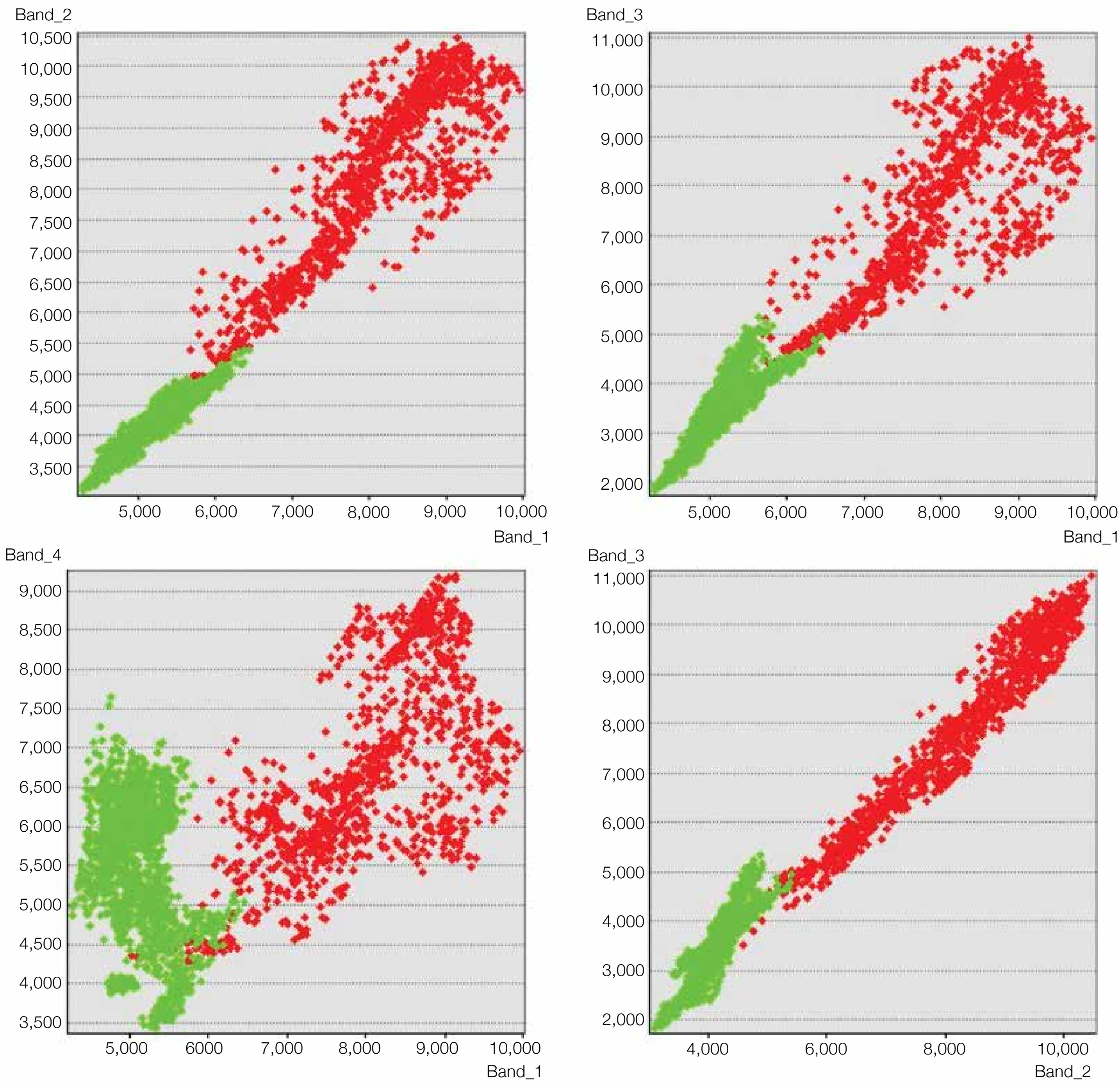

Figure 5: Scatter plots showing band range for bare soil (red) and slash (green)

spectral range and variability for each class. Training samples should not include pixels where the ground-truthing was carried out, as these points are later used to assess the accuracy of the classification tool.

Once the training samples have been created, they are evaluated to ensure they provide an accurate classification. This is done by displaying histograms, scatter plots and the statistics for the band ranges within the group of training samples (Figure 5). Each should be examined so that there is minimal overlap between classes. If there is overlap, this means some training samples need to be removed or re-done. This is an iterative process and is repeated until the user is happy with the training sample set.

Once a good set of training samples is attained, they are saved as a signature file. This signature file is then be used to create both an SVM classifier file and an MLE classifier file, and also to create the final classification for that set of training samples.

A confusion matrix was computed for each site, training sample size and classification method to help analyse the results. Each matrix includes errors of commission and omission, overall accuracy, and derives a Kappa index of agreement between the classified image and the ground-truth data. The Kappa index shows the level of accuracy relative to the simple random probability of getting it right. The errors of commission, known as the user's accuracy or type 1 error, are false positives where pixels are incorrectly classified. For example, the classified image identifies the pixel as bare soil when the ground-truth identifies it as slash.

The errors of omission known as the producer's accuracy, or type 2 error, are false negatives where pixels of a known class are classified as something else. For example, the classified image identifies a pixel as slash, but it should be bare soil. The overall accuracy of the classification is the total number of pixels that agree for all classes in the classification.

Results

Figure 6 provides an illustration of both the original image (left) and the SVM processed image (right). While roads and landings are readily identified, skid tracks and cut-over areas with higher levels of disturbance are also visible on the processed image. However, shading on the image can readily lead to errors of commission, as is readily visible on the south-west facing slopes on the eastern side of the site. These slopes are shown on the processed image as having high levels of exposed soil, yet on the original image no soil disturbance is visible.

Table 1 shows an example set of results when using the SMV classifier for the overall agreement and the Kappa index for the varying sample size. The numbers highlighted in yellow show the best results for each site, for each classifier, and at which training sample size it occurred.

For the larger Nelson sites, as the number of training samples increased so did the accuracy of the classification, while the smaller sites around Christchurch have the best results when only using five or 10 training samples. With the larger sites there is a higher chance that there will be more variability throughout the site, which will require more training samples. While the smaller sites required less samples to cover the variability throughout the site, more training samples increases the chance of mixed pixels being included when training the classifier.

Taking the average results for both overall agreement and Kappa index for all training sample sizes returns an overall agreement of 64% and Kappa index of 0.19 for the MLE classifier, and an overall agreement of 65% and Kappa index of 0.18 for the SVM classifier. The SVM classifier provides

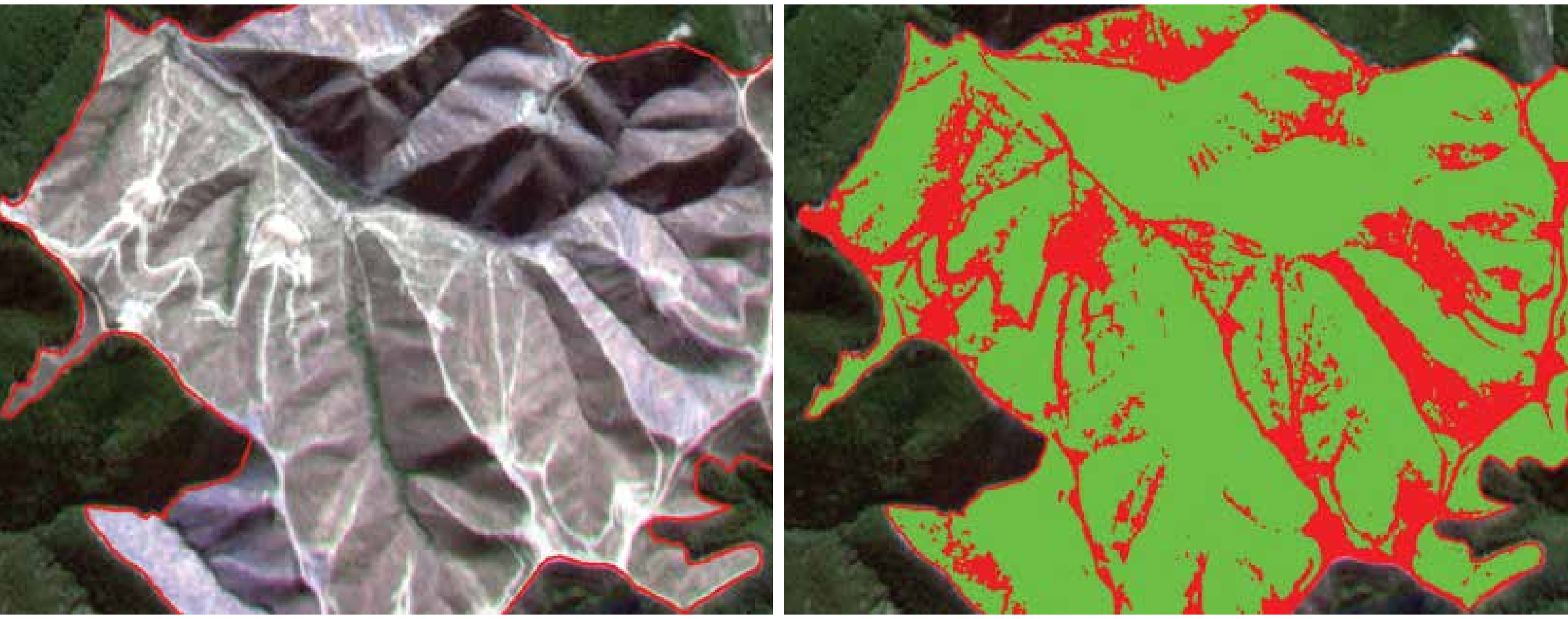

Figure 6: An original satellite image of a harvest site (on the left) and a classified satellite image using the SVM classifier (on the right)

Table 1: Overall accuracy level and Kappa index for SMV classification

		5 Samples		10 Samples		15 Samples		20 Samples	
SVM		Overall	Kappa	Overall	Kappa	Overall	Kappa	Overall	Kappa
Christchurch	Site 1	0.77	0.43	0.5	−0.03	0.67	0.25	0.57	0.11
	Site 2	0.77	0.44	0.73	0.39	0.77	0.39	0.77	0.39
	Site 3	0.57	0.18	0.6	0.23	0.57	0.2	0.53	0.15
	Site 4	0.53	−0.3	0.57	−0.15	0.57	−0.15	0.57	−0.27
Nelson	Site 1	0.57	0.18	0.53	0.06	0.37	−0.21	0.3	−0.34
	Site 2	0.57	0.02	0.87	0.27	0.97	0.65	0.97	0.65
	Site 3	0.73	−0.11	0.73	−0.11	0.77	0.1	0.63	−0.08

a more accurate classification than the MLE classifier in terms of overall accuracy and Kappa index when looking at the best case scenarios. It is also clear that the Christchurch sites are most accurate with smaller training sample sets compared to the larger Nelson sites.

Conclusion

This study aimed to determine if satellite images could be used in conjunction with supervised image classification to accurately identify bare soil on harvested sites. Overall, the two classification methods both have relatively high overall agreement with the ground-truth data. Both classification techniques easily pick up large disturbances (such as skids sites and roads), but struggle with smaller lighter disturbances where pixels contain some of both classes. For example, the pixel may be mainly disturbed, but also contain some heavy slash, which is called a 'mixed' pixel and can be difficult to classify, reducing the accuracy of the classification. Another factor affecting the accuracy of the classifications is shaded areas, as the shade changes the reflectance of the ground, resulting in the misclassification of pixels.

As higher resolution images become more readily available, it will make classifications more accurate by decreasing the pixel size. It will also increase the number of 'pure' pixels (pixels that contain only one class) and reduce the area of mixed pixels at the boundaries between classes.

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