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Disturbance analyses of forests and grasslands with MODIS and Landsat in New Zealand

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ABSTRACT

In this study we present, evaluate and validate an approach to monitor forest and grassland disturbance. We apply the approach to both Landsat and MODIS imagery for the North Island of New Zealand and validate the results based on high resolution OrbView and Ikonos imagery. We found an overall accuracy of the disturbance index of 98% for the two studied land cover types. The kappa value was 0.770 indicating a 77% better agreement than what would have occurred by chance. We found that there is a difference between the accuracy received for grassland areas compared to the accuracy received for forest areas, with the grassland areas outperforming the forest areas (Kappa of 0.855 vs. 0.656). We split the validation results by soil type and also evaluate the effect of different soil types with respect to grazing pressures. The disturbance index behaved consistently for all available soil orders.

We found forest disturbance for approximately 36.2% of the exotic forests, resulting in an annual clearing rate of 2.6% of the forest over the study period. Lastly we present a close-up study to evaluate the changes in grazing in one intensely used catchment. We demonstrate that the December/January disturbance rates have increased from about 6% in 2000 to about 16% in 2012.
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1. Introduction

Grassland ecosystems cover approximately 37% percent of the earth's terrestrial area (O'Mara, 2012), and about 25% of global ice-free land area is grazed using a wide range of management practices and stocking rates (Schipper et al., 2014). Some estimate that the global carbon stock in grasslands is about 50% more than the amount stored in forests globally and grasslands are continuing to sequester carbon (Lal, 2004; O'Mara, 2012). However, many of the global grassland ecosystems are in poor condition; the Land Degradation Assessments in Drylands (LADA) found that approximately 16% of the grasslands are currently undergoing degradation (Conant, 2010). Most of the problems result from overgrazing, leading to soil erosion, weed encroachment and changes in soil organic matter (McSherry and Ritchie 2013; O'Mara 2012). Indeed, grazing land management and pasture improvement was proposed as one of the technical climate change mitigation options (Smith et al., 2008). However, managing grazing intensities is further complicated by the fact that both under- and over-grazing can result in carbon loss from soils and result in lower carbon sequestration (O'Mara 2012).

While high intensity grazing lands have been undergoing tremendous changes, they are less often studied than production forest ecosystems or high intensity croplands, and as a result, there is far less information on the type and amount of change that is occurring in these ecosystems (Pearson, 1997; Weeks et al., 2012 White et al., 2000). One nation that is currently experiencing intense and broad-scale changes in their grassland ecosystems is New Zealand. About 60% of the terrestrial ecosystems of New Zealand are grasslands, with a combination of introduced and indigenous grassland species (Wardle, 1991; Weeks et al., 2013b). As a result of increasing demand and consequently high payouts for dairy products, New Zealand's grazing practices have intensified over the last decade, resulting in a 40% increase in milk production between 2000 and 2010 (O'Mara, 2012) and a 24% growth in the dairy herd between 1996 and 2006 (Ministry for the Environment 2007). Between 2008 and 2012, the number of dairy cattle increased by another 1.1 million, from 5.3 million to 6.4 million (Statistics New Zealand, 2012). To increase profitability, national average stocking rates have increased from 2.1 cows/ha in 1982/83 to 2.85 cows/ha in 2012//13 (DairyNZ, 2013). In addi-

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tion, over the last three decades large plantation forests were planted with exotic species (largely Pinus Radiata) at the expense of grasslands. These plantation forests now cover about 1.8 Mha of New Zealand (Kirschbaum et al., 2011), although between 2002 and 2007, about 50,000 ha of newly planted forests were reverted back to dairy farming (Hewitt et al., 2012). Thus, while the size of pastures decreased, livestock densities and production increased considerably. This type of production increase has only been possible as a result of the introduction of non-native grasses and the conversion of indigenous grasslands into productive lands which are better suited to intensive grazing practices (Weeks et al., 2013b).

To understand the effect of these land management practices and to evaluate the condition of New Zealand's grasslands, spatially explicit information is very important (Weeks et al., 2013a). However, some studies have shown that it is difficult to distinguish between the different grassland cover types in New Zealand with remotely sensed observations (Vescovo et al., 2009; Weeks et al., 2013a). Besides changes in the extent and management of grasslands, forest clearance is still ongoing as well, with 51,000 ha of indigenous forests cleared between 1990 and 2008 (Dymond et al., 2012).

Forest disturbance detection is a regularly studied field and Landsat and MODIS are often used sensors (Healey et al. 2005; Hilker et al. 2009; Masek et al. 2015; Townsend et al. 2009; Tran et al. 2016). Extensive studies have been done evaluating American forest cover changes with Landsat and MODIS based disturbance indices (Healey et al. 2005; Masek et al. 2008).

In this study we will present, evaluate and validate an already existing approach to monitor forest disturbances (Healey et al. 2005) and extend the analysis to evaluate grazing on high intensity grazing lands. We apply the approach to both Landsat and MODIS imagery for the North Island of New Zealand and validate the results based on high resolution OrbView and Ikonos imagery. We split the validation results by soil type and also evaluate the effect of different soil types with respect to grazing pressures. We provide a close-up study of one catchment in the Waikato region, which contains 34% of the national total dairy herds (DairyNZ 2013).

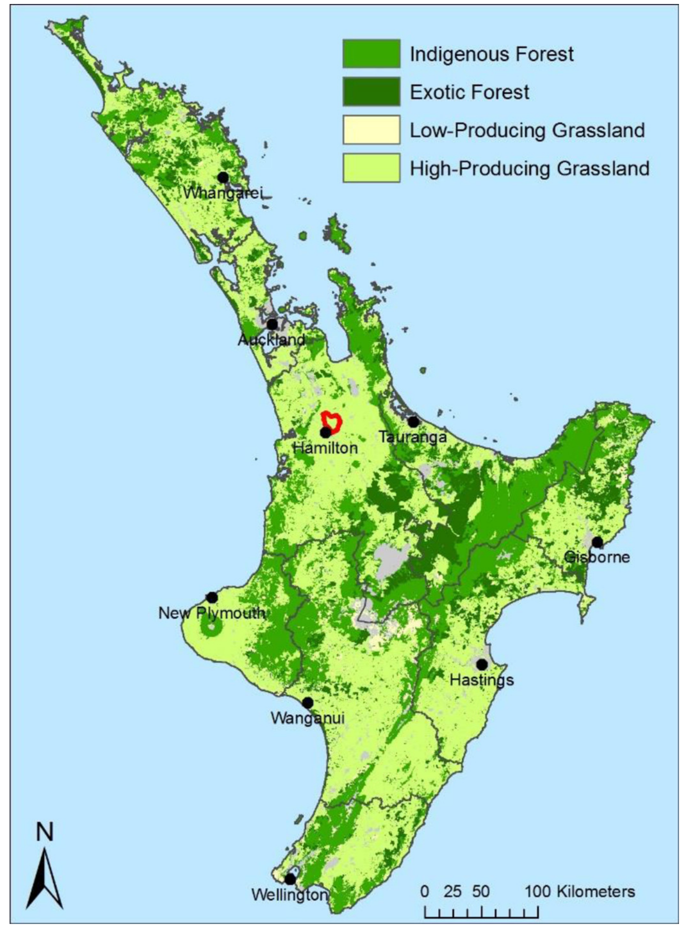

Fig. 1. Study region map with the four different land cover classes investigated. Grey areas have a different land cover classification and are not studied. The red area outlines the Komakorau catchment study area. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2. Study area

In this paper, we will first apply all methods to the entire North Island of New Zealand. The North Island of New Zealand has an approximate size of 115,000 km^2 (Fig. 1). Before human settlement, about 85% of the total land area of New Zealand was covered in primary forests (Kirschbaum et al. 2011). European settlers developed pastures on deforested land starting in the mid-1800s, at which point about half of the island was covered in grassland. As of 2012, the North Island still consisted of approximately 32% indigenous forest, and about 3.5% of the land area is low-producing grassland, which contains a mixture of exotic and indigenous grasses that are not grazed intensively. A little more than 46% of the land area of the North Island has been converted to high-producing grasslands, which are heavily grazed and typically fertilized and/or irrigated. About 12% of the North Island is used for plantation forestry. In all, forests and grasslands make up more than 93.4% of the North Island. The North Island of New Zealand has a warm temperate, maritime climate with mild temperatures and moderately high precipitation. The mean annual rainfall is about 1500 mm.

More than 60% of New Zealand's dairy cows are located on the North Island, and the greatest concentration of dairy herds are located in the Waikato region which supports 34% of New Zealand's dairy herds and 28% of its dairy cows. The Waikato region is the fourth largest region in the country, covering approximately 25,000 km^2. It is divided into 11 districts. In this study, we have selected Komakorau catchment in Waikato district (which is one of the districts in the Waikato region) for a close-up investigation. Komakorau catchment is an intensively managed catchment just north of Hamilton (Fig. 1) predominantly covered with high-producing grasslands. The Waikato region supports a total of 4042 herds for a total of 1.39 million cows. As such it is a very relevant region to study with respect to dairy grazing (DairyNZ 2014).

3. Data

3.1. Climate data

We used long term gridded climate datasets from New Zealand's National Institute of Water and Atmospheric Research (NIWA; Tait and Turner, 2005) to create climate zone classifications. NIWA gridded these data and they were presented at 500 meter spatial resolution based on the interpolation of weather data from 1981 - 2010. Using median annual total rainfall, median annual average temperature, and median annual total sunshine hours, we divided the North Island into distinct climate zones (methods described in Section 4.1).

3.2. Land cover data

Disturbance data was standardized according to a land cover classification which comes from the New Zealand Land Cover Database (LCDB version 3.3) produced by Landcare Research and

Ministry for the Environment. The product provides classifications for the periods of summer 2001/2002 and summer 2008/2009 and is based on both SPOT-5 and Landsat 7 imagery at 10 meter and 30 meter resolution, respectively. The LCDB identifies 33 classes which are designed to correspond with international classification systems (Thompson et al. 2003). In this study we are interested primarily in grassland and forest classes. Using the LCDB for 2001/2002 we assembled a classification dataset based on four distinct groups of classes: indigenous forest (29.7%), exotic forest (11.5%), low producing grasslands (2.3%) and high producing grasslands (48.8%). The exotic forests are generally plantation forests used for timber production. The high producing grasslands are intensively managed and usually heavily grazed, while the low producing grasslands are either non-grazed or have low densities of livestock. These four classes represented 92.2% of the land cover of the North Island of New Zealand in 2001/2002. The remaining 7.8% of the land cover consists of barren/rock, urban areas, cropland and inland water, which we did not investigate in our disturbance analysis.

3.3. New Zealand soil data

Given that our disturbance analyses are based on surface reflectance, we also investigated the potential effect of soil type. Soil types/orders were distinguished using the 1:50,000 New Zealand Land Resource Inventory (Newsome, 1992). Soil orders are based on the New Zealand Soil Classification system (NZCS), and for our area of validation include: Allophanic (L), Brown (B), Gley (G), Granular (N), Organic (O), Recent (R) and Ultic (U). Brown soils have a dark grey–brown topsoil and retain moisture well, but have limited fertility. Gley (dark grey) and Organic (brown–black) soils remain wet for most of the year, often waterlogged. When drained, these soils can be very productive for short periods. Allophanic are very productive volcanic soils with similar topsoil colors as the aforementioned, but are well-drained. Granular are poor-draining, infertile clayey soils that have a dark brown-reddish topsoil. Ultic are strongly weathered clayey soils that are heavily leached and pale in color (light brown–yellow). Recent soils are weakly developed with high spatial variability of color and water retention, but are usually very fertile. More details on these soils can be found in (Hewitt and Dymond 2013).

3.4. Digital elevation model

We used a digital elevation model to calculate the aspect of each 30-m pixel. We chose to use the New Zealand National Digital Elevation Model produced by Landcare Research, at a spatial resolution of 25 m. The product is interpolated from the 20 m contours of the national TOPOBASE digital topographic dataset supplied by Land Information New Zealand (LINZ).

3.5. MODIS data

Three MODIS tiles (h31v12, h31v13, h32v12) cover the North Island of New Zealand entirely. In this study we work with the MODIS Nadir BRDF-adjusted reflectance (NBAR) data at 8-day and 500 m resolution (MCD43A4). We use this dataset because it standardizes the reflectance values to nadir view which results in the minimization of view angle artifacts (Lucht et al. 2000; Schaaf et al. 2012, 2002). In a previous study we used a range of different MODIS reflectance datasets to generate twelve synthetic images corresponding to Landsat images that we had available. We evaluated the accuracy of the synthetic images by comparing the reflectance values of a random sample of the vegetation pixels with the corresponding pixel values of the reference Landsat image on a band-by-band basis. Our results indicated that the NBAR imagery was the optimal dataset to use with Landsat data (Walker et al. 2012).

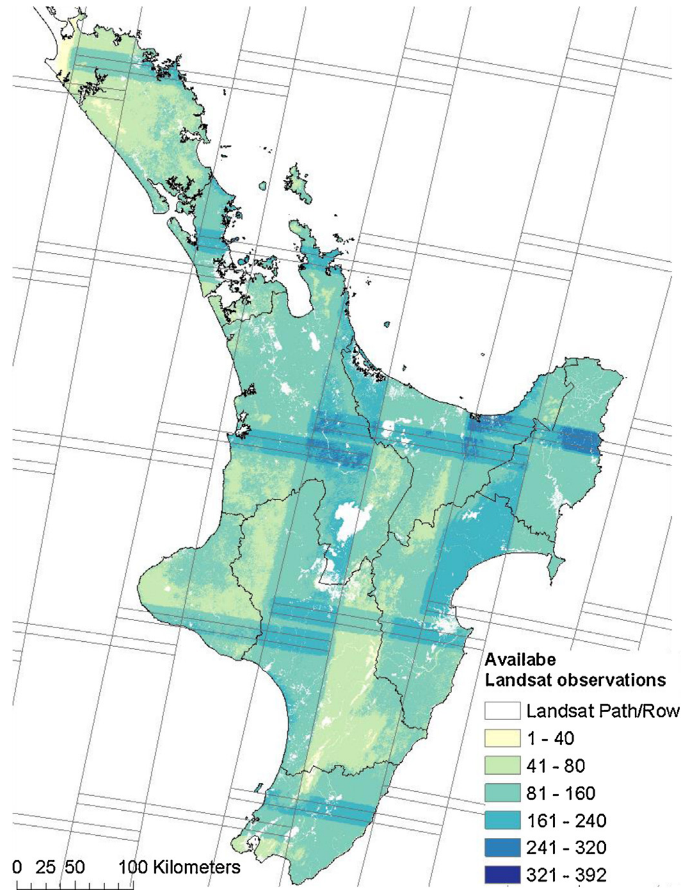

Fig. 2. Total available Landsat observations for each pixel on the North Island of New Zealand from 1999 to 2012. White areas are masked out in the analysis and not used in this study.

We downloaded all available imagery from 2000 to 2013 (638 images for each tile) and we then used the MODIS Reprojection Tool to reproject the data to UTM Zone 60 and mosaic the individual tiles to one image for the North Island. We then calculated the MODIS Tasseled Cap brightness, greenness and wetness based on the coefficients following Lobser and Cohen (2007) and stacked the data accordingly. Missing pixels were filled with NaN values.

3.6. Landsat data

The North Island of New Zealand is covered by 12 Landsat path/rows in UTM Zone 60. A small portion of the island lies in UTM Zone 59 which we ignore for this paper. For each path/row we found approximately 225 images between 1999 and 2012 that were relatively cloud-free for at least 40% of the scene (Fig. 2). We used the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) to atmospherically correct the images and create a cloud mask (Masek et al. 2013). LEDAPS corrects the Landsat data to surface reflectance using the 6S radiative transfer method developed for MODIS (Vermote et al. 1997) and generates a cloud mask according to the Automated Cloud Cover Assessment algorithm (Irish et al. 2006). We then applied the tasseled cap transformation for TM reflectance data according to Crist (1985). Pixels that were part of the cloud mask were set to NaN.

Table 1
High resolution imagery selected for validation of the Landsat data. The images are sorted by Julian date. Some days have multiple high resolution imagery available, resulting in multiple entries in the table. All selected images had a Landsat image available within 14 days. Difference provides the number of days between the high resolution image date and the Landsat image date.

High res sensor	High resolution image date	Landsat path/row	Landsat date	Difference (in days)
OrbView-3	2004–240	73086	2004–237	+3
OrbView-3	2005–081	73085	2005–079	+2
Ikonos	2008–075	73086	2008–064	+11
OrbView-5	2009–205	74085	2009–201	+4
OrbView-5	2009–205	73085	2009–210	−5
OrbView-5	2010–183	73086	2010–181	+2
OrbView-5	2011–142	74085	2011–143	−1
OrbView-5	2011–142	74085	2011–143	−1
OrbView-5	2011–181	74085	2011–191	−10
OrbView-5	2011–181	74085	2011–191	−10
OrbView-5	2011–230	73086	2011–232	−2
OrbView-5	2011–247	74085	2011–239	+8
OrbView-5	2012–024	74085	2012–018	+6
OrbView-5	2012–024	74085	2012–018	+6
OrbView-5	2012–062	73086	2012–075	−13

3.7. Validation data

In this study we used high resolution satellite data from GeoEye OrbView and Ikonos to validate the disturbance output data retrieved from Landsat. OrbView-3 is a commercial satellite which provides high resolution imagery from space. The imagery is available as 1m panchromatic and 4m multispectral data. GeoEye provided unrestricted access to almost 180,000 OrbView-3 images to the USGS. The data are delivered in Basic Enhanced (Level 1B) radiometrically corrected format. We selected all freely available multispectral OrbView-3 images that were within two weeks of a Landsat image that had less than 40% cloud cover from the Earth Explorer website. We also ordered imagery from NASA's NGA Commercial Archive Data (cad4nasa.gsfc.nasa.gov). These images are predominantly located over the Hoteo catchment which is in northwestern North Island. In total we only found two multispectral images which were corresponding with Landsat imagery in the Earth Explorer archive and thirteen images from the NGA Commercial Archive Data, one of which was an Ikonos image; the others were all OrbView-5 images (Table 1).

4. Methods

4.1. New Zealand climate zone classification

The North Island of New Zealand boasts very large climatological differences that greatly affect its seasons and land cover. The calculation of the disturbance index data requires a "standardization" dataset that can be used to evaluate each pixel against. We developed a climate zone classification based on data from New Zealand's National Institute of Water and Atmospheric Research to allow for the standardization of each pixel against pixels in a similar climatological zone. The classification uses median annual total rainfall, median annual average temperature, and median annual total sunshine hours. Because the range of values varies greatly across the datasets, we normalized each dataset as follows:

$$\frac{X-\mu}{\sigma} \tag{1}$$

We calculated the mean (μ) and the standard deviation (σ) based on each climate variable. We then applied an unsupervised ISODATA classification (Tou and Gonzalez 1974) to the standardized climate data. The ISODATA classification calculates evenly distributed spectral means and then clusters pixels according to spectral minimum distance techniques. Means are recalculated and pixels are reclassified with each iteration. The final classification is determined by the number of classes requested, the maximum number of iterations, and the threshold parameters. For our classification we specified a maximum of ten iterations with a pixel change threshold of one percent and a maximum of five classes. The output was aggregated into clusters of no fewer than one hundred pixels. The classification produced 66 clusters for the North Island. We selected the largest seven clusters of pixels to form the base for the climate zones in each area, and we combined the remaining clusters with those zones according to spatial proximity and similarity (Fig. 3).These climate zones were also verified by the Climate Principal Scientist at NIWA. Land cover was not evenly distributed among the different climate zones (Table 2), which is to be expected since climate affects vegetation growth and land use. The percentage of low producing grasslands was low for all zones, while the percentage of high producing grassland varied from 13.2% to 72.5%. The percentage of indigenous forests varied from 10.7% to 71.4%.

4.2. Forest disturbance index

Healey et al. (2005) developed the disturbance index for the detection of forest disturbances based on single scenes. Masek et al. (2008) later adapted this DI algorithm by looking for decadal changes in DI. In this paper, we started with the original approach from Healey et al. (2005) and calculated the DI based on the normalized values of the tasseled cap indices (brightness, greenness and wetness) where the mean and the standard deviation of these indices were based on a standardization dataset. The normalization was carried out as follows:

$$\text{Brightness}_{\text{n}} = (\text{Brightness} - \mu\text{Brightness})/\sigma\text{Brightness} \tag{2}$$

$$\text{Greenness}_{\text{n}} = (\text{Greenness} - \mu\text{Greenness})/\sigma\text{Greenness} \tag{3}$$

$$\text{Wetness}_{\text{n}} = (\text{Wetness} - \mu\text{Wetness})/\sigma\text{Wetness} \tag{4}$$

The Central Limit Theorem states that the distribution of a large number of independent, identically distributed variables will be approximately normal, regardless of the underlying distribution (Larsen and Marx 2006). Here, we assume a normal distribution of brightness, greenness and wetness as a result of the very large number of pixels that are used to create the standardization dataset. We also evaluated a subset of the dataset visually to ensure normality.

When forests are removed, typically the brightness of the landscape increases, the greenness declines and the wetness declines as well (Fig. 4) . As a result, the original forest disturbance index was defined as follows:

$$\text{DI} = \text{Brightness}_n - (\text{Greenness}_n + \text{Wetness}_n) \tag{5}$$

Increasing brightness, and decreasing greenness and wetness result in high DI values in the case of forest disturbances.

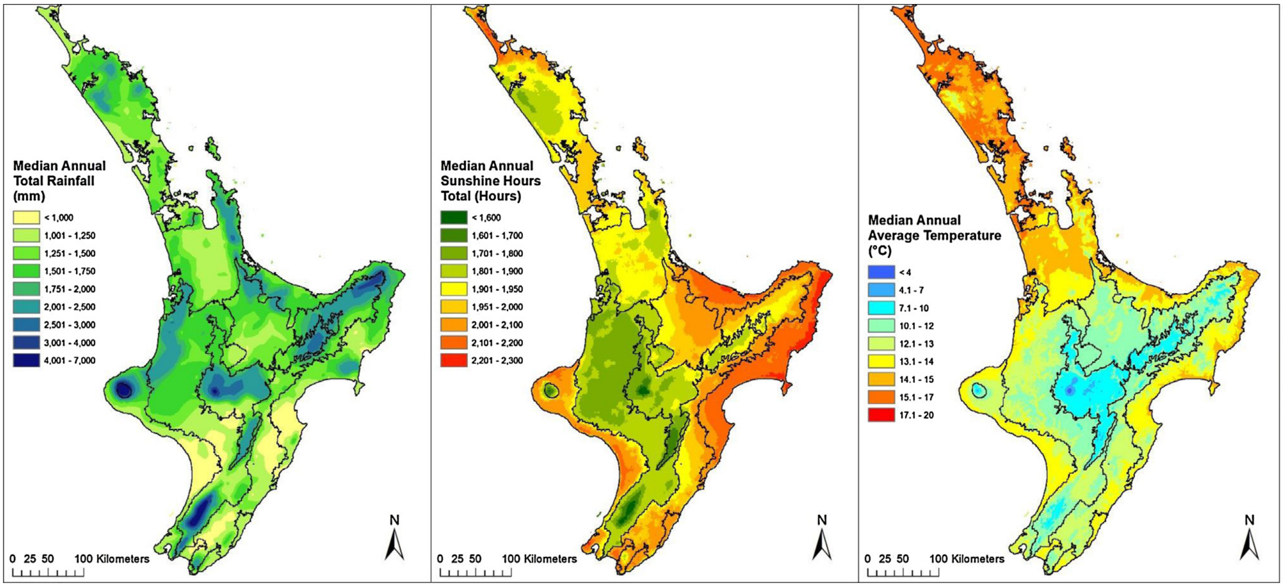

Fig. 3. Seven aggregated climate groups (black lines) for the north island are created based on Median Annual Total Rainfall (left), Median Annual Sunshine Hours (middle) and Median Annual Average Temperature (right).

Table 2
Overview of the land cover and climate characteristics in the seven selected climate zones (R#).

	Natural forest	Exotic forest	Low-producing grasslands	High-producing grasslands	Annual total precipitation (mm)	Median annual average temperature (°C)	Median annual total sunshine (h)
R1	22.0%	5.1%	0.4%	72.5%	1465.5	14.1	1906.2
R2	71.4%	5.7%	9.6%	13.2%	1967.7	9.5	1835.8
R3	18.0%	21.1%	2.2%	58.7%	1445.6	13.4	2123.8
R4	10.7%	4.7%	3.2%	81.3%	1337.6	13.0	2015.1
R5	40.6%	5.4%	2.9%	51.1%	1647.4	12.0	1807.1
R6	31.1%	22.7%	0.9%	45.4%	1502.0	11.8	1988.1
R7	28.6%	13.9%	1.0%	56.5%	1435.0	14.9	1924.5

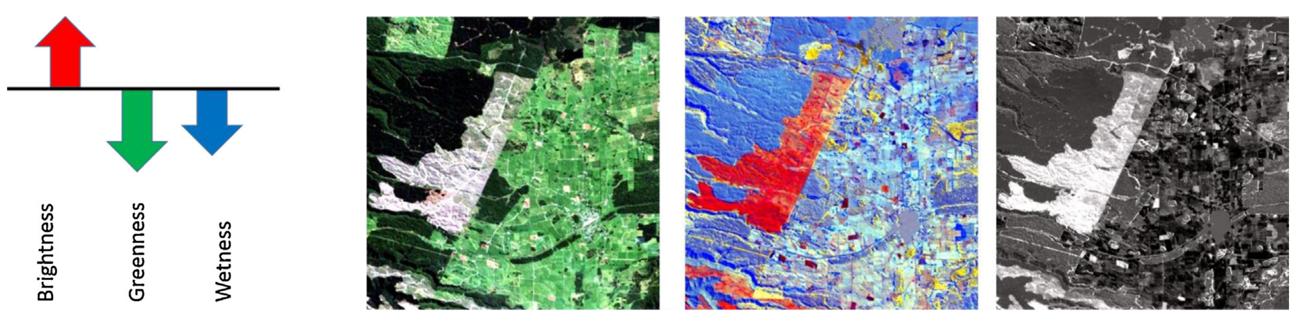

Fig. 4. From left to right, there are the conceptual diagram of the forest disturbance index, a true color example of a forest disturbance, a tasseled cap image of the same disturbance and the resulting disturbance index image.

In this study we standardized each forested MODIS pixel against other pixels with the same land cover type (either indigenous forests or exotic forests) within the same climate zone, described in Section 4.1. For Landsat images we standardized according to land cover class within each path/row, and we also kept track of the aspect and standardized according to general direction (either north facing or south facing slopes). We evaluate each pixel only to other pixels in the same image and thus process each image independent of the other images in the time series. We also evaluated the DI results without the standardization by north vs south facing slopes, however, we found that south facing slopes were regularly identified as disturbed when standardized against north facing slopes which receive more sunlight and reveal more vigorous vegetation growth. As a result, DI records the normalized spectral distance of each pixel from a pixel with a mature indigenous or exotic forest. The idea is that since the majority of the pixels are mature forests (which are relatively dark, green and wet), the clear-cut areas will appear different (brighter, less green and less wet). Thus according to Eq. (5), clear cut forests will result in high DI values. We applied this methodology to both the MODIS data and the Landsat data.

4.3. Grassland disturbance index

The spectral surface reflectance properties of grasslands (particularly grazed areas) are fairly different from mature forests. Grazing areas are a lot brighter to begin with and because of the mostly dark soils in New Zealand, grazed areas appear darker when grazed

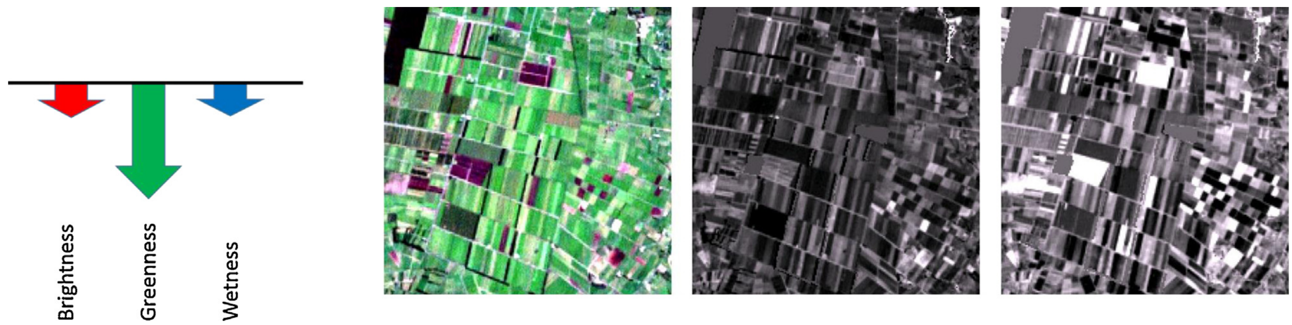

Fig. 5. From left to right, there are the conceptual diagram of disturbed (grazed) grasslands, a true color example of a partially grazed grassland, an example of the disturbance outcome when the original disturbance index is used and an example of the adjusted disturbance data.

down, instead of brighter as is the case for forests. Thus, we find that areas which are grazed down and are exposing soils generally look darker, less green and less wet than areas that are not grazed down to the soil (Fig. 5). As a result, the original DI equation does not result in high DI values for grazed areas. Thus, under disturbance, all tasseled cap components reveal a decline. This means that technically the DI will be very low (negative). We have adapted the DI time series specifically for grasslands as follows:

$$DI_G = -(\text{Brightness}_n + \text{Greenness}_n + \text{Wetness}_n) \quad (6)$$

We take the negative to ensure that the areas that are disturbed reveal high DI values, instead of low DI value. We prefer to depict disturbed areas with high DI value to allow for a unified image look when we have areas with both forests and grasslands. We use similar standardization procedures and the same threshold as described for forest disturbance.

4.4. Establishment of a threshold value for disturbance

In previous studies (Healey et al. 2005; Masek et al. 2008) a threshold value of two was used to determine whether a pixel was sufficiently different from forested pixels to be identified as disturbed. Some have applied manually adjusted thresholds in California (Potter 2013), and others a threshold value of 0.79 when applied to RapidEye images to detect stand-level disturbances in British Columbia, Canada (Arnett et al. 2014). Here we establish a higher threshold as follows. The disturbance index is a summation of three normalized distributions. Normalized distributions have a mean of zero and a standard deviation of one. When normalized distributions are added or subtracted, the mean and standard deviations are added (they are never subtracted). As a result, the disturbance index values have a normalized distribution mean of zero and a standard deviation of three. Thus, the probability that a pixel has a value of two in a normalized distribution with a mean of zero and a standard deviation of three is 25.2%. This means that if we use a threshold of two, we may identify a pixel as disturbed while in fact it is not, 25.2% of the time. To ensure that we only misidentify disturbances 5% of the time, we could set the threshold as high as 4.9. In fact, when we investigated our results, we found that most of the clearly disturbed areas had values higher than five. However, in this study we have set the threshold of disturbance at three. This means that we have a 15.9% probability that we identify a pixel as disturbed while in fact it is not. This is still relatively high, but we want to be sure that we do not miss any disturbances and thus like to err on the conservative side. To compare our result with previous papers, we also evaluated a threshold of two. In addition, when we linked Landsat disturbances with the coarser MODIS disturbances, we also kept a DI of 2.

4.5. Validation

We validated the Landsat disturbance image data by investigating the 15 available high resolution Orbview-3 and Ikonos images. We applied a stratified random sampling approach where we selected 100 random pixels where the Landsat data was above two and 400 random pixels where the Landsat data was below two for each high resolution image, for a total of 7500 pixels. Statistically we expect only a small amount of pixels to reveal a disturbance. We selected just 100 random pixels with a disturbance over two, as to not oversample the disturbed areas in our final sample. For each of these random pixels we visually determined whether the pixel was disturbed or undisturbed based on the available high resolution image. Some of the randomly selected pixels were covered by clouds and could be not evaluated. We also omitted pixels where the Landsat pixel straddled two or more land cover types, where the Landsat pixel showed a mixed disturbance and land cover profiles and pixels which were clearly misclassified in the land cover data. In total, we omitted 36.5% of the pixels. Occasionally, it was difficult to visually determine whether a pixel was disturbed. In that case, we used NDVI from the high resolution imagery to guide our decision process.

We calculated overall accuracy, producer and user accuracy, and the Kappa statistic. The Kappa statistic identifies whether the map is significantly better than if it had been generated randomly and thus compensates for change agreement (Congalton 1991). We stratified the validation pixels by forest and grassland to determine if there were significant differences in how well the disturbance indices performed. We also stratified the validation points by soil order, to ensure that background soil effects did not significantly affect the performance of the disturbance indices.

We validated the MODIS imagery by investigating the image time series. We selected 1% of the pixels in forests and grasslands for a total of 1193 random pixel time series, 282 in exotic forest and 911 in high producing grasslands. Since we have multiple temporal observations for each investigated MODIS pixel, we had a total of 66,460 observations to compare. There are 225 Landsat pixels within the extent of each MODIS pixel. For each MODIS pixel we evaluated all available Landsat observations. We calculated the percentage of Landsat pixels that were disturbed ($DI > 2$) based on all Landsat pixels within each MODIS pixel and also calculated the standard errors. We analyzed the results for exotic forests and high producing grasslands separately.

5. Results

5.1. MODIS disturbance results

The percentage of time that each pixel was disturbed between 2000 and 2013 varied considerably across the North Island (Fig. 6).

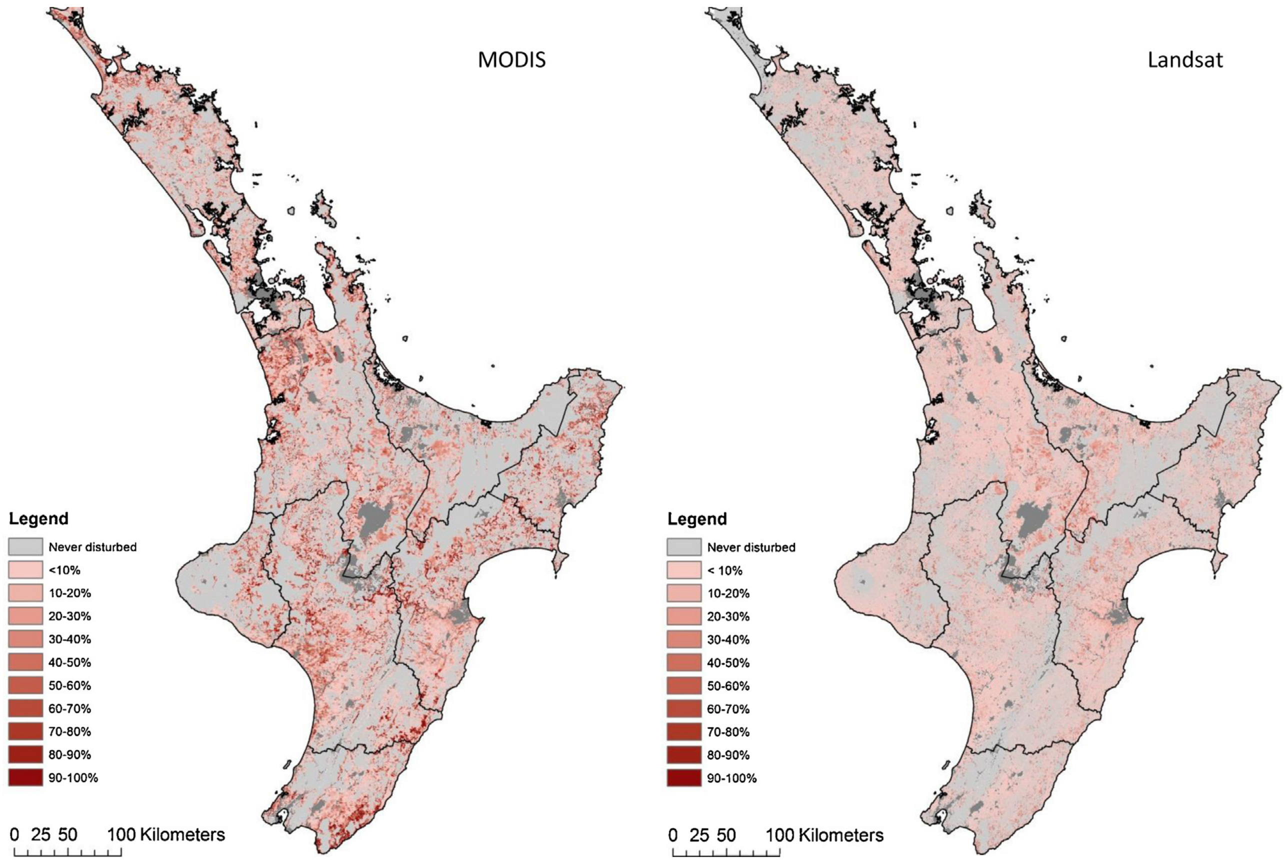

Fig. 6. Percent of time that each pixel is disturbed over the entire time period based on MODIS data (left) and the entire Landsat archive (right).

We found that 34.7% of the pixels were never disturbed between 2000 and 2013. On the flip side, we found that 0.07% of the study area was continuously disturbed. Pixels that are continuously disturbed always behave differently than other pixels in their land cover and climate zone, most likely as a result of misclassification in the original classification data or edge effects. There was a certain amount of variability by land cover class. For example, we found that 73.5% of the low producing grasslands were never disturbed and 93.4% were disturbed less than 6 months (Table 3). As expected, high producing grasslands were disturbed much more regularly, and we found no disturbance for just 21.4% of the pixels; 68.6% of these grasslands were disturbed less than 6 months (Table 3). As expected, the exotic forests and the high producing grasslands were the most disturbed areas, while the indigenous forests and the low producing grasslands had much less disturbance. We have made the MODIS disturbance results available on a public website: http://tethys.dges.ou.edu/NZ_disturbance/.

5.2. Landsat disturbance results

For 53% of the North Island we found at least 100 Landsat observations from 1989 to 2012, with some pixels having as many as 392 observations (Fig. 2); for about 8.5% of the pixels we have more than 200 Landsat observations. The overlapping path/row values in the east—west direction provided the best data availability, while the north—south overlap did not provide real increased data availability because the data came from the same swath. White areas in the image are masked and were not investigated in this study.

Approximately 75% of the island was disturbed less than 10% of the time (Fig. 6). Less than 0.3% of the island was almost continuously disturbed (i.e. disturbed more than 90% of the time). Only 2.6% of the island was disturbed more than 50% of the time. We cannot provide the exact length of time of disturbance because of the variable number of observations for each pixel (Fig. 2). The general picture agrees between MODIS and Landsat, but the Landsat time series is not complete and the pixels are much smaller, making it more difficult to see the disturbed areas on the overview map.

We investigated the percent disturbance in Komakorau catchment, which is an intensively managed catchment just north of Hamilton (Fig. 1) predominantly covered with high-producing grasslands. Fig. 7 provides an example of grassland disturbance in the intensively-grazed Komakorau catchment for April in three years (1990, 2005 and 2012). The Landsat data clearly show differences in grazing intensity or grassland management, with some paddocks exposing bare soil (i.e. disturbance). Occasionally, the outlines of the paddocks are visible as well, as a result of ungrazed borders and roads (which come out as highly disturbed because the original land cover data classified them as grasslands). We inves-

Table 3
Average length of disturbance (using MODIS 8-day time-series; DI > 3) by land cover type and percentages of each land cover that are disturbed a certain amount of time.

	Average	Std deviation	Never	<6 months	>12.5 year	Always
Natural forest	22 months	43 months	52.5%	75.1%	4.7%	0.17%
Exotic forest	18 months	24.4 months	37.7%	63.8%	0.062%	0.002%
Low-producing grasslands	3.8 months	13.2 months	73.5%	93.4%	0.065%	Never
High-producing grasslands	19 months	29.1 months	21.4%	68.6%	0.798%	0.032%

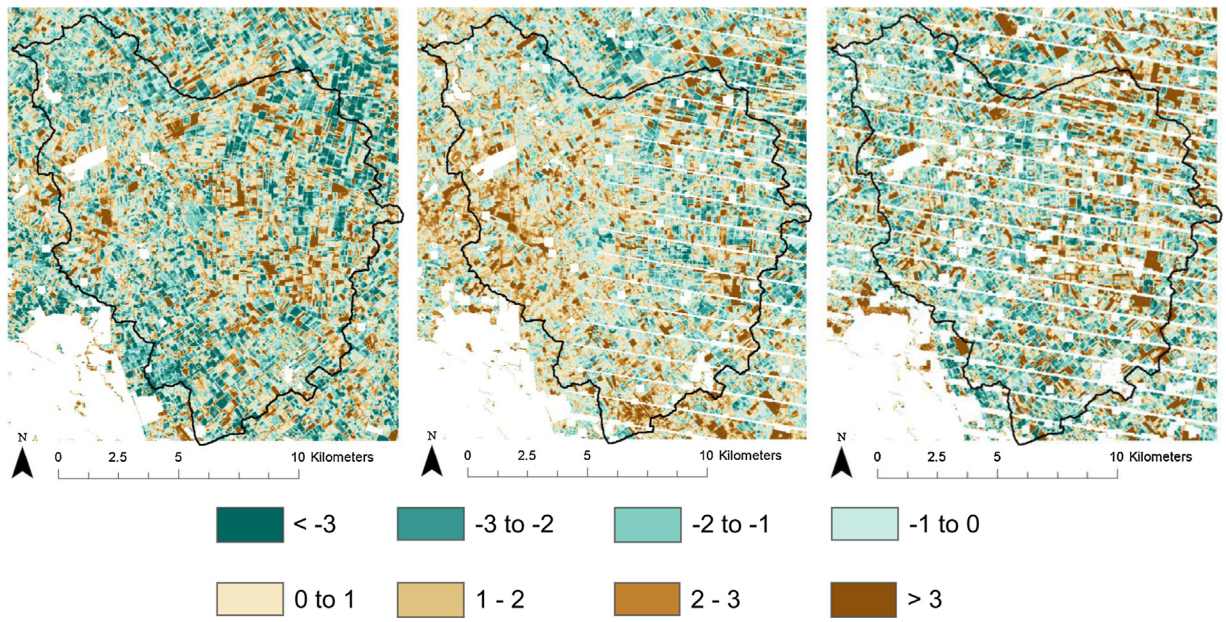

Fig. 7. Komakorau Catchment (black outline) disturbance for April 1990, 2005 and 2012. Dark brown pixels (DI > 3) are counted when calculating the percent disturbance. White pixels represent masked areas, mainly urban areas, clouds and sensor errors.

tigated the percentage of disturbed pixels (DI>3) based on Landsat data between 1990 and 2012. Fig. 8A shows the disturbance rate for Komakorau for two years (2005 and 2010), for which we have eight cloud free Landsat images. For both years there is a fair amount of intra-annual variability in the disturbance pattern with high disturbance in the summer months (December / January), low disturbance in February and July and a slight increase in disturbance around day 120, late April / early May. We compared the disturbance rates for the years 1990 to 2012 for April, July and December / January (Fig. 8B). The disturbance in all three months is increasing, with lowest increases in the month with the lowest disturbance (July) and the highest disturbance rates with the highest increases in December/January. The disturbance rates in these months have increased from about 6% in 2000 to about 16% in 2010 and 2012. Unfortunately, we did not have cloud free images in this season before 2000. A 6% disturbance rate results in a turnover over period of about 16 years, while a disturbance rate of 16% results in a 6.5 year turnover rate.

5.3. Validation of the MODIS disturbance results based on Landsat data

Since we had multiple temporal observations for each investigated MODIS pixel, we had a total of 66,460 observations to compare. We had 225 Landsat pixels within the extent of each MODIS pixel. Fig. 10 provides the basic comparison between the MODIS DI and the percentage of Landsat pixels that are flagged as disturbed with a threshold of 2. We found that forested MODIS pixels with a DI value between 1.5 and 2.5 were representative of areas where 35% ± 2% of the Landsat pixels were disturbed. MODIS pixels with DI value between 2.5 and 3.5 were typically representative of areas where 50% (±1%) of the Landsat pixels had a DI value over 2. Since we are mainly focusing on plantation forests, it is not surprising that there is a good correspondence between the MODIS DI values and the percentage of the Landsat pixels disturbed. The harvest of plantation forests typically involves large clear-cuts that are easily identifiable in both the MODIS and Landsat imagery.

Grassland disturbance results were not as straightforward. The paddocks that were grazed bare are much smaller than a MODIS pixel, typically covering just a few Landsat pixels and rotating rapidly; in addition, the disturbance is relatively ephemeral, with grazed areas recovering quickly. As a result, the MODIS pixels over grasslands cover a mixture of Landsat pixels ranging from completely grazed bare to fully vegetated. This variability is easily visible in Fig. 10 as fewer MODIS pixels with very high DI. Nevertheless, the relationship between the MODIS DI and the percentage of Landsat pixels with DI over 2 is as expected. For MODIS pixels with DI values lower than 0.5, we find 8% (±0.2%) of Landsat pixels with DI values over 2, while for MODIS pixels with DI values between 2.5 and 3.5, we find that on average 26% (±1%) of the Landsat pixels reveal a DI over 2.

5.4. Validation of Landsat data with high resolution images

We investigated 500 Landsat pixels at each of the 15 high resolution images available for a total of 7500 pixels (Fig. 9). We

Table 4
Summary of the accuracy assessment of the Landsat disturbance dataset for all pixels combined and for the broad categories of grasslands and forests.

Class	DI	Overall accuracy	Kappa	User accuracy		Producer accuracy		
				D	*U*	*D*	*U*	*N*
Everything	DI2	94.0%	0.581	45.7%	99.5%	91.4%	94.2%	4761
	DI3	98.0%	0.770	88.9%	98.4%	69.5%	99.5%	
Grasslands	DI2	94.0%	0.646	52.6%	99.6%	94.5%	93.9%	1929
	DI3	98.2%	0.855	88.5%	98.9%	84.4%	99.2%	
Forests	DI2	94.0%	0.517	39.5%	99.5%	87.8%	94.3%	2832
	DI3	97.8%	0.656	89.7%	98.0%	53.0%	99.7%	

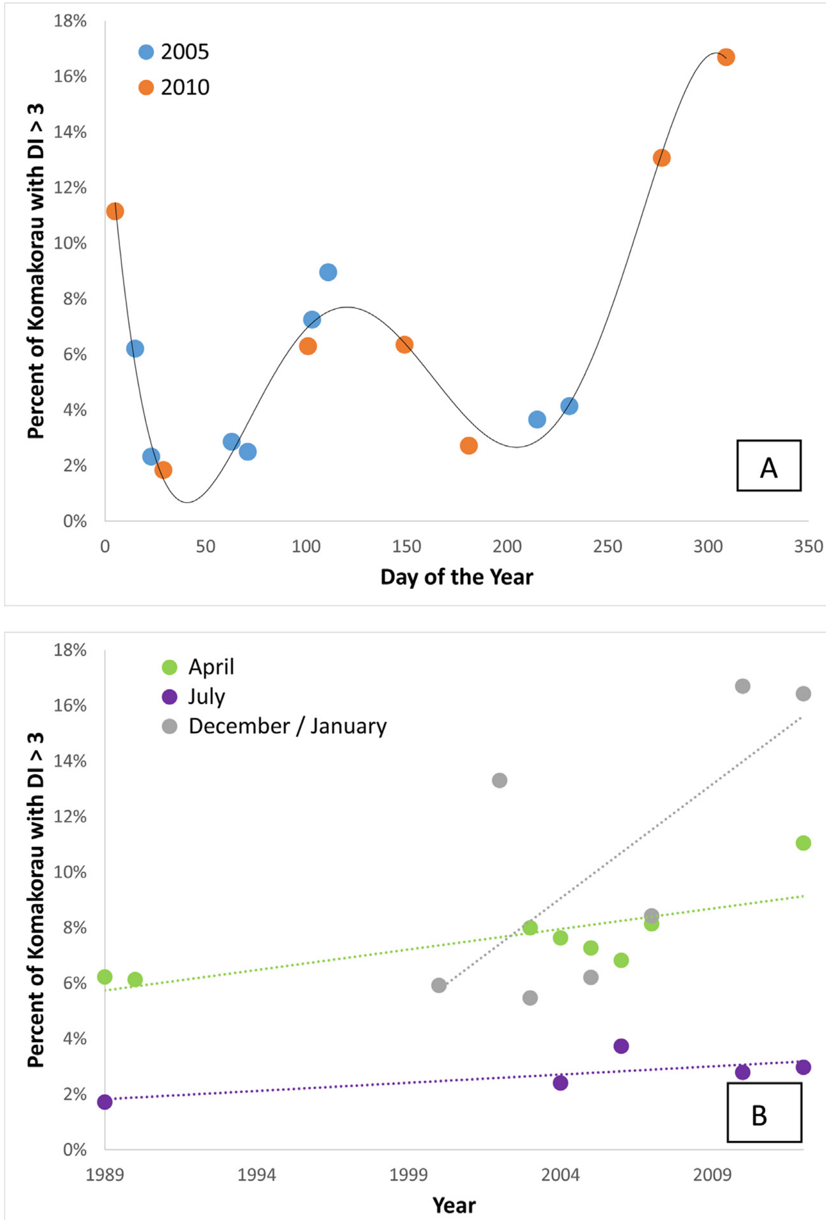

Fig. 8. Percent disturbed of the Komakorau Catchment for two years (2005 and 2010), black line just for guidance (A) and for three periods (April, July, December/January) by year (B).

found valid data for 63.5% of the Landsat pixels and we present the accuracy assessment below (Table 4). The overall accuracy of the disturbance index is 94% and 98%, respectively for the thresholds of two and three. The kappa values are however significantly higher ($p < 0.01$) when we use a DI threshold of three compared to a threshold of two. The kappa statistic for the threshold of three is 0.770 indicating a 77% better agreement than what would have occurred by chance. There is a difference between the accuracy received for grassland areas compared to the accuracy received for forest areas, with the grassland areas outperforming the forest areas (Kappa of 0.855 vs. 0.656), which is mainly a result of the lower producer accuracy for the disturbed forested areas; 53% of the disturbed forested areas were accurately classified as disturbed compared to 84.4% of the grassland areas.

It is important to remember the difference between kappa and the overall accuracy. Kappa quantifies the level of agreement corrected by chance. In our results there appears to be a discrepancy between the overall accuracy (e.g. 94% and 98%) and the kappa values (e.g. 0.58 and 0.77). This seemingly discrepancy is a result of the uneven distribution between the number of disturbed pixels and the number of undisturbed pixels. Disturbance is still a relatively infrequent occurrence. However, the accuracy of the methodology to detect pixels that are undisturbed is higher than the accuracy of the methodology to detect disturbed pixels resulting in a very high overall accuracy, and a reasonably high kappa value.

The disturbance index behaved consistently for all available soil orders (Table 5). The overall accuracy is above 95% for all soil orders and the lowest Kappa statistic is 0.719 which indicates substantial agreement. As long as the more representative DI threshold of 3 is used, it appears that soil type does not significantly affect the accuracy of the disturbance index.

Fig. 9. Location of the validation pixels on the North Island of New Zealand.

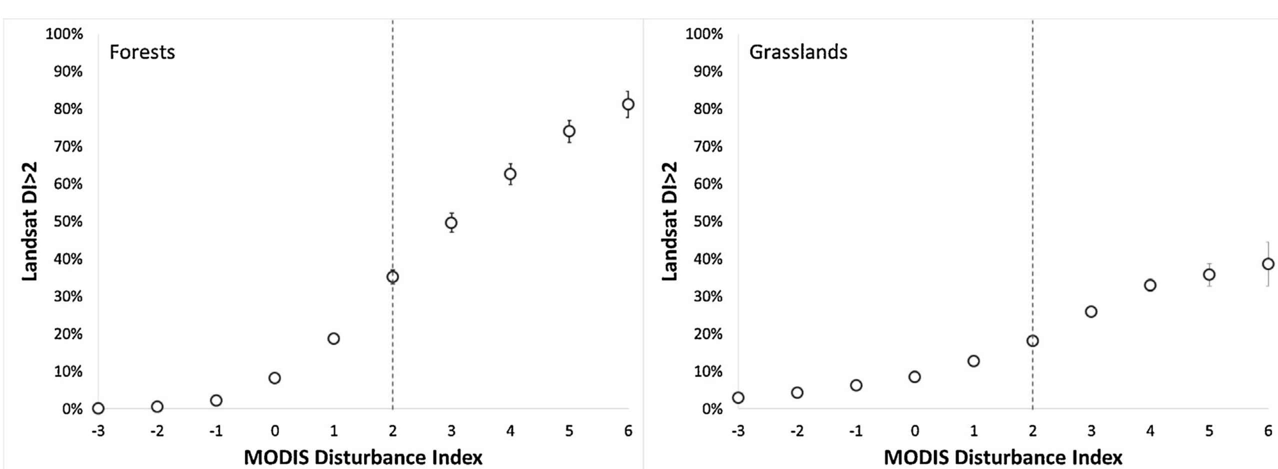

Fig. 10. Relationship between the percentage of Landsat pixels with a DI over 2, and the Disturbance Index value based on MODIS data for forests (left) and grasslands (right). Error bars represent two standard errors.

Table 5
Summary of the accuracy assessment of the Landsat disturbance dataset organized by soil order.

Soil order	DI	Overallaccuracy	Kappa	User accuracy		Producer accuracy		*N*
				D	*U*	*D*	*U*	
Brown (B)	DI2	90.6%	0.436	31.7%	99.7%	94.1%	90.5%	758
	DI3	98.0%	0.759	80.6%	98.8%	73.5%	99.2%	
Gley (G)	DI2	96.3%	0.554	44.4%	99.4%	80.0%	96.9%	328
	DI3	99.1%	0.837	88.9%	99.4%	80.0%	99.7%	
Allophanic (L)	DI2	96.8%	0.810	70.6%	100%	100%	96.5%	313
	DI3	99.0%	0.928	100%	99.0%	87.5%	100%	
Granular (N)	DI2	91.6%	0.342	22.6%	100%	100%	91.4%	287
	DI3	99.0%	0.795	75.0%	99.6%	85.7%	99.3%	
Organic (O)	DI2	90.6%	0.659	62.5%	97.1%	83.3%	91.8%	85
	DI3	95.3%	0.775	100%	94.8%	66.7%	100%	
Recent (R)	DI2	95.2%	0.659	55.1%	99.4%	90.0%	95.5%	519
	DI3	97.7%	0.757	90.9%	98.0%	66.7%	99.6%	
Ultic (U)	DI2	94.6%	0.596	47.4%	99.5%	90.3%	94.8%	2093
	DI3	97.8%	0.719	86.7%	98.0%	63.1%	99.5%	

6. Discussion

In this study we first evaluated an already existing approach for forest disturbance detection for both MODIS and Landsat data and confirmed the validity of the method for New Zealand, which is a region that was not previously studied in this way. In the next step we evaluated an extension of the method for the high producing grasslands of New Zealand which have been undergoing tremendous change.

6.1. Forest disturbances

We have validated the forest disturbances for both forest types (exotic and indigenous) and found substantial accuracies in Landsat data. Kappa values for the forest areas were 0.656 for a DI threshold of 3, while kappa values were 0.517 for a DI threshold of 2. These values were comparable to the kappa values found by others (Healey et al. 2005). Masek et al. (2008) indicated that for the LEDAPS system, the error of commission (i.e. pixels mistakenly mapped as disturbance) is low, with much higher omission errors (i.e. actual disturbance that is missed). We find similar results, with a commission error for forest disturbance of 10.3% and an omission error of 47.0%, compared to 27.0 ± 4.5% and 44.6 ± 5.8% for the national (USA) mean errors from Masek et al. (2008). We expect that some of the omission errors are resulting from the long lasting visible effects of forest disturbance on high resolution satellite imagery. Even after new forests have been planted, the effect of the initial forest clearing is visible on the high resolution satellite imagery, while the disturbance is not as visible on the coarser Landsat imagery as a result of regrowth.

Over the ten year period of our investigation, 37.7% of the exotic forests were never disturbed and 63.8% revealed disturbance shorter than 6 months. Most significant forest harvests result in disturbances that lasted longer than 6 months; we found such disturbances that lasted longer than 6 months for approximately 36.2% of the exotic forests (Table 3). This results in an annual clearing rate of 2.6% of the forest over the 14 year period (2000–2013). Within the United States, the highest clearing rates were between 2 and 3% per year, which were found in the southeast, Maine, and the Pacific Northwest (Masek et al. 2008). A clearing rate of 2.6% per year as we find for the exotic forests in the North Island of New Zealand results in a turnover period of 38.5 years. This is slightly longer than would be expected for the short rotation schedule for most exotic forests in New Zealand, which is about 25–30 years (Kirschbaum et al. 2011). The disturbance rate for the indigenous forests is 1.7% per year, which is a little higher than the annual disturbance rate of 0.9% for the USA. Official New Zealand forestry statistics indicate that 508,747 ha of the exotic forests in the North Island are currently between one and 15 years old, which might indicate that these forests were harvested and replanted within the past 15 years. According to our land cover data, we find that approximately 12% of land area of the North Island is exotic forests used for plantations, which translates to an area of 1380,000 ha. We find that 36.2% of those forests (499,560 ha) reveal disturbances that last longer than 6 months, which corresponds very closely with the official New Zealand statistics (National Exotic Forest Description, 2014).

6.2. Grassland disturbances

The commission errors for grassland disturbances based on Landsat (DI > 3) were comparable to the commission error for forest disturbances but the omission error was much lower (15.6% vs 47.0%). We suspect that this difference results from less ambivalence of disturbance detection on the high resolution satellite imagery. Many papers evaluating grassland degradation are focused on large (often semi-arid) grasslands that are far less intensely grazed than the regions in New Zealand, e.g. the Tibetan Plateau (Lehnert et al. 2015), southern Africa (Wessels et al. 2012), and the Sahel (Mbow et al. 2015). Several methods have been developed to study these areas, many using vegetation index data, even though linking vegetation index data with degradation has been shown to be complicated in some occasions (Karnieli et al. 2013). We have not found other papers using the disturbance index for grassland ecosystems.

When validating the Landsat disturbance data, we found that the accuracy of the disturbance index was not affected by soil type (Table 5). However, we did find that frequency/duration of disturbance did vary by soil order (Table 6). Allophanic and Gley soils revealed the lowest durations of disturbance, with 42.8% of Gley soils in high producing grasslands disturbed regularly (more than 6 months), and only 35.6% of Allophanic soils disturbed more than 6 months out of the entire time period, compared to 50–60% for other soil orders. Schipper et al. (2014) were interested in determining whether differences in soil C and N stocks under different grazing practices might be related to soil order. Interestingly, they found that Allophanic and Gley soils lost significant amounts of carbon on flat lands, while no carbon loss could be found for the other soil orders. They found no relationship with grazing types, but instead deduced that soils having higher initial carbon stocks were also the soils most susceptible to carbon loss. Allophanic soils generally have a lower turnover rate, as well, potentially making these soils more vulnerable under intensive agriculture; however, when these soils occur in high-producing grasslands they receive generous amounts of phosphate fertilizer. Schipper et al. (2014) also indicated that the relatively high C content in Gley soils could

Table 6
Frequency and duration of disturbances by land use and soil order. Number of Landsat pixels for each soil order is in parentheses.

	Never	<6 months	>12.5 year	Always
Exotic forest	37.7%	63.8%	0.001%	0.004%
Brown (B) (11,195)	38.3%	58.9%	0.004%	0.009%
Gley (G) (401)	27.9%	52.6%	0.000%	0.000%
Allophanic (L) (2999)	32.5%	50.5%	0.007%	0.000%
Granular (N) (1115)	34.2%	64.6%	0.000%	0.000%
Organic (O) (123)	26.8%	51.2%	0.000%	0.000%
Recent (R) (11,062)	39.2%	55.9%	0.008%	0.001%
Ultic (U) (3617)	25.1%	47.9%	0.008%	0.000%
High-producing grasslands	21.4%	68.6%	0.798%	0.032%
Brown (B) (64,022)	14.8%	47.1%	0.113%	0.010%
Gley (G) (20,157)	17.6%	57.2%	0.023%	0.001%
Allophanic (L) (47,106)	24.7%	64.4%	0.045%	0.001%
Granular (N) (9125)	10.3%	40.2%	0.045%	0.001%
Organic (O) (6325)	14.3%	48.3%	0.040%	0.003%
Recent (R) (28,079)	18.6%	49.7%	0.109%	0.009%
Ultic (U) (17,744)	12.3%	48.5%	0.041%	0.000%

be attributed to slow organic matter decomposition in these soils. Many Gley pasture soils naturally have high water tables that are drained to improve topsoil aeration, which subsequently increases decomposition. Thus, while we find relatively fewer disturbances on Allophanic and Gley soils, these soils could potentially contribute more significantly to carbon losses with more intensive grazing. On the other hand, McSherry and Ritchie (2013) indicate that moderate grazing in tropical grasslands could actually generate a positive soil carbon storage. More information on grassland management, particularly irrigation and fertilizer application, would be needed to explain differences in disturbance among soil types.

The high grassland disturbances we find in the Komakorau catchment can be a result of either grazing down to virtually bare soil or of pasture turnover. Pasture turnover (i.e., the pasture gets cropped, plowed and resown with new grass) is the result of the pasture becoming ‘worn out’ (i.e., slower recovery and reduced productivity), which requires that it be replanted periodically. From interviews with farmers, agricultural agencies and researchers across the North Island, one of the authors (personal communication) learned that historical pasture turnover on high-producing grasslands occurred approximately every 10 years. But with increased livestock densities and thus higher grazing pressure over the last decade, pasture turnover now occurs every 6–7 years, which matches the results from our grassland disturbance analyses for this heavily-grazed area of the North Island (Figs. 7 and 8B).

7. Conclusion

Demand for agricultural land and products is increasing, with a major consequence being broad-scale (and sometimes intense) disturbances to grassland ecosystems. To fully understand the extent and effects of these grassland disturbances, it is critical to have spatially- and temporally-explicit data. While good methodology has been developed to evaluate forest disturbances, grassland disturbances (particularly those resulting from over-grazing) in high intensity grasslands are far less studied. In this study we have extended an approach which has previously been proven useful for forest disturbance monitoring to allow for the monitoring of grasslands. We used the North Island of New Zealand as the study area because it is undergoing tremendous changes to both its forests and grasslands, largely resulting from increased agricultural productivity. Our combined disturbance index worked well for both forests and grasslands. We found that the adapted method for grasslands was very effective with accuracies that were comparable or higher than for forested areas. We found that the methodology worked comparably well for a variety of soil orders, but also found that some soil orders revealed more grazing than others. In future work we intend to extend the methodology toward the South Island and to link the results with water quality observations.

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