

Contents lists available at [SciVerse ScienceDirect](#)

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Using a remotely sensed optimized Disturbance Index to detect insect defoliation in the Apostle Islands, Wisconsin, USA



Jonathan Boyd Thayne*

Department of Geography – Geology, Illinois State University, Normal, IL 61790-4400, United States

ARTICLE INFO

Article history:

Received 6 February 2013

Received in revised form 5 May 2013

Accepted 7 May 2013

Available online xxx

Keywords:

Disturbance Index

Nelder-Mead optimization

Gypsy Moth

Apostle Island National Lakeshore

ABSTRACT

The Disturbance Index (DI) proposed by [Healey et al. \(2005\)](#) has been used successfully to locate and monitor disturbances by various researchers and in many locations. Here, a modification of the DI is presented that adapts it to local conditions by weighting each of its input components to maximize the difference between disturbed and undisturbed forest canopy. The weights reduce the effects of background variation while emphasizing the variation caused by disturbance. The weighted DI was applied to the severe insect defoliation of 2006 in the Apostle Island National Lakeshore with promising results. A supervised maximum likelihood thematic map based on the unweighted DI was 59% accurate and one based on the weighted DI was 62%. A classification with only two classes, defoliated and not defoliated, was also more accurate when based upon the weighted DI (77% versus 69%). In nearly all instances, the user's and producer's accuracies were significantly higher for the weighted DI image, suggesting that weighting the DI to fit local conditions is a superior approach, at least for small-area studies.

© 2013 Elsevier Inc. All rights reserved.

1. Introduction

Detecting and monitoring forest disturbances are important for understanding global biogeochemical cycles and forests' response to perturbation and climate change. To more easily detect forest disturbance, [Healey et al. \(2005\)](#) introduced a Disturbance Index (DI) based on the brightness, greenness and wetness components of a Kauth-Thomas tasseled cap transformation (TCT; [Crist & Cicone, 1984](#); [Kauth & Thomas, 1976](#)) of Landsat imagery:

$$DI = B_r - (G_r + W_r) \quad (1)$$

where B_r is the brightness component, G_r is the greenness component, and W_r is the wetness component, all of which have been rescaled by converting them to z-scores using the mean and standard deviation of healthy, undisturbed forest vegetation. The underlying theory is that disturbed forest will have higher brightness values and lower greenness and wetness values than undisturbed forest ([Healey et al., 2005](#)). The DI is essentially the distance in tasseled cap space between healthy forest and disturbed forest. DI values larger than zero indicate that the pixel has been disturbed, DI values less than zero indicate a recent flush of vegetation (possibly recovery), and DI values near zero indicate no change in canopy cover ([DeRose et al., 2011](#)). The simplicity and effectiveness of the DI has encouraged its use. As of this writing, the [Healey et al. \(2005\)](#) paper has been cited nearly 130 times – for example, see

[Healey et al. \(2006\)](#), [Masek et al. \(2008\)](#), [Hayes et al. \(2008\)](#), [Hilker et al. \(2009\)](#), and [Deel et al. \(2012\)](#). The DI is a SWIR-dominated vegetation index and is highly correlated with the wetness component of the TCT in many datasets ([Hais et al., 2009](#); [Healey et al., 2006](#); [Masek et al., 2008](#)).

The equation for the DI implies that each of the three TCT input components; brightness, greenness, and wetness; are equally important predictors of forest disturbance. While the DI has been very useful in many scenarios, it is likely that the importance of the contribution of each TCT component varies by location and disturbance. [Healey et al. \(2005\)](#) suggests that the contrast of DI values between disturbed and undisturbed forests is likely different between ecosystems and that the DI might be improved by adapting it to local conditions by giving higher weights to the TCT components that are most useful, thus maximizing its sensitivity to specific disturbances of interest. The DI as calculated with equation one is likely the best option for detecting general disturbance in study areas with various environmental conditions; however, adding weights to fit the DI to specific disturbances could improve results at local scales.

In the current paper, a weighting scheme is introduced, where the TCT components (B_r , G_r , and W_r) in equation one are weighted by coefficients indicative of their contribution to mapping the disturbance of interest. The weights are derived by optimizing the difference between disturbed and undisturbed areas, making it an optimized Disturbance Index (DIopt). The severe gypsy moth (*Lymantria dispar* L.) defoliation of 2006 in the Apostle Islands National Lakeshore (AINL) in northern Wisconsin is used as a case study to achieve the following objectives: 1) derive an optimized DI and assess its utility in detecting

* Tel.: +1 309 438 8112.

E-mail address: jthayne@ilstu.edu.

various severity levels of gypsy moth defoliation, and 2) use the weights from the optimized DI to better understand how the individual TCT components contribute to detecting gypsy moth defoliation. Not only could this advance understanding of the biophysical effects of gypsy moth defoliation, it may also lead to the establishment and use of a more effective disturbance index.

2. Background

2.1. Gypsy Moths in Northern Wisconsin

The gypsy moth was accidentally released in 1868 or 1869 in Medford, Massachusetts by Étienne Léopoldo Trouvelot, who was trying to breed a robust silk-producing moth for North America (Liebhold et al., 1989). The moths have spread to become the most detrimental insect defoliator in the northeastern US (Joria & Ahearn, 1991), costing the U.S. Government \$11 million annually in control and prevention programs (Pimentel et al., 2005). The problem will worsen since gypsy moths currently occupy only one-fourth of their potential range in North America (Liebhold et al., 2000).

A tree defoliated by gypsy moths will usually recover (Joria & Ahearn, 1991), although it will produce 10–20% less foliage the following year (Hurley et al., 2004). The probability of tree mortality increases with the number of consecutive infestations (Campbell & Sloan, 1977; Eisenbies et al., 2007; Wilson & McComb, 2005). Ten years or more may be required for complete recovery (Campbell & Sloan, 1977). Predation by small mammals, primarily mice, of larvae is the most significant control of gypsy moth population (Liebhold et al., 2000 and the papers cited therein). In years of general mast failure, when fewer acorns are produced, these small mammals do not have sufficient food reserves to overwinter and small mammal mortality increases, reducing predation pressure on gypsy moth larvae during the following spring (Jones et al., 1998; Liebhold et al., 2000). The result are episodic and spatially synchronous one to two year outbreaks of large gypsy moth populations that cause severe defoliation, the last of which occurred in the AINL in 2006–2007.

2.2. The Disturbance Index

The DI has been especially useful for mapping forest canopy damage caused by insect defoliation. Wulder et al. (2006) used several spectral vegetation indices (the DI among them), elevation, slope, and solar irradiance to predict mountain pine beetle damage with 86% accuracy. DeRose et al. (2011) used the DI to map Engelmann spruce mortality caused by spruce beetle outbreaks in southern Utah with accuracy as high as 79%. DeRose and his coauthors noted that the utility of the DI in discerning insect-caused tree mortality increased as the infestation progressed and canopy damage and tree mortality increased. This is in line with other researchers' observation that the DI is especially sensitive to severe disturbances (Hais et al., 2009; Healey et al., 2005; Kuemmerle et al., 2007; Masek et al., 2008).

2.3. The Nelder–Mead Optimization

Determining the weighting coefficients for the Dlopt requires an optimization function. The Nelder–Mead method is a widely popular nonlinear optimization technique used for multidimensional unconstrained minimization (Bélisle, 1992; Lagarias et al., 1998). The method uses an iterative downhill simplex approach to find a local optimum of a multivariate problem where the function is unimodal. It is particularly useful when applied to functions with multiple interdependent variables (Nelder & Mead, 1965), like the brightness, greenness, and wetness TCT bands. The Nelder–Mead method can be converted to a maximizing optimization by applying a negative overall scaling. In geography, the Nelder–Mead method has been used to automate the projection of aerial photographs (Gede, 2010), optimize cell

tower placement (Akella et al., 2010), improve estimates of forest biomass (Bortolot & Wynne, 2005), calculate the effects of the ionosphere on GPS satellites (Strangeways & Ioannides, 2002), and optimize forest stand management (Pukkala, 2009).

3. Methodology

3.1. Study Area

The Apostle Islands are an archipelago of 22 islands extending from northern Wisconsin into Lake Superior. Twenty-one of the islands and about 18 km of shoreline on the mainland (a total of 42,500 acres), were designated as the Apostle Island National Lakeshore (AINL) in 1970. The islands are sandstone, and the park contains several abandoned quarries that once supplied material for brownstone construction in Chicago. Precipitation averages about 75 cm annually, including about 200 cm of snow. The growing season is about 120 days (Judziewicz & Koch, 1993). The mean July temperature is around 65 °F (Beals, 1960) and the mean January temperature is about 7 °F (Judziewicz & Koch, 1993).

Pre-settlement hemlock (*Tsuga canadensis*) and white pine forests (*Pinus strobus*) have been replaced by trembling aspen (*Populus tremuloides*) and white birch (*Betula papyrifera*), especially in places that were logged or burned (Judziewicz & Koch, 1993). Sugar maple (*Acer saccharum*) and red maple (*Acer rubrum*) have also increased (Beals, 1960). Red oak (*Quercus rubra*) may appear at higher elevations (Beals, 1960). Aspen, maple, and oak are among the gypsy moths' preferred species (Campbell & Sloan, 1977; Foss & Rieske, 2003).

3.2. Data

The most critical element of choosing satellite imagery for studying gypsy moth defoliation is finding a cloud-free image that closely corresponds to the peak of defoliation while ensuring that the image was not collected after refoilation had begun (de Beurs & Townsend, 2008). Using imagery with shorter revisit periods, like MODIS, would make this easier, unfortunately the concomitant loss of spatial resolution would mean that important areas of defoliation in this small study site would not be detected. Problems with the timing of image collection could also be mitigated by using imagery from Landsat 5 and from Landsat 7 (Hurley et al., 2004). Unfortunately, the scan line correction failure of Landsat 7 dramatically reduces image quality over the Apostle Islands. The analysis focused on 2006, the year of the last episode of severe defoliation in the Apostle Islands. Fortunately, two Landsat 5 images were collected at appropriate times: the pre-defoliation image is from June 2, 2006, and the peak-defoliation image is from August 12, 2006. Landsat imagery was also used since the DI relies on the TCT, which was initially prepared for the Thematic Mapper family of sensors.

A sketch map of defoliation drawn during an aerial survey performed on August 8, 2006, was generously provided by the resource managers at the AINL (Fig. 1). The map shows the severity of defoliation by labeling each location as severely, moderately, slightly, or not defoliated. These severity classes were used to create different samples for performing the optimization and for assessing the accuracy of the results (Table 1). In both cases, stratified random sampling was used to ensure that equal numbers of points were generated for each of the defoliation severity classes. The points for calculating the z-scores of the TCT bands were all selected from the non-defoliated class, so that the z-scores of each pixel represent the distance from each pixel to non-defoliated forest in z-score TCT space. For the optimization, 100 points were randomly generated from each severity class, for a total of 400 points. These data are z-scores, so the means should be close to zero and the standard deviations should be close to one; notice, however, that the means increase with increasing defoliation, i.e., these points are further from the mean of the non-defoliated pixels.

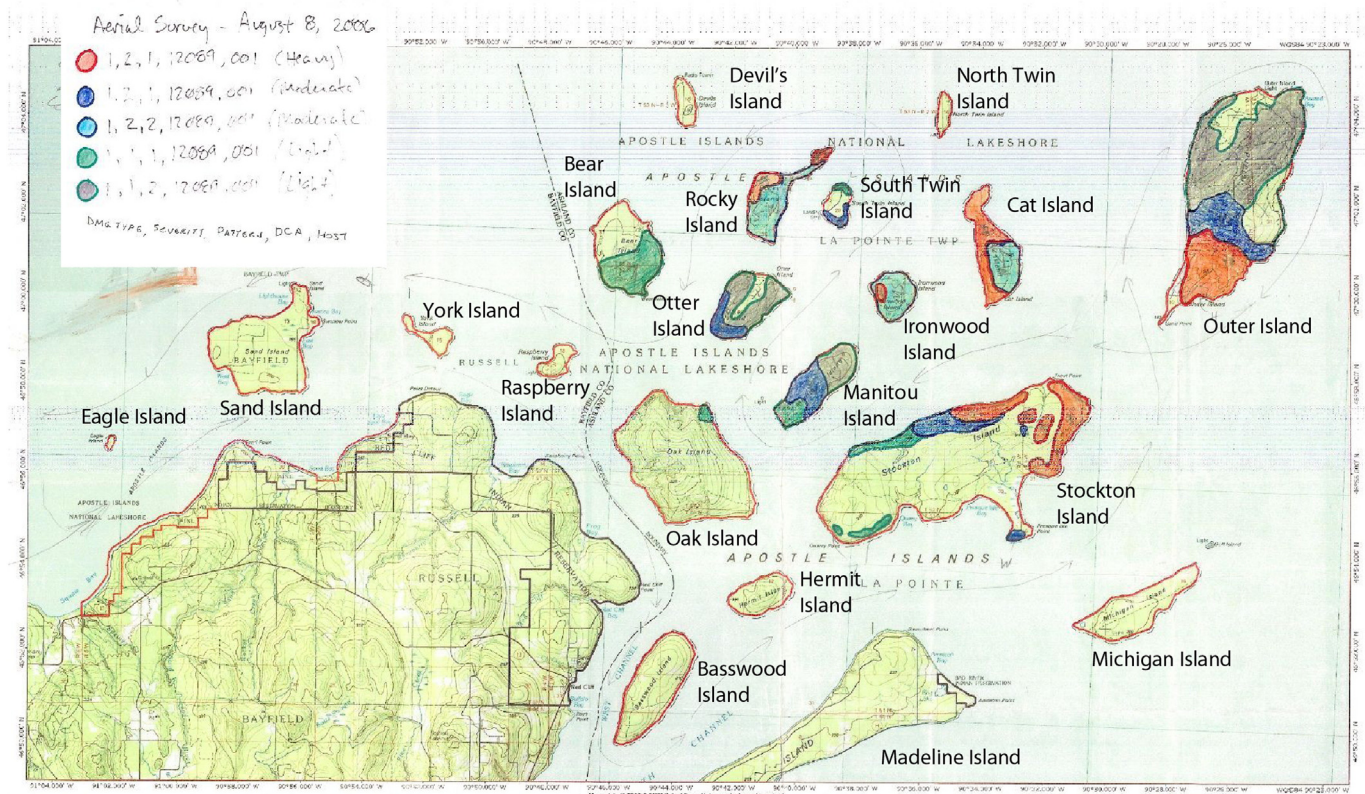


Fig. 1. Map of the study area — the sketch map provided by resource managers at the Apostle Island National Lakeshore.

3.3. Image Processing

Non-forest classes, e.g., water, urban (on Madeline Island), and beach, were masked from the data and excluded from subsequent analysis.

The images were transformed to the brightness, greenness, and wetness components of the Kauth-Thomas tasseled-cap transform (TCT, Kauth & Thomas, 1976). These components were then converted to z-scores (Burt et al., 2009, p. 236), using the mean and standard deviation of nearly 500 randomly selected healthy, non-defoliated forest pixels (Table 1). Converting the data to z-scores is a normalization method, which, like dark object subtraction (Chavez, 1988), can reduce the effect of atmosphere in imagery with relatively homogenous atmospheric conditions (Huang et al., 2010; Masek et al., 2008). Since conversion to z-scores limits atmospheric effects, and since training samples were drawn from the data (Song et al., 2001), no other atmospheric correction was applied. The Disturbance Index (DI) was then calculated using the z-score TCT components and equation one (Healey et al., 2005).

Healey et al. (2005) converted the Kauth-Thomas tasseled-cap components to z-scores before submitting them to equation one so that each component would have essentially equivalent ranges and

therefore equivalent weight in the calculation of the DI. In the present analysis, an optimized DI (Dlopt) was calculated according to the following equation:

$$DI = \beta_1 B_r - (\beta_2 G_r + \beta_3 W_r) \quad (2)$$

where β_1 , β_2 , and β_3 are coefficients that are multiplied by the respective TCT components. These weights were derived using a Nelder-Mead simplex optimization (Nelder & Mead, 1965) that maximized the χ^2 statistic of a Kruskal-Wallis test (Burt et al., 2009, p. 393–395) run on stratified-randomly selected samples of severely, moderately, slightly, and not defoliated pixels (Table 1). One hundred pixels were randomly selected from each of the forest condition classes and were independent of the locations used to calculate z-scores. The non-parametric Kruskal-Wallis test was used because the samples were negatively skewed by the lower values of the defoliated sites. Applying the coefficients effectively rotates the plane of transformation in three-dimensional tasseled-cap space to achieve maximal separation of the defoliation classes based on a model defined by the training data. The optimization was performed using the “optim” function in the R Statistical Environment (R Core Team, 2012).

Table 1

Descriptive statistics of the training data used to convert the images to z-scores and to derive the weighting coefficients.

	n	None	Slight	Moderate	Severe
		$\bar{x}$	s	$\bar{x}$	s
Z-scores					
Band 1	491	105.730	9.610	—	—
Band 2	491	52.550	12.040	—	—
Band 3	491	—8.240	3.970	—	—
Optimization					
Band 1	400	0.179	0.941	0.140	0.799
Band 2	400	0.317	0.790	0.063	0.686
Band 3	400	0.158	0.979	—0.549	0.813
				—0.203	0.993
				—0.624	0.779
				—0.894	1.390
				—0.656	0.904
				—1.489	0.838
				—1.155	1.642

The pre- and post-disturbance images can be compared to better visualize forest canopy change (Deel et al., 2012; Masek et al., 2008; Potere et al., 2008). They were displayed using write function memory insertion (Jensen, 2005, pp. 475) with the peak-defoliation image displayed in red and the pre-defoliation image displayed in green and blue (Fig. 2).

The DI and the Dlopt images were classified using a supervised maximum likelihood classification to facilitate comparisons to the sketch map. The DI and Dlopt peak-defoliation images were classified into the four forest classes (severe, moderate, slight, and non-defoliated). The training data locations were selected based on the sketch map and the same locations were used for the classifications of the DI and the Dlopt images. Accuracy assessments were performed using 1553 proportional stratified random points that were collected independently of the datasets used to derive the weighting coefficients and those used to train the classification algorithm. The same points were used to assess the DI and the Dlopt classified images. The confusion matrices were analyzed using the equations of Olofsson et al. (2013), Stehman and Foody (2009), and Olofsson et al. (in review), which use occurrence-weighted values to calculate estimated defoliated area and confidence intervals for the user's, producer's and overall accuracies. Overall accuracy was used rather than kappa in keeping with the suggestion of Olofsson et al. (2013) and the papers cited therein.

4. Results

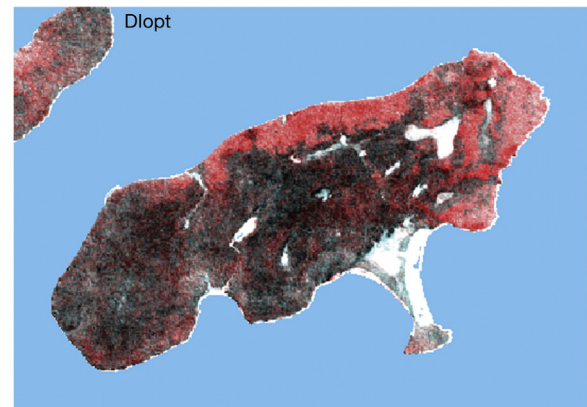
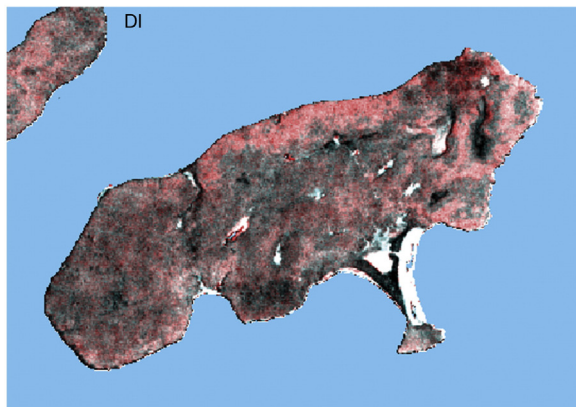
The Nelder-Mead optimization required 107 iterations to arrive at the following results: $\beta_1 = 0.158$, $\beta_2 = 1.726$, and $\beta_3 = 0.822$ ($\chi^2 = 248.822$, $p < 0.000$), which were used to create the Dlopt image.

A visual inspection shows that the DI and the Dlopt images both reliably capture the outline of defoliated regions and that both indices have relative strengths. In general, the boundary between the disturbed and undisturbed forest is more clear in the Dlopt image since that difference has been maximized by the weighting coefficients (Fig. 2). This is especially true of the severely defoliated regions where the exaggeration is even more pronounced. This agrees with DeRose et al. (2011) observation that DI-based classification accuracy increased as the duration and severity of infestation increased. For example, the patterns of defoliation on Cat, Ironwood, Otter, and Manitou Islands are more clear in the Dlopt image and they align more closely with the sketch map. The pocket of defoliation on the northeastern promontory of Oak Island is also more clear on the Dlopt image (Fig. 2b), as is the patch of defoliation at the end of the tombolo extending southward from Stockton Island (Fig. 2a).

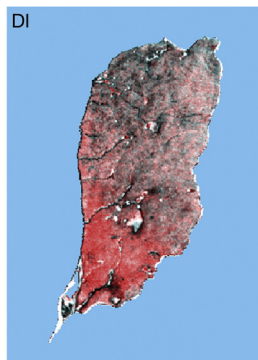
Healey et al. (2005) note that the DI is relatively less sensitive to slight disturbances. This seems to be somewhat mitigated in the Dlopt image, again, because of the weights that maximize the differences between disturbed and undisturbed forest. Areas of slight defoliation are much more apparent in the Dlopt image (see the larger red areas on the Dlopt image in Fig. 2c).

A box plot of DI and Dlopt values from the peak-defoliation image (Fig. 3) shows that the overall range of the Dlopt is less than that of the DI, but that the ranges of the defoliation classes are more exclusive in the Dlopt image than in the DI image. Accordingly, the Dlopt data should be more useful for discerning between the discrete classes. There is still considerable overlap between classes however, which will lead to confusion during classification. The range of DI and Dlopt values for disturbed forests (2–5 with a few larger outliers) is in line with the range presented by Healey et al. (2005).

a) Stockton Island



b) Outer Island



c) Rocky, South Twin, Otter, Manitou, and Oak Islands

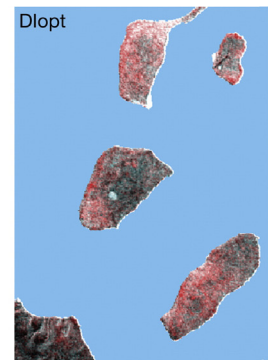
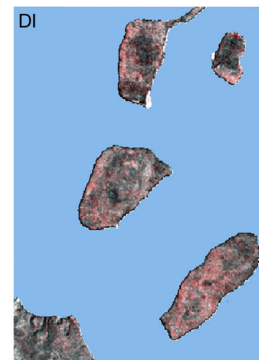


Fig. 2. Select islands displayed in DI and Dlopt images. The peak defoliation image is shown in the red color gun and the pre-defoliation image is shown in the green and blue color guns. The same contrast stretch has been applied to the DI and the Dlopt images. Water has been masked from the images and displayed as blue.

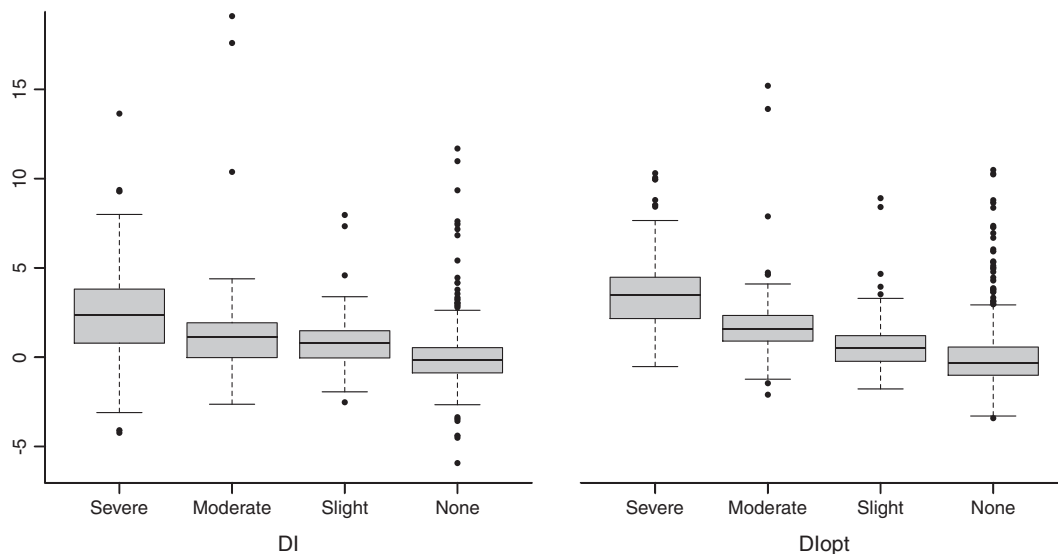


Fig. 3. Boxplot showing the differences between original DI and weighted Dlopt values. Notice that the DI has a larger range, but that the classes' ranges of the Dlopt are more exclusive.

A scatterplot comparing DI values to Dlopt from the peak-defoliation image shows that they share a linear relationship ($r^2 = 0.502$, $p < 0.000$). The Dlopt has a slightly larger range for values below and up to about 2 (Fig. 4). Most of the values for both indices are near zero, although the Dlopt seems to have a slightly larger range there. The Dlopt values tend to be larger than those of the DI, since they have been maximized by the weights.

The estimates of defoliated area in the islands were consistent between the DI and Dlopt images (Table 2). Just over 6% of the islands (~109 km²) showed no detectable levels of defoliation. The slightly defoliated class occupied over 17% of the islands (~31 km²) and the moderate class encompassed over 11% (~21 km²). About ten percent of the islands were severely defoliated (~18 km²).

The producer's and user's accuracies for the Dlopt were consistently higher than those of the DI (Table 2). The most dramatic improvements were in the user's accuracy, where the moderate and none classes each improved by 8%. The user's accuracy for the severe

class remained unchanged. The most dramatic improvement in the producer's accuracy was for the severe class, which increased by over 18%. Producer's accuracy for the moderate class increased by over 4% and that of the slight class increased by nearly 10%. Producer's accuracy for the none class decreased slightly, as did user's accuracy for the slight class. For both the DI and the Dlopt images, the none class was the most accurately mapped, followed closely by the severe class. Most of the confusion was between the moderate and slight classes. Overall accuracy for the DI image was $59 \pm 2\%$ and that of the Dlopt image was $62 \pm 2\%$. The estimates of the area of each class were fairly consistent between the DI and the Dlopt images.

Most research projects that use the DI generate a binary classification, either disturbed or not disturbed. To enable comparison with those studies, another set of weights were derived to create a disturbed versus undisturbed classification. Sixty iterations were required to converge at the following results: $\beta_1 = 0.306$, $\beta_2 = 1.563$, and $\beta_3 = 0.908$ ($\chi^2 = 114.516$, $p < 0.000$). Notice that these weighting coefficients are in keeping with the earlier set. The resulting Dlopt image, and the DI image, were classified as either not-defoliated or defoliated using a supervised maximum likelihood classifier. The accuracy of these classifications were assessed using the same 1553 proportional stratified random points that were used to assess the initial 4-class images. User's accuracies for both the defoliated and the not-defoliated classes were nearly 8% higher in the Dlopt image than in the DI image (Table 3). Producer's accuracy for the defoliated class increased by nearly 10%. Producer's accuracy for the not defoliated class was nearly 7% higher in the Dlopt image than in the DI image. The overall accuracy of the DI classification was $69 \pm 2\%$, and that of the Dlopt classification was $77 \pm 2\%$.

The estimates of defoliated and not-defoliated area from the two-class map were also consistent between the DI and Dlopt images, and they, like the four-class image, indicate that about 40% of the islands were defoliated to some degree in 2006 (Table 3).

The accuracy values compare respectably with other studies (DeRose et al., 2011; Healey et al., 2005), however they are lower than expected. The reference data used in the accuracy assessments were from hand-drawn sketch maps prepared by resource managers while viewing defoliation from a small airplane (Fig. 1). It is very likely that there were errors in the sketch map (de Beurs & Townsend, 2008; Williams, 1975), and that these errors were perpetuated into the current analysis resulting in depressed estimates of detection accuracy. The sketch maps were also used as guides when selecting training data for the

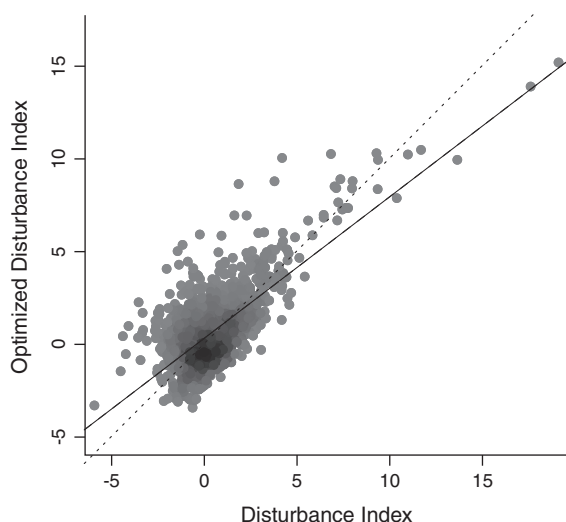


Fig. 4. Scatterplot of original DI and weighted Dlopt values. The darker area near the center of the point cloud indicates a greater concentration of points. The dotted line is the 1:1 line and the dashed line is the primary axis.

Table 2

Confusion matrices for classified DI and Dlopt images using four classes of defoliation intensity: severe, moderate, slight, and none. The rows contain the classification results and the columns contain the sketch map reference data. W_i are the area-weights used to calculate the estimates of area and the user's, producer's and overall accuracies (Stehman & Foody, 2009), which are presented with 95% confidence intervals.

Sketch map reference										
	Severe	Moderate	Slight	None	Total	W_i	Area	User's	Producer's	Overall
<i>DI</i>										
Severe	72	28	9	35	144	0.087	17.562 ± 2.366	0.500 ± 0.082	0.442 ± 0.064	0.593 ± 0.022
Moderate	35	80	74	101	290	0.165	20.999 ± 2.744	0.276 ± 0.052	0.388 ± 0.061	
Slight	16	26	91	130	263	0.178	31.446 ± 3.285	0.346 ± 0.058	0.350 ± 0.049	
None	36	56	100	664	856	0.570	108.995 ± 3.964	0.776 ± 0.028	0.727 ± 0.020	
Total	159	190	274	930	1553	1.000				
<i>Dlopt</i>										
Severe	95	35	6	49	185	0.122	17.874 ± 2.219	0.514 ± 0.072	0.625 ± 0.064	0.617 ± 0.021
Moderate	43	92	73	52	260	0.140	20.654 ± 2.630	0.354 ± 0.058	0.430 ± 0.061	
Slight	13	42	114	179	348	0.240	31.338 ± 3.248	0.328 ± 0.049	0.449 ± 0.051	
None	8	21	81	650	760	0.498	109.136 ± 3.679	0.855 ± 0.025	0.699 ± 0.020	
Total	159	190	274	930	1553	1.000				

optimization and for the classification, further compounding the effects of extant error. Unfortunately, a more reliable source of defoliation in 2006 does not exist.

5. Discussion

5.1. Gypsy Moth Defoliation in the Apostle Islands

Gypsy moths were first trapped in the Apostle Island National Lakeshore in 1997 (Tobin et al., 2010) and have since steadily advanced until they are now present on many, if not all, of the islands of the archipelago. Monitoring the spread of the moths is an essential part of mitigating their effects and preserving the park. The current distribution of gypsy moths in the park suggests that human transport plays a significant part in establishing gypsy moths in the park (Tobin et al., 2010).

The Dlopt clearly showed that the bulk of defoliation occurs on Stockton, Manitou, Otter, Rocky, Ironwood, Cat, and Outer Islands (Fig. 2b) with higher intensity and density of defoliation on islands farthest from the mainland. No appreciable defoliation is detected on Sand or York Islands. Newer outbreaks of defoliation have appeared at several locations, most of which are areas with high tourist traffic. Defoliation has appeared on the southern end of the tombolo extending from Stockton Island (Fig. 2a), which is near the ranger station and visitor's center. Also on Stockton Island, a band of defoliation has appeared running from Quarry Bay to the southwestern-most point of the island, which corresponds to a popular hiking trail connecting a camp site at Quarry Bay to an abandoned sandstone quarry. A campsite is also located on the northeastern point of Oak Island where some new defoliation has appeared (Fig. 2c). Defoliation has appeared on the southern edge of York Island, near where Tobin and Hajek (2012) trapped moths. There are no campsites on York Island, but a hiking trail runs along this defoliated area. New defoliation has also appeared on Hermit Island. There are no campsites or trails on Hermit Island so these moths were likely carried by the wind from Stockton Island.

5.2. The Optimized Disturbance Index

The Dlopt differs from the DI by being adapted to local conditions using weights that maximize the difference between disturbed and undisturbed forest. In this paper, a method of deriving weights using an optimization that maximizes the χ^2 statistic of a Kruskal–Wallis test performed on forest disturbance classes of interest is proposed. The weights are unique to each disturbance scenario and should be derived separately for each image, which could limit its utility in broader scale studies that require multiple scenes. In the Dlopt, variation caused by different forest types, atmospheric conditions, or phenology is discounted while the differences related to the disturbance of interest are maximized, similar to work done by He et al. (2011). Not surprisingly, the accuracy of classifications based on the Dlopt are higher than those based on the standard DI; however, this is likely only true for the scale and extent at which the weighting coefficients were derived. The unweighted DI is probably more accurate at coarser scales or in study sites with significant variation in landcover type or condition, although further research is needed to verify this conclusion.

The weighting coefficients used to calculate the Dlopt can be considered relative weights since the TCT components were normalized when they were converted to z-scores. In the current example, greenness ($\beta_2 = 1.726$) was twice as important as wetness ($\beta_3 = 0.822$) and brightness ($\beta_1 = 0.158$) was the least important TCT component. Several researchers who have used the DI to study insect defoliation have found that the wetness component is the most important (Healey et al., 2005; Wulder et al., 2006). Hais et al. even removed the greenness component from the calculation of the disturbance index because “instead of the expected decrease in greenness values during [defoliation], ...the values significantly increased, although with a few years of delay” (2009 pp. 841). The decrease in greenness that usually follows defoliation was offset by an increase in understory greenness that occurred because of increased insolation due to the open canopy. Healey et al. (2005) also noted that the DI is less effective when the

Table 3

Confusion matrices for classified DI and Dlopt images using only two classes: defoliated and not defoliated. The rows contain the classification results and the columns contain the sketch map reference data. W_i are the area-weights used to calculate the estimates of area and the user's, producer's and overall accuracies (Stehman & Foody, 2009), which are presented with 95% confidence intervals.

	Defoliated	None	Total	W_i	Area	Users	Producers	Overall
<i>DI</i>								
Defoliated	402	263	665	0.414	80.954 ± 4.643	0.605 ± 0.037	0.631 ± 0.030	0.690 ± 0.023
None	221	667	888	0.586	123.501 ± 4.643	0.751 ± 0.028	0.729 ± 0.020	
Total	623	930	1553	1.000				
<i>Dlopt</i>								
Defoliated	474	221	695	0.403	77.354 ± 4.214	0.682 ± 0.035	0.726 ± 0.031	0.768 ± 0.021
None	149	709	858	0.597	127.102 ± 4.214	0.826 ± 0.025	0.794 ± 0.019	
Total	623	930	1553	1.000				

understory is intact. The present study was conducted using imagery from the year of the forest disturbance so the understory did not have sufficient time to offset the decline in greenness. Thus, the greenness component is twice as important as the wetness component. It seems likely that the importance of the greenness component would decrease and the importance of the wetness component would increase as the understory develops.

The DI is simple to calculate and to interpret – values greater than zero indicate disturbance, values less than zero indicate regrowth or recovery (Deel et al., 2012; DeRose et al., 2011; Healey et al., 2005). Unfortunately, weighting the values of the Dlopt may make this simple threshold classification method problematic. Also, comparing disturbance index values across multiple images is straightforward with the DI but inappropriate with the Dlopt since the weights are derived separately for each image, although deriving the weights using data from all the images, and then applying the same weights to each image, would eliminate this problem. Calculating the Dlopt is more complicated than calculating the DI – the researcher must select and process training data to derive weights that then need to be applied. The method presented here for deriving the weights is only one of many methods that could be used. Different weighting methods would surely return different results.

Nonetheless, the weighted Dlopt is a more reliable source of information than the DI for mapping forest disturbance. As expected, the accuracies of thematic maps based on the Dlopt are higher than those of the DI since the data have been fitted to local conditions and specific disturbances. Also, the weights used to calculate the Dlopt provide useful information about the relative importance of the TCT brightness, greenness, and wetness components. The weights are indicators of biophysical conditions, properties, and processes that are affected by or result from the disturbance. The unweighted DI does not provide this information. While additional applications of the Dlopt are needed to verify its utility, it seems to be a more useful index of forest disturbance, at least for local area studies.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version, at <http://dx.doi.org/10.1016/j.rse.2013.05.008>. These data include Google map of the most important areas described in this article.

References

- Akella, M. R., Delmelle, E., Batta, R., Rogerson, P., & Blatt, A. (2010). Adaptive cell tower location using geostatistics. *Geographical Analysis*, 42, 227–244.
- Beals, E. (1960). Forest Bird Communities in the Apostle Islands of Wisconsin. *The Wilson Bulletin*, 72, 156–181.
- Bélisle, C. J. P. (1992). Convergence theorems for a class of simulated annealing algorithms on Rd. *Journal of Applied Probability*, 29, 885–895.
- Bortolot, Z. J., & Wynne, R. H. (2005). Estimating forest biomass using small footprint LiDAR data: An individual tree-based approach that incorporates training data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 59, 342–360.
- Burt, J. E., Barber, G. M., & Rigby, D. L. (2009). *Elementary statistics for geographers*. Guilford Press.
- Campbell, R. W., & Sloan, R. J. (1977). Forest stand responses to defoliation by the gypsy moth. *Forest Science*, 23 (a0001-z0001).
- Chavez, P. S. (1988). An improved dark-object subtraction technique for atmospheric scattering correction of multispectral data. *Remote Sensing of Environment*, 24, 459–479.
- Crist, E. P., & Cicone, R. C. (1984). A physically-based transformation of thematic mapper data – The TM tasseled cap. *Geoscience and Remote Sensing, IEEE Transactions*, CE-22, 256–263.
- de Beurs, K. M., & Townsend, P. A. (2008). Estimating the effect of gypsy moth defoliation using MODIS. *Remote Sensing of Environment*, 112, 3983–3990.
- Deel, L. N., McNeil, B. E., Curtis, P. G., Serbin, S. P., Singh, A., Eshleman, K. N., et al. (2012). Relationship of a Landsat cumulative disturbance index to canopy nitrogen and forest structure. *Remote Sensing of Environment*, 118, 40–49.
- DeRose, R. J., Long, J. N., & Ramsey, R. D. (2011). Combining dendrochronological data and the disturbance index to assess Engelmann spruce mortality caused by a spruce beetle outbreak in southern Utah, USA. *Remote Sensing of Environment*, 115, 2342–2349.
- Eisenbies, M. H., Davidson, C., Johnson, J., Amateis, R., & Gottschalk, K. (2007). Tree mortality in mixed pinehardwood stands defoliated by the European gypsy moth (*Lymantria dispar* L.). *Forest Science*, 53, 683–691.
- Foss, L. K., & Rieske, L. K. (2003). Species-specific differences in oak foliage affect preference and performance of gypsy moth caterpillars. *Entomologia Experimentalis et Applicata*, 108, 87–93.
- Gede, M. (2010). The use of the Nelder–Mead Method in estimating projection parameters for globe photographs. *Acta Geodaetica et Geophysica Hungarica*, 45, 17–23.
- Hais, M., Jonášová, M., Langhammer, J., & Kučera, T. (2009). Comparison of two types of forest disturbance using multitemporal Landsat TM/ETM+ imagery and field vegetation data. *Remote Sensing of Environment*, 113, 835–845.
- Hayes, D. J., Cohen, W. B., Sader, S. A., & Irwin, D. E. (2008). Estimating proportional change in forest cover as a continuous variable from multi-year data. *Remote Sensing of Environment*, 112, 735–749.
- He, L., Chen, J. M., Zhang, S., Gomez, G., Pan, Y., McCullough, K., et al. (2011). Normalized algorithm for mapping and dating forest disturbances and regrowth for the United States. *International Journal of Applied Earth Observation and Geoinformation*, 13, 236–245.
- Healey, S. P., Cohen, W. B., Zhiqiang, Y., & Krankina, O. N. (2005). Comparison of Tasseled Cap-based Landsat data structures for use in forest disturbance detection. *Remote Sensing of Environment*, 97, 301–310.
- Healey, S. P., Yang, Z., Cohen, W. B., & Pierce, D. J. (2006). Application of two regression-based methods to estimate the effects of partial harvest on forest structure using Landsat data. *Remote Sensing of Environment*, 101, 115–126.
- Hilker, T., Wulder, M. A., Coops, N. C., Linke, J., McDermid, G., Masek, J. G., et al. (2009). A new data fusion model for high spatial- and temporal-resolution mapping of forest disturbance based on Landsat and MODIS. *Remote Sensing of Environment*, 113, 1613–1627.
- Huang, C., Goward, S. N., Masek, J. G., Thomas, N., Zhu, Z., & Vogelmann, J. E. (2010). An automated approach for reconstructing recent forest disturbance history using dense Landsat time series stacks. *Remote Sensing of Environment*, 114, 183–198.
- Hurley, A., Watts, D., Burke, B., & Richards, C. (2004). Identifying Gypsy Moth defoliation in Ohio using Landsat data. *Environment and Engineering Geoscience*, X, 321–328.
- Jensen, J. R. (2005). *Introductory Digital Image Processing* (3rd ed.) Upper Saddle River, NJ: Pearson Prentice Hall.
- Jones, C. G., Ostfeld, R. S., Richard, M. P., Schaubert, E. M., & Wolff, J. O. (1998). Chain reactions linking acorns to gypsy moth outbreaks and lyme disease risk. *Science*, 279, 1023–1026.
- Joria, P. E., & Ahearn, S. C. (1991). A comparison of the SPOT and Landsat thematic mapper satellite systems for detecting gypsy moth defoliation in Michigan. *Photogrammetric Engineering and Remote Sensing*, 57.
- Judziewicz, E. J., & Koch, R. G. (1993). Flora and vegetation of the Apostle Islands National Lakeshore and Madeline Islands, Ashland and Bayfield Counties, Wisconsin. *Michigan Botanist*, 32, 43–193.
- Kauth, R. J., & Thomas, G. S. (1976). The Tasseled Cap – a graphical description of the spectral-temporal development of agricultural crops as seen by Landsat. *Proceedings of the Symposium on Machine Processing of Remotely Sensed Data*. West Lafayette, Indiana: Purdue University (44B41–44B51).
- Kuemmerle, T., Hostert, P., Radeloff, V. C., Perzanowski, K., & Kruhlov, I. (2007). Post-socialist forest disturbance in the carpathian border region of Poland, Slovakia, and Ukraine. *Ecological Applications*, 17, 1279–1295.
- Lagarias, J. C., Reeds, J. A., Wright, M. H., & Wright, P. E. (1998). Convergence properties of the Nelder–Mead simplex optimization method in low dimensions. *SIAM Journal on Optimization*, 9, 112–147.
- Liebold, A. M., Elinton, J. S., Williams, D., & Muzika, R. M. (2000). What causes outbreaks of the gypsy moth in North America? *Population Ecology*, 42, 257–266.
- Liebold, A., Mastro, V., & Schaefer, P. W. (1989). Learning from the legacy of Léopold Trouvelot. *Bulletin of the Entomological Society of America*, 35, 20–22.
- Masek, J. G., Huang, C., Wolfe, R., Cohen, W., Hall, F., Kutler, J., et al. (2008). North American forest disturbance mapped from a decadal Landsat record. *Remote Sensing of Environment*, 112, 2914–2926.
- Nelder, J. A., & Mead, R. (1965). A simplex method for function minimization. *The Computer Journal*, 7, 308–313.
- Olofsson, P., Foody, G. M., Herold, M., Stehan, S. V., Woodcock, C. E., & Wulder, M. A. (2013). *Good practices for assessing accuracy and estimating area of land change*. (in review).
- Olofsson, P., Foody, G. M., Stehman, S. V., & Woodcock, C. E. (2013b). Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sensing of Environment*, 129, 122–131.
- Pimentel, D., Zuniga, R., & Morrison, D. (2005). Update on the environmental and economic costs associated with alien-invasive species in the United States. *Ecological Economics*, 52, 273–288.
- Potere, D., Felerabend, N., Strahler, A. H., & Bright, E. A. (2008). Wal-Mart from space: A new source for land cover change validation. *Photogrammetric Engineering and Remote Sensing*, 74, 913–919.
- Pukkala, T. (2009). Population-based methods in the optimization of stand management. *Silva Fennica*, 43, 261–274.
- R Core Team (2012). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing.
- Song, C., Woodcock, C. E., Seto, K. C., Lenney, M. P., & Macomber, S. A. (2001). Classification and change detection using landsat TM Data: When and how to correct atmospheric effects? *Remote Sensing of Environment*, 75, 230–244.
- Stehman, S. V., & Foody, G. M. (2009). Accuracy assessment. In T. A. Warner, M. D. Nellis, & G. M. Foody (Eds.), *The SAGE handbook of remote sensing* (pp. 288–309). SAGE Publications.

- Strangeways, H. J., & Ioannides, R. T. (2002). Rigorous calculation of ionospheric effects on GPS earth-satellite paths using a precise path determination method. *Acta Geodaetica et Geophysica Hungarica*, 37, 281–292.
- Tobin, P. C., & Hajek, A. E. (2012). Release, establishment, and initial spread of the fungal pathogen *Entomophaga maimaiga* in island populations of *Lymantria dispar*. *Biological Control*, 63, 31–39.
- Tobin, P. C., Van Stappen, J., & Blackburn, L. M. (2010). Human visitation rates to the Apostle Islands National Lakeshore and the introduction of the non-native species *Lymantria dispar* (L.). *Journal of Environmental Management*, 91, 1991–1996.
- Williams, D. L. (1975). Computer analysis and mapping of gypsy moth defoliation levels in Pennsylvania using Landsat-1 digital data. *Proceedings of the NASA Earth Presentations*, 1A, 167–181.
- Wilson, B. F., & McComb, B. C. (2005). Dynamics of dead wood over 20 years in a New England oak forest. *Canadian Journal of Forest Research*, 35, 682–692.
- Wulder, M. A., White, J. C., Bentz, B., Alvarez, M. F., & Coops, N. C. (2006). Estimating the probability of mountain pine beetle red-attack damage. *Remote Sensing of Environment*, 101, 150–166.