Large area monitoring with a MODIS -based Disturbance Index (DI) sensitive to annual and seasonal variations

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ABSTRACT

Disturbance of the vegetated land surface, due to factors such as fire, insect infestation, windthrow and harvesting, is a fundamental driver of the composition forested landscapes with information on disturbance providing critical insights into species composition, vegetation condition and structure. Long-term climate variability is expected to lead to increases in both the magnitude and distribution of disturbances. As a consequence it is important to develop monitoring systems to better understand these changes in the terrestrial biosphere as well to inform managers about disturbance agents more typically captured through specific monitoring programs (such as focused on insect, fire, or agricultural conditions). Changes in the condition, composition and distribution pattern of vegetation can lead to changes in the spectral and thermal signature of the land surface. Using a 6-year time series of MODerate-resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature (LST) and Enhanced Vegetation Index (EVI) data we apply a previously proposed Disturbance Index (DI) which has been shown to be sensitive to both continuous and discontinuous change. Using Canada as an example area, we demonstrate the capacity of this disturbance index to monitor land dynamics over time. As expected, our results confirm a significant relationship between area flagged as disturbed by the index and area burnt as estimated from other satellite sources (R^2 = 0.78, $p < 0.0001$). The DI also demonstrates a sensitivity to capture and depict changes related to insect infestations. Further, on a regional basis the DI produces change information matching measured wide-area moisture conditions (i.e., drought) and corresponding agricultural outputs. These findings indicate that for monitoring a large area, such as Canada, the time series based DI is a useful tool to aid in change detection and national monitoring activities.

Key words: MODIS, disturbance, insect, fire, drought, land surface temperature (LST), enhanced vegetation index (EVI), coarse spatial resolution, Disturbance Index (DI)

1. INTRODUCTION

Vegetation is inherently dynamic, changing constantly over a range of spatial and temporal scales. Composition, succession, and the distribution pattern of species vary subtly over long time frames, whereas anthropogenic land cover change, fire, windthrow, and agricultural and forestry activities result in discontinuous, often catastrophic, disturbances to the vegetated landscape (Linke et al., 2006; Oliver and Larson, 1996). Within forested environments, minor disturbances occurring over long time frames, often favour competitive tree species while major disturbances generally favour colonizing species. Similarly landscapes with frequent, severe disturbances (stand replacing) are often dominated by young even-aged stands of shade-intolerant species such as aspen whereas old stands of shade-tolerant species such as hemlock dominate where severe disturbances are rare (Frelich, 2002). Disturbance therefore is a fundamental component of a forested landscape and often is a key explanitor of the current vegetation species and structure.

Disturbance events also occur and vary over a wide range of spatial scales (Gong and Xu, 2003). At the individual tree level, windthrow and selective harvesting can result in changes in foliage and stem properties. At the stand level, disturbances can cause changes in canopy structure, such as reduced canopy closure and increased gap size, as well as changes in the number of layers and density of understorey cover (Attiwill, 1994). At the landscape level, disturbances to vegetation cover can be manifest spatially as fragmentation (i.e., as an aggregate function of activities such as forest harvest, industrial activities, or urban developments), disease and insect outbreaks (Linke et al., 2006; Houghton, 1994; Meyer and Turner, 1994). Finally at the global scale, disturbance to vegetation is also evident due to anthropogenic human-induced environmental changes as well as the increasing impact of variable climate (Canadell et al., 2000; Potter et al., 2003).

The impacts of disturbance upon long-term biomass accumulation are becoming an increasingly important consideration for forest managers (Kauppi and Sedjo, 2001). Forests are managed to meet a range of stakeholder interests, requiring increasingly detailed information on disturbance. Government agencies require information on the role of disturbance on natural vegetation, such as land clearing and land conversion, and conservation agencies (both governmental and non-governmental) require information about disturbance and its subsequent impact on available habitat. These disturbances can range significantly in temporal and spatial scales (see Table 1), and thus the role of remote sensing can also vary depending on the extents, rates, and magnitude of change occurring (Gong and Xu, 2003). For example, the remote observation of phenological change would require a number of scenes within one growing season to ensure green-up and green-down were sufficiently well captured (Morisette et al., 2009). Conversely change that occurs at longer time scales such as insect induced mortality could be detected using sets of imagery acquired annually or every two years (Wulder et al., 2006).

Table 1: Types of forest change and an indicative temporal and spatial scale of occurrence.

Type of Change	Temporal Duration	Spatial Extent
Phenological	Days - months	All levels
Regeneration	Days-decades	Individual - stand
Climatic adaptation	Years	All levels
Wind	Minutes - hours	Individual - stand

Type of Change	Temporal Duration	Spatial Extent
throw/flooding		
Fire	Minutes - days	All levels
Disease	Days - years	All levels
Insect attack	Days - years	All levels
Mortality	Days - years	All levels
Pollution	Years	Stand - watershed
Thinning/ pruning	Days	Stand - watershed
Clear-cutting	Days	Stand - watershed
Plantation	Days-decades	Stand - watershed

Waring and Running (1998) define a disturbance as any factor that brings about a significant change in the ecosystem leaf area index (LAI) for a period of more than one year. This definition closely matches that of an ecological disturbance which is often defined as an event that results in a sustained disruption of ecosystem structure and function (Pickett and White, 1985; Tilman, 1985). Changes in LAI can occur both in a positive (increase) and negative (decrease) direction; thus implying that a disturbance event can be also both negative (e.g., wildfire) and positive (e.g., irrigation). Similarly changes in LAI may occur naturally (e.g., wildfires, storms, or floods) or may be human induced, such as anthropogenic land cover change, clear-cutting in forests, urban development, or agricultural practises (Dale et al., 2000).

Remote sensing technology has been shown to be successful at monitoring ecological disturbances (Foody et al., 1996; Rignot et al., 1997) particularly rapid events which result in stand replacement such as fire, clear cut harvesting, and windthrow (see reviews by Gong and Xu, 2003; Coppin et al., 2004). By comparison, disturbance events which happen (comparatively) slowly through time such as thinning, infestation, and succession are more difficult to consistently detect, due to more subtle changes in the spectral responses (Coops et al., 2006). A key aspect in many applications of remotely sensed data to detect and map disturbance is the role that vegetation occupies in the detection and discrimination of change. As captured in the above reviews, numerous studies have concluded that the monitoring of vegetation change can be undertaken using two potentially complementary approaches. The first is through the use of spectral vegetation indices such as enhanced vegetation index (EVI) which are sensitive to change in vegetation condition (Huete et al., 2002), and secondly radiometric land surface temperature (LST) which is strongly related to vegetation density (Schmugge et al., 2002). Generally, a negative relationship is expected between vegetation indices and LST (Goward et al., 1985; Price, 1990; Wan et al., 2004; Nemani et al., 1996). The basis for this relationship lies in the unique spectral reflectance and emittance properties of vegetation relative to bare ground with vegetated surfaces having a lower temperature than soil, resulting in the LST decreasing with an increase in vegetation density through latent heat transfer (Mildrexler et al., 2007). The coupling of LST and the normalised difference vegetation index (NDVI) was found to improve land cover characterization for regional and continental scale land cover classification (Lambin and Ehrlich, 1995; Nemani and Running, 1997; Roy et al., 2005).

Running et al. (1994) suggested that the addition of LST to spectral vegetation indices could increase the discrimination of regional land cover classes. Likewise Borak et al. (2000) found that using LST with NDVI improved the statistical relationship between temporal and spatial change detection metrics. Lambin and Ehrlich (1996) explored the biophysical justification for such a combination and recommended land cover/land use studies utilize the LST-NDVI feature space as it provided more information on biophysical attributes and processes than vegetation indices alone. Goetz (1997) reported that the negative correlation between LST and NDVI, observed over a range of scales, was largely related to changes in vegetation cover and soil moisture and indicated that the surface temperature can rise rapidly with water stress.

Mildrexler et al. (2007) recently capitalized upon this relationship in demonstrating a continental disturbance index (DI) to serve as an automated, economical, systematic disturbance detection index for global application using MODIS/Aqua Land Surface Temperature (LST) and Terra/MODIS Enhanced Vegetation Index (EVI) data. The index was initially applied using 2003 and 2004 satellite imagery over a subset of the United States, with initial results indicating the index was capable of detecting the location and spatial extent of wildfire with precision. The index was sensitive to the incremental process of recovery of disturbed landscapes, and showed strong sensitivity to irrigation.

Since the launch of Terra in 1999 MODIS data has become a critical data source for monitoring global vegetation condition. We take this opportunity to apply and validate the DI as proposed by Mildrexler et al., (2007) with this longer term archive to assess its capacity as an automated and systematic disturbance detection index. Our aim is to test the existing algorithm and verify it with available complementary data, rather than develop a new approach. As a consequence, we apply the DI algorithm over Canada from 2000 to 2006 allowing 7 years of disturbance to be detected, and compare the results to a suite of auxiliary datasets to verify both the temporal and spatial resolution robustness of the predictions. The sensitivity of a time-series based change index is important to capture and spatially portray a wide-range of dynamics occurring over

Canada. Canada is nearly a billion hectares in size, typically monitored by provincial and territorial agencies, resulting in differences in attributes, timing, and consistency in implementation (Wulder et al., 2007). A remote sensing based disturbance index is desired that is sensitive to a range of change agents, both continuous and discontinuous and that is applicable for large area implementation in a systematic and transparent manner.

2. STUDY AREA AND DATA

The focus of our investigations is the terrestrial land base of Canada. To obtain descriptions of the various biomes across Canada, we utilized the National Ecological Framework of Environment Canada (Rowe and Sheard, 1981). Stratification of biomes are based on a classification system whereby each region is viewed as a discrete ecological system, with interactions between geology, landform, soil, vegetation, climate, wildlife, water, and human factors considered. Reviews of the history and the applications of ecological regionalization in Canada are given by Bailey et al. (1985) amongst others. Ultimately, seven levels of generalization are available with 15 terrestrial “ecozones” forming the broadest classes (Rowe and Sheard, 1981; Wiken, 1986). Utilizing the national ecozone stratification links our findings to national level reporting activities and enables us to integrate and understand our findings with reference to other ecosystem level disturbance products.

We obtained the 8-day maximum LST (MOD11A2) and 16-day EVI (MOD13A2) level 3 MODIS products (collection 4) from 2000 to 2006 from the MODIS archive. Terra, launched in late 1999, has a morning (AM) overpass, whereas Aqua, launched in early 2002, has an afternoon (PM) overpass. Generally, LST is expected, under cloudless conditions, to be warmer in the early afternoon than the morning due to the link between maximum skin temperature and solar isolation peak time; therefore, the Aqua PM LST is likely to be closer to the maximum daily LST than Terra. In order to utilise the full MODIS archive from 2000 to 2006 we applied a published adjustment to Terra AM LST estimates, to approximate a “synthetic” Aqua PM LST product from 2000 to mid-2002 thereby providing a seamless afternoon MODIS LST product from 2000 to 2006 (Coops et al., 2007).

3. METHODS

3.1 Disturbance Index (DI) calculation

The Mildrexler et al. (2007) DI is designed to capture long-term variations in the LST/EVI ratio on a pixel-by-pixel basis, on an annual time step. The basis of the index is the development of a “long-term” annual maximum LST/EVI ratio for all pixels in an image. In subsequent years the annual maximum LST/EVI is then compared to this long-term record. Pixels which are significantly different from the long-term mean are deemed to have undergone disturbance (Mildrexler et al., 2007). The index is computed as the ratio of annual maximum composite LST and EVI, such that:

$$DI_i = \frac{LST_{i\max} / EVI_{i\max}}{\sum_{i-1}(LST_{\max} / EVI_{\max})}$$

where DI_i is the disturbance index (DI) value for year *i*, LST_{imax} is the annual maximum eight-day composite LST for year *i*, EVI_{imax} is the annual maximum 16-day EVI for year

i, LST_{max} is the multiyear LST_{max} up to but not including the analysis year *(i-1)* and $\overline{EVI}_{\max}$ is the multi-year mean of EVI_{max} up to but not including the analysis year *(i-1)*. As stated in Mildrexler et al. (2007) $DI_{LST/EVI}$ is a dimensionless value that, in the absence of disturbance, approaches unity.

The index was developed to reveal both the positive and negative changes in the land surface energy partitioning while avoiding the natural synoptic variability associated with daily and seasonal LST (Mildrexler et al., 2007). Disturbances resulting in decreased vegetation density would lead to an increase in LST as sensible heat flux increases. Conversely, disturbance resulting in increased vegetation density (e.g., irrigated farmland) should be coupled with decreasing LST. Pixels that fall within ±1 standard deviation of the long-term mean are considered to be within the natural variability defined for that individual pixel. Pixels that depart significantly (> ±1sd) from the long-term mean LST/EVI ratio are flagged as areas of potential disturbance events. Instantaneous disturbances such as wildfire result in an immediate departure of the LST/EVI ratio from the range of natural variability, whereas non-instantaneous disturbances such as drought and insect defoliation depart incrementally, or can return toward the range of natural variability after a brief departure, as in the case of short-term drought. It is therefore critical that users of the index develop an understanding of the long-term natural variability or range of the ratio values over a multiple-year data set.

The annual LST_{max} and EVI_{max} values were computed for each of the 7 years and the LST_{max} for each year then divided by the corresponding EVI_{max} value on a pixel-by-pixel basis, resulting in a ratio of LST_{max} to EVI_{max} from 2000 to 2006. These annual layers are then divided by the long-term average of the index for that pixel, averaged over all previous years. For example, the annual 2005 ratio is divided by the long-term average of the index from 2000 to 2004. The 8- and 16-day compositing methods, and the derivation of annual maximums minimise the impact of cloud cover on this approach and, as with the Mildrexler implementation, cells with an EVI value less than 0.025 are removed prior to the analysis on the assumption these cells were non-vegetated (primarily water bodies and/or snow/ice) (Huete et al., 1999). Any DI values within the range of natural variability (defined as between 0.68–1.32, which was ±1sd) were considered as no change; whereas, pixels outside of this central range were flagged as subject to disturbance.

3.2 Auxiliary datasets

In order to assess the capacity of the DI to accurately detect disturbance we utilised a range of publically available datasets, focused on the major disturbance events expected within Canadian terrestrial ecosystems. These datasets consisted of the key forest disturbances of fire and insects, as well as broad scale agricultural production statistics. Each of the auxiliary datasets will be explained in more detail below.

3.3 Fire

In order to obtain information about the location of fires, fire hotspot thermal information is collected by the Canadian Forest Service (CFS) using three remote sensing sensors: Advanced Very High Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS), and the Along Track Scanning Radiometer (ATSR). Data from these sensors are combined, and those with the smallest zenith angle used to identify actively burning fires and smoke plumes (see Li et al. (2000)). This hotspot data is then combined with other imagery acquired by SPOT VGT (1 km resolution) and MODIS 250-m data to estimate the area burned. Data on fire area for each year from 2002 to 2006 formed the basis of this comparison. Area estimated by CFS to have burned on an annual basis within each ecoregion was compared to the number of DI pixels flagged as disturbed over the same time frame. As with most remote sensing-based change detection approaches the particular cause of a disturbance is not provided by the index. As such we do not expect a 1:1 relationship between the area of flagged DI pixels and fire extent over all Canadian ecosystems. Therefore to increase the reliability of the comparison, we constrained the fire area comparison to ecozones where fire is known to be the dominant disturbance regime such as the Boreal and Taiga ecoregions.

3.4 Insect Infestation

In order to assess the capacity of the DI to detect more subtle changes in forest condition we utilised information on the current outbreak of mountain pine beetle (*Dendroctonus ponderosae*) in western Canada. The current outbreak of mountain pine beetle in western Canada is of unprecedented proportions with over 10,000,000 ha of forest in the interior of British Columbia infested to some degree by 2007 (Westfall and Ebata 2008). Aerial overview surveys (AOS), which identify patches of attacked trees by trained observers from aircraft, are the primary means for accounting annually for the area and severity of impacts attributable to the beetle. In these surveys severity is classified into one of five attack levels with the lowest, trace, indicative of locations with light levels of attack (by definition, <1 % of the trees impacted). Conversely, the highest class, very severe, has significant levels of attack (≥50 % of the trees impacted). In this comparison we utilised a 1-ha tessellation of the AOS data throughout British Columbia populated with the corresponding severity code from each year of AOS survey data from 2001 to 2006 (Westfall 2007). Using only cells classified as moderate or severe levels of attack, we resampled the 1 ha dataset into 1 km cells, and summed the levels of attack over the 6 years to provide a single cumulative index of infestation which was then compared with cells flagged with the DI over the 6 years (Wulder et al. In press).

3.5 Agricultural Statistics

Finally in order to assess the ability of the DI to detect broad scale changes in the condition of grasslands and crops within the Canadian Prairie ecozone we compared the DI results to crop production records for the region. These records provide information on the total production of principal field crops in Alberta tabulated by the Department of Agriculture and Rural Development (www.agric.gov.ab.ca) for each year from 2000 to 2006. Records are compiled by crop with records indicating that 2002, a year of significant drought, had the lowest production over the 6-year interval with production almost 20% lower than the 10-year average. By comparison, in 2005, almost 30% more production occurred due to above normal rainfall and cooler temperatures. In order to compare the non-spatial agricultural statistics with the DI, we summed the number of cells flagged by the DI each year and compared them to the area statistics of production for the corresponding year within the Alberta portion of the Prairie ecozone.

3.6 Analysis Approach

As discussed, the Mildrexler et al. (2007) index relies on detecting significant changes in the relationship between the LST and EVI on an individual pixel basis. Pixels that significantly change (defined as > ± 1sd) from the long-term mean of this ratio are flagged as disturbed. As a result our first set of analyses considers the maximum EVI and LST for each ecozone, for each analysis year, across Canada. We investigate this relationship within the framework described by Nemani and Running (1997) who propose in LST / EVI space: water-limited biomes (barren, shrub-lands) occupy the high-LST/low-EVI; areas characterized by annual herbaceous vegetation (grasslands, savannah, and croplands) occupying the center of the LST / EVI space; and atmospherically coupled land cover types (e.g., forests, wetlands) occupying the low-LST / high-EVI area of the LST / EVI space.

Annual variation in the DI ratio, even at this broad scale, provides an indication of the natural variation that is likely to occur in the ecozone. We then present the individual results for the area burned, insect infestation, and agricultural statistics and finally discuss issues with and application of this type of index across Canada.

4. RESULTS

The underlying basis behind the DI is the detection of changes in the relationship between LST and landscape greenness and, as a result, investigation of this relationship across Canada provides an initial assessment of the inherent natural spatial variation of vegetation conditions. The stratification of the ecozones by EVI and LST indicate, as expected, ecozones further north such as the Arctic Cordillera, and the

Northern Arctic have the lowest LST and EVI (Figure 1). Ecozones with moderate greenness included most of the boreal and the highly productive coastal forests. The ecozones with the most difference from the general trend are the Prairies and the Atlantic Maritime ecozones. In the case of the Prairies, the ecozone has warmer LST values associated with the EVI than the other ecozones; the deciduous vegetation of the Atlantic Maritime ecozone has lower LST. Between years, changes in LST and EVI is similar to that discussed by Nemani and Running (1997). The Prairie ecozone, dominated by agriculture, the Taiga Plain, Taiga Cordillera and the Arctic ecozones, dominated in winter by snow cover, all have the greatest annual variation indicating significant natural variation. In the case of the Arctic ecozones this LST variation between years, is as much as 6ºC. In contrast, the Taiga Shield and the Hudson Plain have some of the lowest annual variation indicating a more consistent LST / EVI ratio through time. The implications of these annual differences relates to the detection capacity of the index. Ecozones which have more consistent LST / EVI ratios are likely to be more sensitive to changes in this ratio due to disturbance through time.

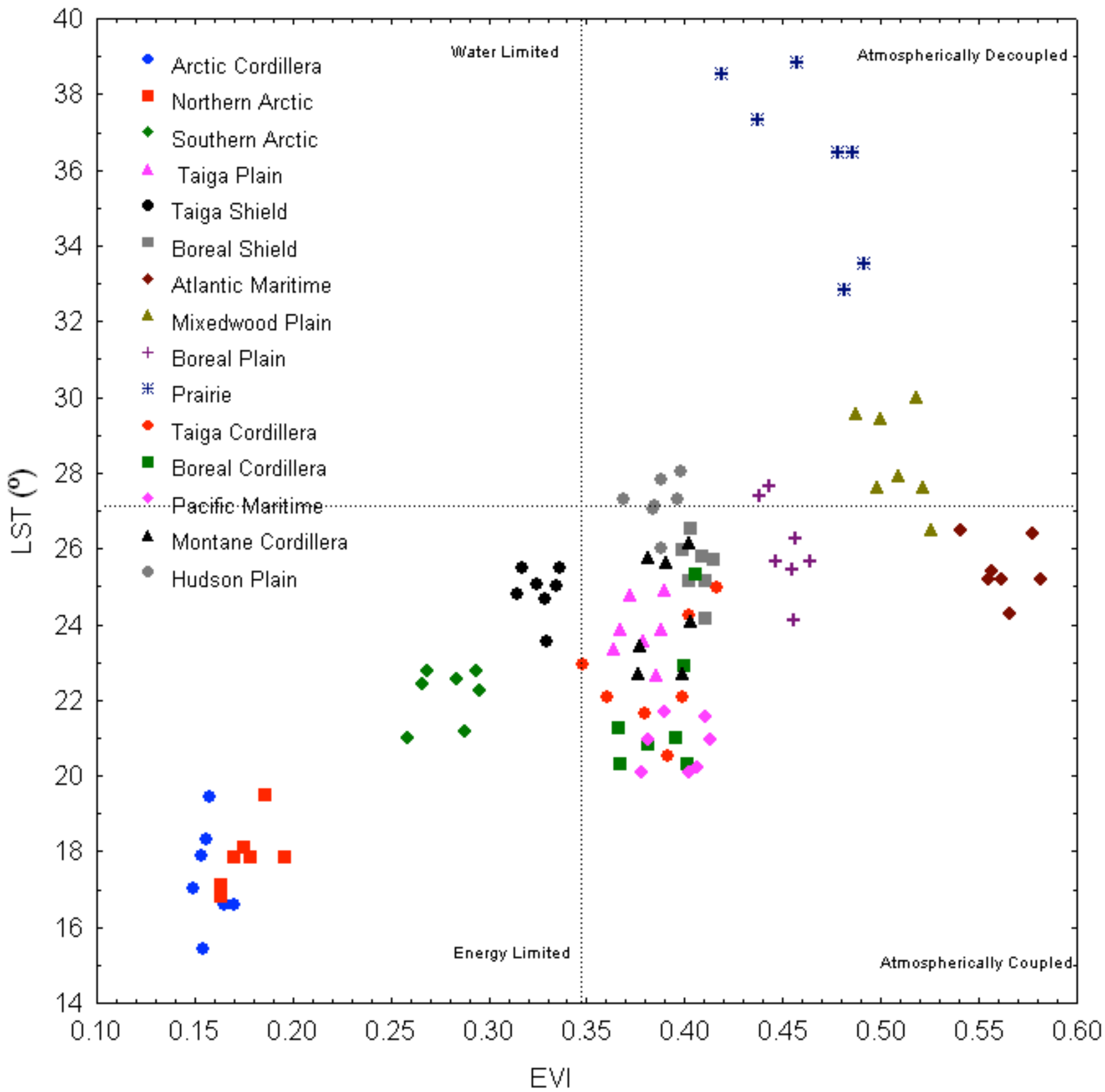
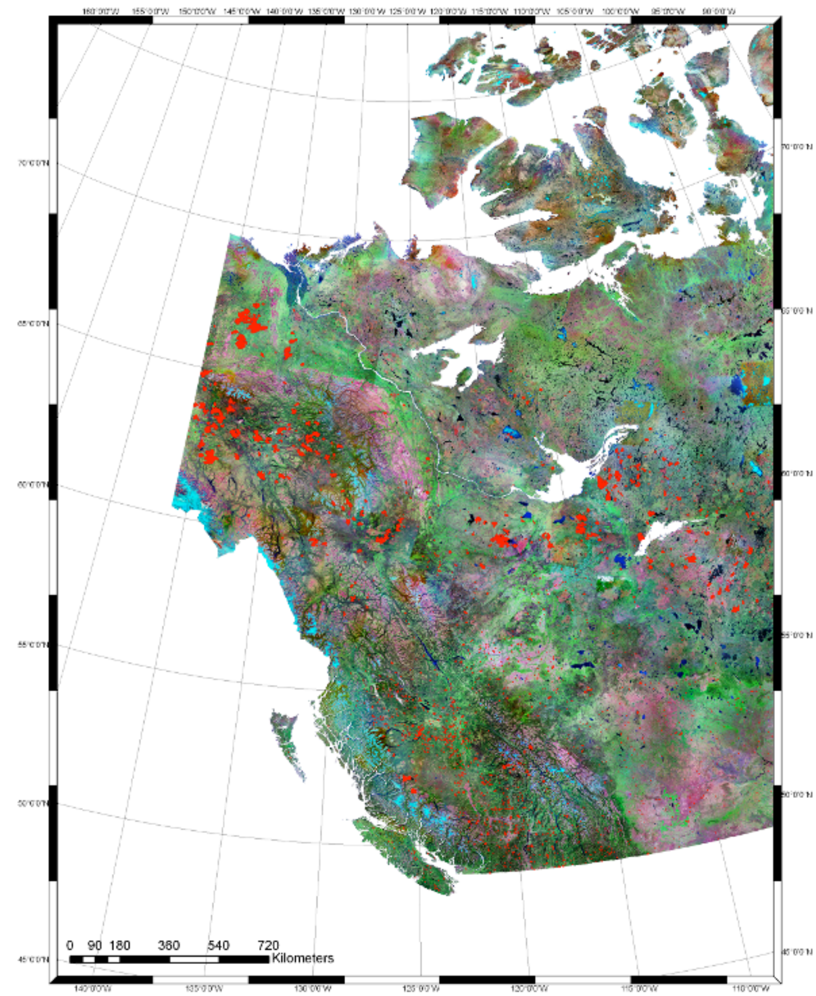


Figure 1: 2000 to 2006 Maximum EVI and maximum LST by Canadian ecozones.

4.1 Fire

Fire is a prominent disturbance event in Canada (Amiro et al., 2001) and as expected many fires occurred throughout the 2000 to 2006 time period. Visually, the DI clearly delineates fire events such as MODIS hot spots from 2004 (Figure 2(a) and 2(b)). In some cases the fire area as detected by the DI appears in the subsequent year due to the fact that the DI algorithm uses the maximum EVI in the year, which may occur prior to the fire outbreak. Across the scene there is a wide variety of land cover types including forest, crops, and grassland. The apparent consistent detection by the DI implies the algorithm is relatively independent of underlying cover type.



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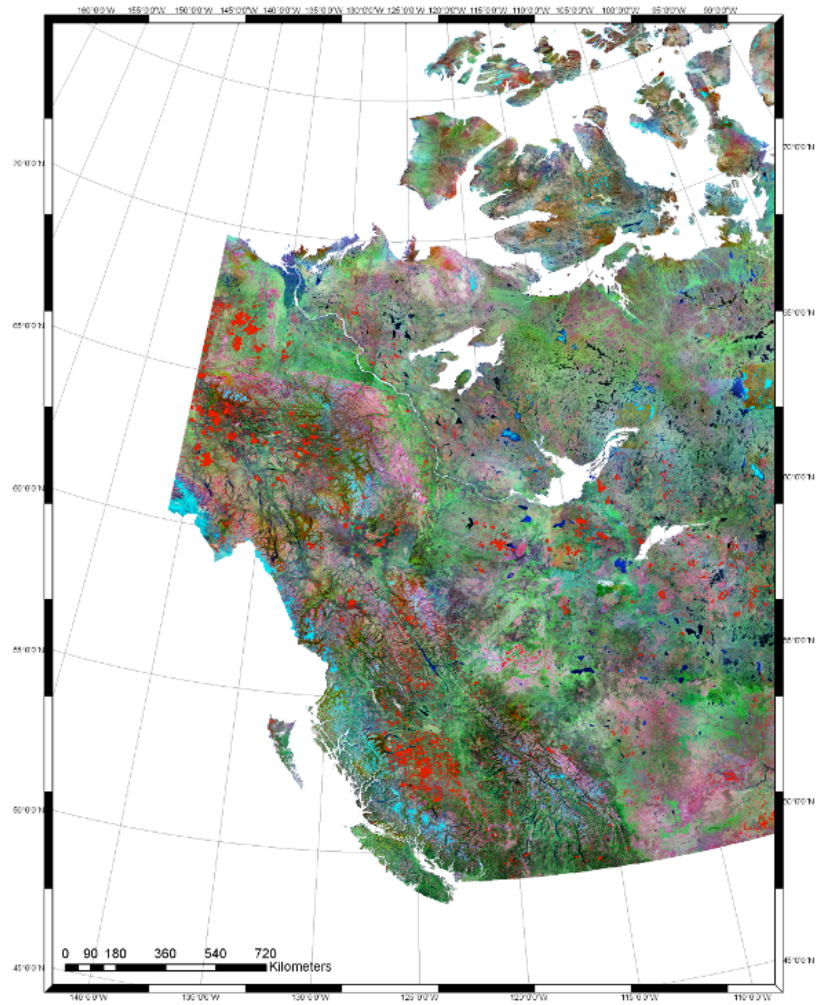


B

Figure 2: 2004 MODIS hotspots (Inset A) and 2005 DI for western Canada (Inset B). Underlying image circa year 2000 Landsat-7 ETM+ composite provided by EOSD, CFS).

The area estimated as burnt using the CFS statistics in the northern forested ecozones where fire is the dominant disturbance regime (Boreal Cordillera, Boreal Shield, Taiga Cordillera, Taiga Shield and Hudson Plain) from 2002 to 2005 is compared with the number of DI pixels flagged as disturbed over the same timeframe (Figure 3). The results show a strong relationship (r^2 =0.78, $p < 0.0001$) however overall the area estimated as burnt using the combination of MODIS hotspots and other remote sensing data by CFS is smaller than that pixels detected by the DI algorithm by a factor of 2. In these cases, other disturbance agents such as harvesting, insect infestation may be attributing to this difference.

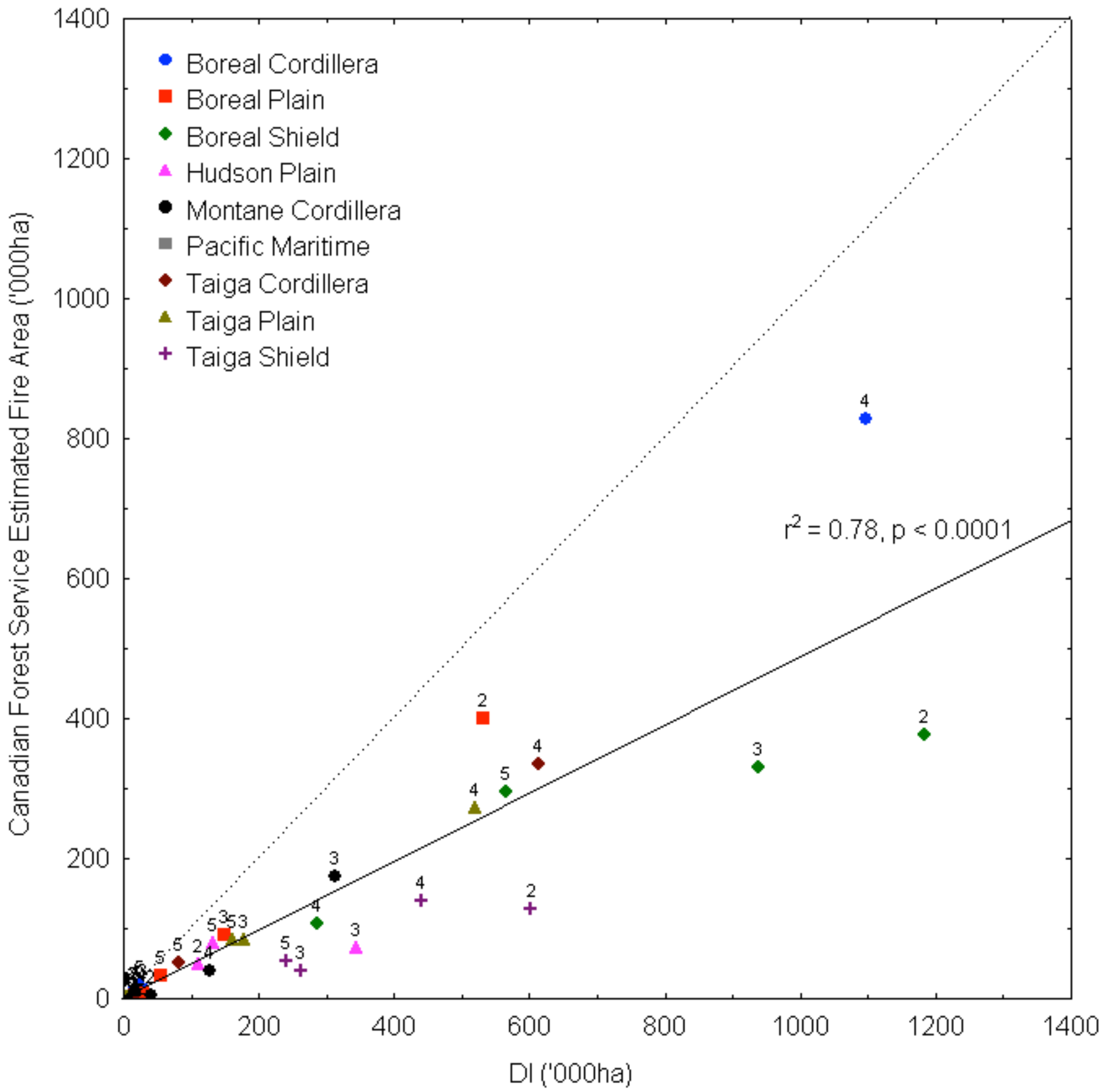


Figure 3: Relationship between the DI and CFS estimates of area burnt by wildfire in northern ecozones by year. Numbers refer to years after 2000 (i.e. 4 = 2004).

Tracking the DI from 2000 to 2006 for a major fire (48,000 ha) in the Yukon Territories (-127.09º W, 59.98N) in late summer of 2003 provides an indication of the mean, and range of the DI at the time of disturbance for all cells averaged within the fire boundary (Figure 4). In this case it is clear the index is relatively stable prior to the fire, lying within the standard deviation bounds of DI previously established. After the fire event occurred in 2003 the index increases above the threshold of natural variability. In addition, the variability of the index within the pixels detected by the MODIS hotspot approach also increases. Post fire, the index remains above the threshold for the two subsequent years.

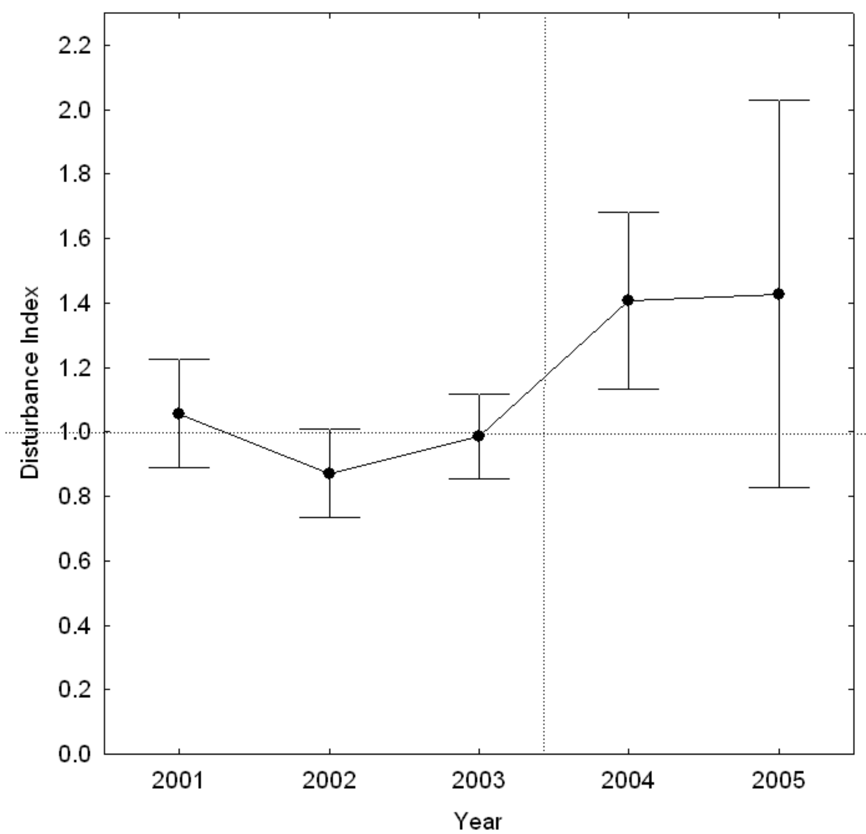
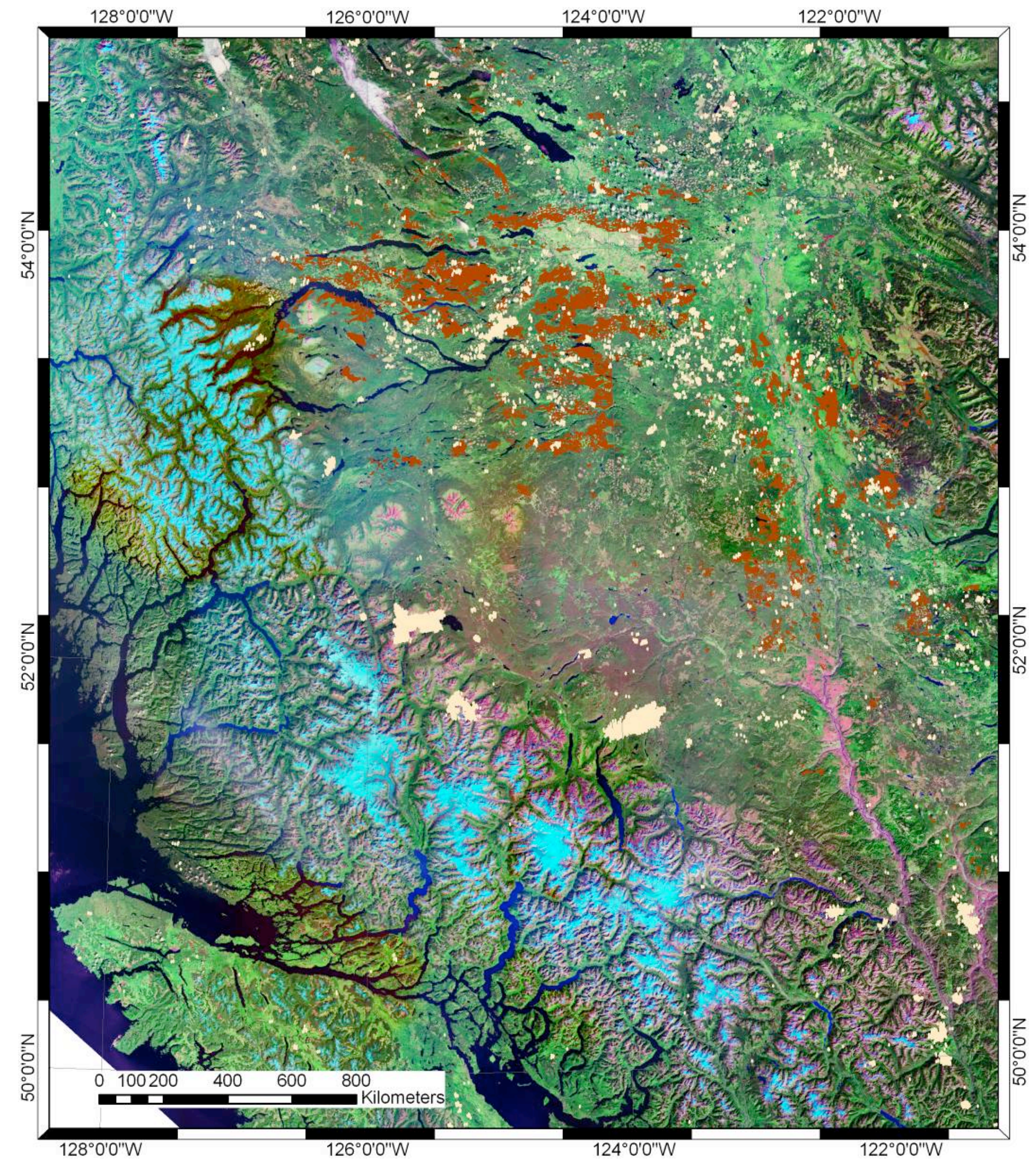


Figure 4: Temporal tracking of the DI from 2001 to 2006 for a major fire in the Yukon Territory.

4.2 Insect Infestation

As a disturbance insect infestation represents a more subtle change in the landscape than fire, as at the 1 km scale, healthy trees often remain after the infestation due to the trees either being unsuitable (with respect to age or species), or due to the patchy nature of a given infestation. In addition, the temporal aspect of the infestation is important. In the case of mountain pine beetle damage, remote sensing detection typically occurs a year after the initial attack as foliage fades post-attack and generally turns red over the subsequent growing season, due to disruption of the translocation of nutrients and water as consequence of girdling and secondary fungi infestation. Moderate and severe attack as classified from the aerial overview data when compared to pixels detected by the DI indicates the index is able to pick up key regions of the infestation especially damage occurring over large homogenous areas (Figure 5(a) and (b)). The smaller infested areas, such as those scattered along the eastern perimeter is less well differentiated. In addition, it is clear from the comparison that fire is an important component of this ecosystem, with the DI capable of detection, resulting in both disturbance types being captured and depicted over this time period.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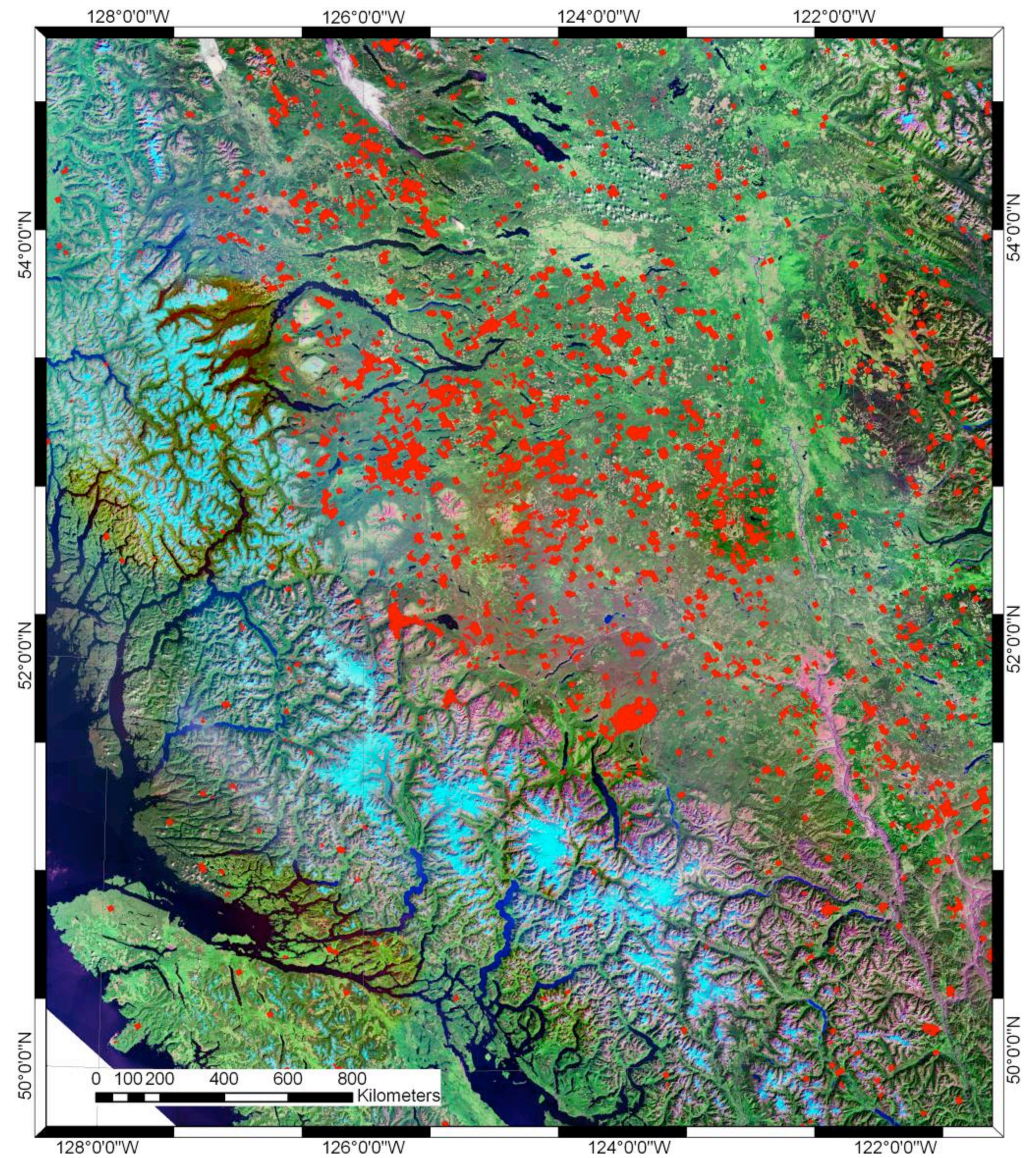

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Figure 5 (a) and (b): Moderate and severe mountain pine beetle infestation as observed from the aerial overview data collected from aircraft and (B) gridded to 1km over the stands from 2004 to 2005 and the corresponding area for the DI. Underlying image circa year 2000 Landsat-7 ETM+ composite provided by EOSD, CFS).

Comparing the number of years where individual pixels were flagged as disturbed, with the MPB gridded aerial overview survey data, shows a clear trend (Figure 6) with pixels which have been tagged as having significant disturbance for multiple years corresponding to pixels with increased severity as mapped by the survey. The results show that as the cumulative impact of the infestation becomes more severe over the landscape (i.e., red attack stands being delineated in the same 1 km cell over multiple years) the disturbance index flags significant deviations. The cells which experience the most severe infestation correspond to cells where the DI detects a disturbance over the majority of the analysis period.

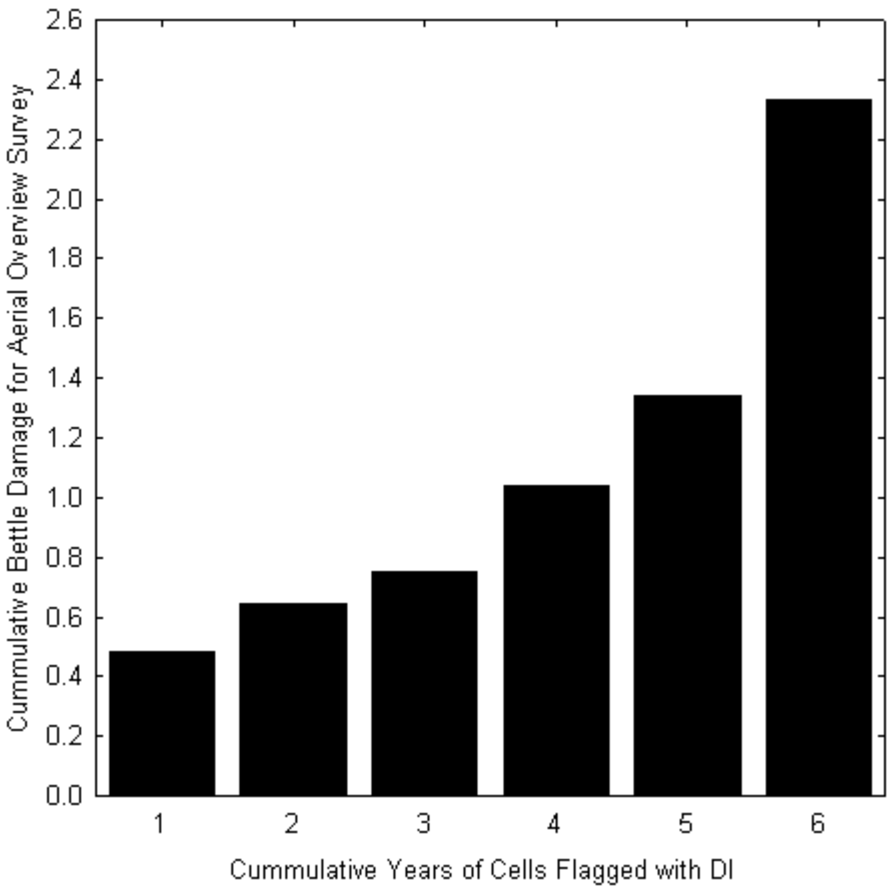

Figure 6: Comparison of the number of years where individual pixels were flagged as disturbed, compared by the average level of infestation as computed using the Mountain Pine Beetle 1 km gridded aerial overview survey data (where a lower score is indicative is less severe read attack damage).The figure shows pixels which experience the most severe infestation correspond to pixels where the DI detects a disturbance over the majority of the analysis period.

The agricultural and grassland areas located in the Canadian Prairies have significant inter-annual variability resulting in the DI detecting in select years a large number of cells which have deviated from the range of defined natural variability. In order to quantify these changes we compared the proportion of the ecozone flagged with a negative disturbance with an annual measure of the agricultural production of the region (Figure 7). The relationship confirms a strong link between agricultural production, and the deviation of cells away from the long-term mean, with large numbers of negative disturbance pixels associated with a reduction in the annual production of the region. In this case, 2002 was the poorest year of agricultural production in Alberta between 2000 and 2006, with approximately 1200 million tonnes of production. Conversely 2004, 2% of the ecoregion was flagged as disturbed, coinciding with one of the most productive years with 2700 million tonnes of production. The results for cells with a positive disturbance were the opposite, with the largest number of positive disturbance cells (2006) associated with an above average production year. A similar comparison was made by Mildrexler et al. (2007) who found a strong correlation between precipitation anomaly maps of the western United States at 4 km resolution and the coverage of the DI. The temporal and spatial correspondence between these changes in annual production and significant variations in the number of cells flagged as DI is strong evidence that the index is detecting these types of landscape dynamics (Figure 8).

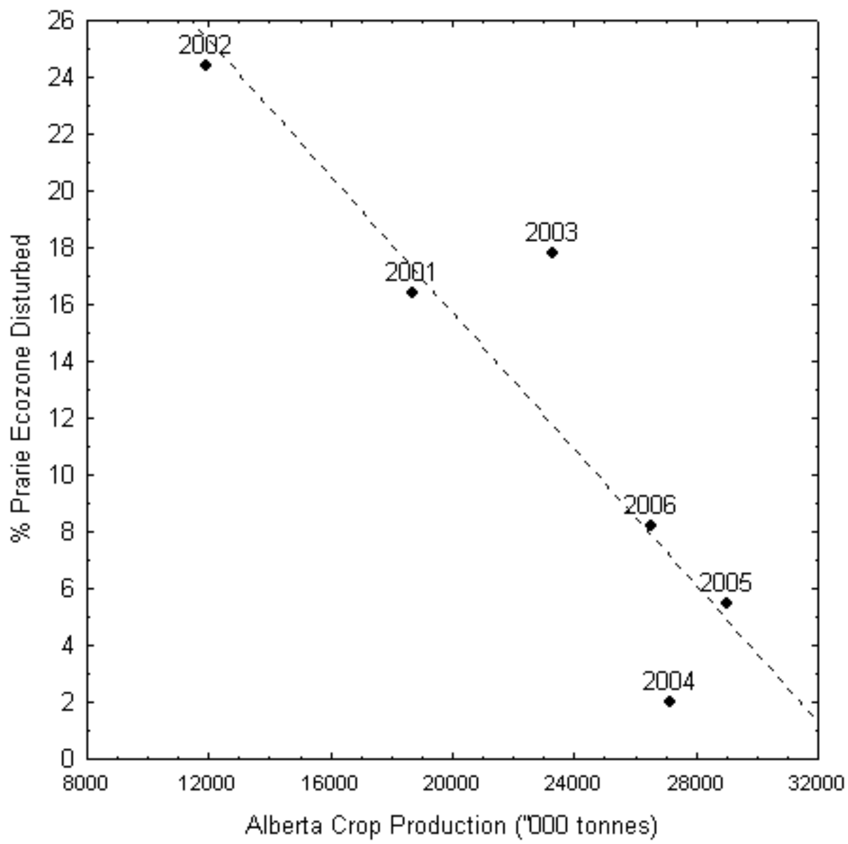

Figure 7: Relationship between agricultural production, and the deviation of cells way from the long-term mean, with large numbers of negative disturbance pixels associated with a reduction in the annual production of the region.

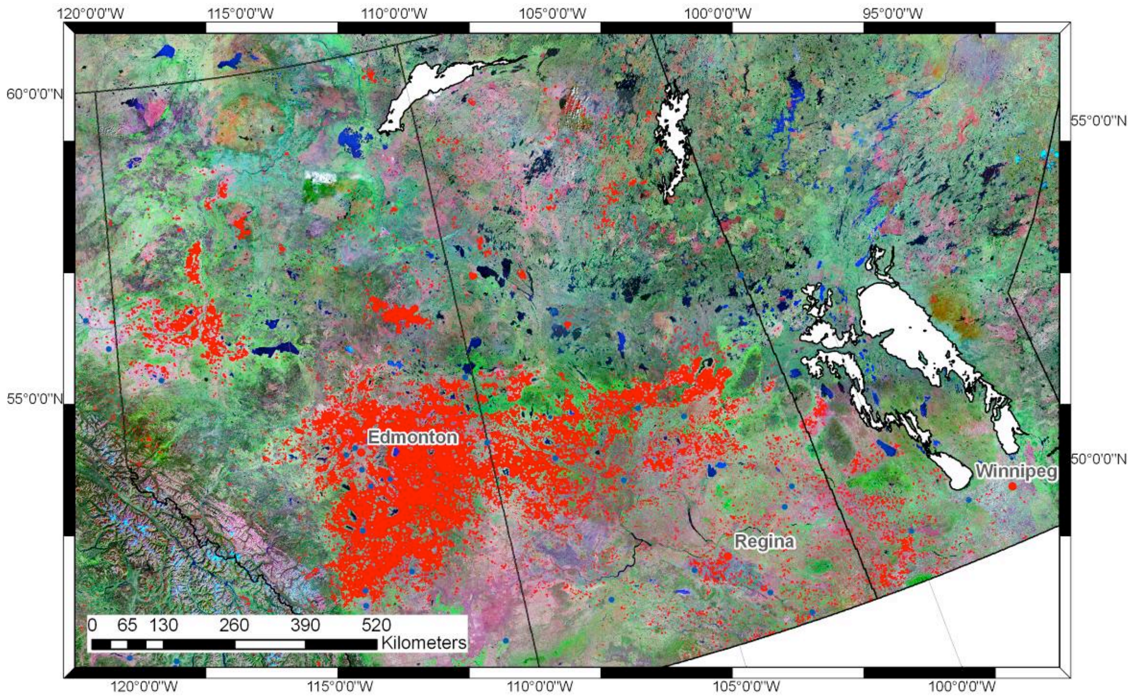

Figure 8: Agricultural region of the Canadian Prairies with 2002 DI highlighted. (Underlying image circa year 2000 Landsat ETM+ image composite provided by CFS).

5. DISCUSSION

In this research we have applied a newly proposed algorithm to detect landscape disturbance using MODIS 1 km LST and EVI data. The results confirm many of the original hypothesised responses discussed by the original developers (Mildrexler et al., 2007) undertaken over a different region and shorter time interval. Annual changes in the maximum LST / EVI ratios closely corresponding to fire hotpots, insect disturbance, and changes in agricultural production associated with drought. Given that fire and insect infestation are two of the major disturbances within the forested ecoregions of Canada these are encouraging results and indicate that the index has notable potential for implementation as a component of an on-going monitoring system.

A key issue discussed by Mildrexler et al (2007) was the initial limited time period over which the original analysis was undertaken (2 years). In this project we extended the time series, with the generation of the long-term mean computed from a maximum of 7 annual values. This increase in the index length significantly increases our capacity to understand the inter-annual variability, and thus assess which cells fall outside the natural variability range. This time span however is still limited when compared to the time scales of many of the disturbance processes listed in Table 1. Over time as the index incorporates an increasingly long archive the robustness of the approach will improve. The power of this approach is that, over time, each pixel is self-normalized, defining a local range of natural variability (Mildrexler et al., 2007).

One key area which is difficult to assess at the 1km scale is the effect of forest harvesting or land clearing across the country. Obviously if harvest activities were being undertaken at very large spatial scales we would potentially expect to see a similar negative pulse response, similar to fire across the landscape. In most regions of the country large area clear cutting is no longer an accepted or common harvesting practise with smaller harvest units and partial cutting more typical. This change in harvesting strategy makes detection of these types of anthropogenic changes at the 1 km scale difficult to detect and monitor over 7 years of the MODIS archive. We find limited evidence of this harvesting pattern in southern areas of Ontario and British Columbia; however, a lack of a clear signal, as well as difficulty in accessing harvesting records over large areas across a range of tenure makes verification of these signals difficult. This result is similar to that found by Fraser et al. (2005) who concluded that much of the harvesting in British Columbia was at, or near, the size limit for change detection procedures using composited 1 km spatial resolution imagery.

The issue of minimum detectable patch size will depend on several factors, including the magnitude of the change signal, degree of within patch fragmentation, and clustering of changed patches within the effective sensor resolution. For instance, a decline in disturbance predictability can be expected when comparing Landsat and MODIS imagery (Collins and Woodcock, 1996; Jin and Sader, 2005; Zhan et al., 2002) related to the differences in spatial resolution and signal to noise ratio of both sensors. Further, in a forest monitoring context, single large disturbances have a greater influence on spectral response of a given coarse spatial resolution pixel than a number of small disturbances aggregating to a similar area. The increase in non-clearcut harvesting practices have served to reduce the detectability of forest harvesting activities.

Similar to Mildrexler et al (2007) we recognise a limitation of the use of an annual maximum compositing index is that any rapid recovery, or binomial vegetarian cycle, such as short rotation cropping which results in two harvests per year, or alternatively post-fire recovery of grasses and shrubs which may occur within a 12 month period, will not be detected. This is because whilst EVI will decrease following disturbance, it would return to a peak level soon after, thereby missing the event on an annual time step. A more seasonal based calculation could be incorporated to accommodate this type of behaviour. However detailed information may be more difficult to define when these temporal windows would occur, and may well be ecozone specific.

6. CONCLUSIONS

This coarse spatial resolution (1-km) application of a MODIS disturbance index provides a cost-effective coverage of the Earth's surface, and offers critical insights as a 'first pass' filter to identify regions and the annual occurrence of major change activity. Unlike many other change indices, the disturbance index applied here produces information regarding both discontinuous and continuous change. Following application of this disturbance index, areas of interest can then be targeted for more detailed investigation using finer spatial resolution imagery or field surveys, or used to identify annual trends on a regional basis (in support of more detailed yet less temporally dense data sources in a monitoring system). This type of hierarchal approach is required in most large, sparsely populated countries, as they require cost-effective monitoring of their terrestrial ecosystems for sustainable management of natural resources, to ensure ecological integrity, report on international conventions and agreements, and identifying and modeling the impacts of weather events and climate change. Coarse spatial resolution imagery offers temporally dense data source that can be used to provide annual information in conjunction with more spatially detailed, yet less temporally dense, data sources used in sample- or ecosystem-based monitoring systems. Systematic monitoring of large areas for a range of important dynamics, as demonstrated in this research, is enabled through application of this index.

The DI is based on two sound fundamental principles: (1) that vegetation, when left undisturbed, will achieve maximum coverage for a specified environment, and (2) that disturbance of vegetation will result in a significantly different surface coverage and a commensurate change in the maximum surface temperature. The maximum LST / EVI ratio takes into account both the potentially most vulnerable biotic (vegetation) and abiotic (LST) components of the terrestrial ecosystem to disturbance. The capture of these elements of ecosystem structure and function and related dynamics, both in terms of positive and negative changes, provides a powerful tool for national level monitoring in Canada.

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