Characterising spatiotemporal environmental and natural variation using a dynamic habitat index throughout the province of Ontario

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Abstract

Understanding changes in landscape productivity patterns is critical for management of ecosystems, characterising biodiversity, and monitoring climate change. Vegetation productivity, a key functional component of terrestrial ecosystems, can be readily monitored using remote sensing and can also be combined with other spatial information, such as land cover and topography, to provide a more comprehensive understanding, at the landscape scale, of ecosystem dynamics. Ontario is the second largest and most populated province in Canada covering approximately 1 million km^2 with a population of 13 million. Befitting such a large and complex area, Ontario is characterised by high environmental and land cover diversity. In order to assess temporal trends in vegetation productivity across the province we utilised a series of ten-day composites of Medium Resolution Imaging Spectroradiometer (MERIS) fraction of Photosynthetically Active Radiation (fPAR) over a 6-year period (2003-2008). Indicators of annual productivity, seasonality and the minimum amount of vegetated cover were all calculated from the fPAR time-series to evaluate vegetation condition. To define the level of observed natural variability and areas which fall within, and beyond, the variability thresholds, we utilised the Theil-Sen's non-parametric statistical trend test. Results indicate that over the 6 year period decreasing trends in productivity dominated the Ontario landscape. Using spatial data layers of potential drivers of vegetation variability, we found that different land cover types exhibited significantly different trend amplitudes and proportions with elevation a significant correlate for most of the observed trends. Distance from nearest road or human settlement, indicative of anthropogenic drivers, was not significantly related to the observed trends. Recent and older burn areas were linked to decreasing and increasing trends in satellite derived productivity respectively. Our findings suggest that characterising trends in landscape productivity patterns over large areas is possible using remote sensing technology and the integration of productivity trends with explanatory spatial data sets can provide insights into drivers of productivity dynamics. These insights can aid in provincial and national monitoring activities as well as be used to focus more detailed analysis to regions of specific interest.

1 Introduction

Understanding the natural variability of landscapes has become a critically important issue for land managers charged with maintaining ecosystem function and the protection of species diversity (Petraitis et al., 1989,Landres et al., 1999). Landres et al. (1999) defines ecosystem natural variability as the ecological conditions, and the spatial and temporal variation in these conditions, that are relatively unaffected by people, within a period of time and geographical area appropriate to an expressed goal. Understanding the range of natural variability is also critical when assessing the current and potential impact of climate variation and disturbances on ecosystems (Landres et al., 1999).

Satellite imagery is uniquely capable of monitoring vegetation productivity over large areas in a repeatable and cost effective manner and therefore is a critical tool when assessing changes in environmental conditions (Goward et al., 1985,Balmford et al., 2005). A number of studies have utilised remote sensing data to characterise ecosystem productivity and functioning (Goward et al., 1985,Box et al., 1989,Defries and Townshend, 1994,Kerr and Ostrovsky, 2003), and to predict changes in key vegetation characteristics (Wulder, 1998). To do so, one of the most common methods is to utilise the Normalised Difference Vegetation Index (NDVI) which is a ratio of the near infrared and visible regions of the electromagnetic spectrum. Multi-year NDVI time-series, which are becoming increasingly available, have successfully been used to understand the temporal dynamics of terrestrial vegetation (Paruelo et al., 2001,Pettorelli et al., 2005,Alcaraz et al., 2006,Wessels et al., 2010). In addition, researchers have also used this temporal information to depict trends in vegetation productivity and monitor environmental landscape scale changes (Vicente-Serrano and Heredia-Laclaustra, 2004, Alcaraz-Segura et al., 2009, 2010a,b, Donohue et al., 2009).

In addition to NDVI however, there are a number of other remote sensing indices which more directly capture vegetation biophysical attributes. These indices utilise knowledge of land cover, seasonal and locational solar conditions to derive the amount of solar irradiance captured by the vegetation (Knyazikhin et al., 1998). For example, the fraction of Photosynthetically Active Radiation absorbed by vegetation (fPAR) is derived from a physically based model of the propagation of light in plant canopies (Tian et al., 2000) and unlike the NDVI, which use a ratio of two spectral bands, utilises multiple bands (Gobron et al., 1999).

The dynamic habitat index (DHI) (Berry et al., 2007,Coops et al., 2008), a composite index derived from fPAR time series data, is composed of three indicators of the underlying vegetation dynamics; the cumulative annual productivity, the minimum apparent cover and the variation of the photosynthetic activity all of which have been demonstrated to be of biological significance (Coops et al., 2009a,Andrew et al., 2010). Relationships between DHI and species abundance has been demonstrated in a number of studies. Changes in DHI productivity were significantly correlated to avian species richness across different functional groups (Coops et al., 2009a) in the United States and in Ontario, grassland bird species richness was found to be highly correlated with the minimum cover and seasonality (Coops et al., 2009b). Andrew et al. (2010) found that beta diversity of Canadian butterfly communities was positively correlated with DHI minimum and cumulative annual productivity.

In this paper, we ask whether this type of composite remote sensing indicator can be used to characterise the natural variability of vegetation over a 6-year period for the province of Ontario, Canada. Our approach was as follows. First we transformed 10-day composites of fPAR data into the DHI habitat index. A non-parametric statistical test was then used to define the level of observed natural variability and highlight those areas which fall within, and beyond, the variability thresholds. Once these areas were defined, we utilised a number of environmental variables to investigate if the observed patterns can be linked to specific natural and anthropogenic conditions. We conclude with an assessment of the approach and its use as an ecological indicator of natural ecosystem variability.

2 Materials and methods

2.1 Study area

Ontario is the second largest province in Canada, covering approximately 1 million km^2, extending over 15 degrees of latitude and 20 degrees of longitude. Ontario's climate is humid continental with the exception of the Northern Hudson Bay region, which has a maritime character (Baldwin et al., 2000). At the higher latitudes, the Hudson Plains have significant snow cover over an extended period of the year, relatively flat topography, and poor drainage with deep organic soils typified by bogs, fens, lichens and small conifer stands (Rowe 1972). In central Ontario uplands, the growing season is longer with more pronounced terrain and coarse-textured soil on bedrock and, as a result, coniferous and evergreen forests dominate. Southern Ontario is highly urbanised, with a heterogeneous mosaic of urban areas, roads, mixed forests, and agriculture and experiences milder weather in comparison to more northerly locations.

2.2 Data description

2.2.1 Fraction of Photosynthetically Active Radiation

Medium Resolution Imaging Spectroradiometer (MERIS) sensor on board of ENVISAT (ENVIronmental SATellite) provides, since 2002, acquisition of the MERIS Global Vegetation Index (MGVI), which is analogous to fPAR (Gobron et al., 1999). MGVI is calculated using the blue, red and near-infrared top-of-atmosphere reflectance (Gobron et al., 1999) from a physically based algorithm which utilises radiative transfer models to account for the atmosphere, soil perturbing factors and angular effects (Gobron et al., 2007). We used the time composite product which selects the most representative valid value of a 10 days sequence to provide a more spatially uniform and complete coverage (Pinty et al., 2002). Our study was based on a 6-year (2003-2008) fPAR dataset provided by the European Space Agency (ESA) and the original 1.2 km x 1.2 km spatial resolution fPAR data was resampled using a nearest neighbour routine to 1.0 km x 1.0 km for this research.

2.2.2 Dynamic habitat index (DHI) indicators

The three dynamic habitat index components are explained below. Annual productivity is of biological interest since it drives resources availability and indirectly can explain species distribution and abundance (Skidmore et al., 2003,Evans et al., 2005). This indicator is estimated by summing all the fPAR value throughout the year. Minimum cover refers to the lowest (minimum value) level of vegetative cover over the snow free period (June 11th to September 31st) which can be an indicator of the capacity of the landscape to sustain adequate level of food and habitat resource during this period. Seasonality is a surrogate of habitat quality as it affects essential resources (e.g., food, water and nutrients) and is expected to exert selective pressure on life history traits (Mcloughlin et al., 2000). To evaluate the variation of the vegetation cover throughout the year, we calculated the mean and standard deviation of the yearly 10 days fPAR composite and calculated the annual coefficient of variation.

2.2.3 Land cover

Land cover is recognised as a critical driver of environmental productivity (Mildrexler et al., 2007) and is an important component when interpreting landscape productivity and DHI behaviour at a broad scale (Coops et al., 2009b). Land cover information was extracted from the Canadian Forest Service (CFS) and Canadian Space Agency (CSA) Earth Observation for Sustainable Development of Forests (EOSD) product which classified circa 2000 Landsat Enhanced Thematic Mapper Plus (ETM+) imagery using an unsupervised classification, followed by a manual labelling of the 23 land cover classes (Wulder and Nelson, 2003) at 25 x 25 m spatial resolution (Wulder et al., 2008). In order to retrieve land cover information over agricultural areas, we utilised the National Land and Water Information Service (NLWIS), an Agriculture and Agri-Food Canada (AAFC) product which is also derived from ETM+ imagery circa 2000 (Fisette et al., 2006).

2.2.4 Topography

Topographic information was derived from the Shuttle Radar Topography Mission (SRTM) which provides global elevation data at a spatial resolution of 90 m and a vertical resolution of ~ 5m (Farr and Kobrick, 2000).

2.2.5 Large Fire Database

Fire history data was retrieved from the Large Fire Database (LFDB) which is a CFS aggregated dataset using provincial and territorial fire management data. This dataset represents the extent of all fire events larger than 200 ha recorded by satellite and aerial imagery, aerial observation or on the ground using global positioning system (GPS) data from 1959-1997. This information was coupled to burned polygons derived from the annual national burned forests maps prepared by the CFS and Canadian Centre for Remote Sensing (CCRS) for the 1995-2008 period. This data was computed from annual hotspot map from the Advanced Very High Resolution Radiometer (AVHRR) or MODIS which is combined with observed annual changes in vegetation indices from AVHRR (1.1 km resolution), Satellite Pour l'Observation de la Terre(SPOT) Vegetation (VGT) sensor (1.0 km resolution) or MODIS high resolution (0.25 km) imagery. This annual mapping technique is intended to document spatial and temporal distribution of large burns (> 1000 ha) over the boreal forest (Fraser et al., 2000).

2.2.6 Anthropogenic disturbances

To identify potential anthropogenic drivers of changes in vegetation productivity we derived distance measures from anthropogenic activity which were calculated as the either distance from the nearest road or human settlement. We estimated the nearest distance from road using the 2006 Road Network File (RNF) compiled by Statistics Canada (Statistics Canada, 2006); and the nearest distance from human settlement using the circa 2006 Version 4 DMSP-OLS Nighttime Lights Time Series processed by the NOAA National Geophysical Data Center (NOAA, 2006).

2.2.7 Ecological classification

A stratification of Ontario's biomes was derived from Canada's hierarchical classification of ecosystems which provide information on terrestrial ecozones and their ecological distinctiveness (Rowe and Sheard, 1981).

2.3 Trend characterisation and analysis

The Theil Sen's non-parametric test was used to assess variability in the three annual DHI components (annual productivity, minimum cover and seasonality) from 2003 to 2008 (n=18). The Theil Sen's test is a rank-based test which is robust against non-normality of the distribution and missing values (Theil, 1950), and unlike the Mann-Kendall test, detects not only if a trend exists, but also provides the amplitude of that trend (Sen, 1968). The Theil Sen's test calculates individual slope estimates for each data pair and then computes the median slope (Q) of the time-series (Gilbert, 1987). To capture broad trends, and to reduce spatial misregistration in the fPAR data, we removed the fPAR values within 2 km of water bodies (as defined from a national coverage available from the CanMap Water v2006.3 compiled by DMTI Spatial) and we averaged the DHI and resampled spatial data layers into a 10 km x 10 km grid. For each cell, we normalised the slope value by its 6-year mean, in order to express the trends as a percent of the mean cell which allowed all three indicators to be compared. To determine which 10 km x 10 km cells had a notable trend we used a fixed threshold, similar to the approach used by Wulder et al. (2007), i.e., 20%, based on the entire distribution of trend values for each DHI component.

Our approach was then as follows: we first assessed the overall observed trends for each component of the DHI across the study area. To assess the effect of land cover on the amplitude of the observed trends, we applied a generalised least square modelling approach. To do so we stratified all pixels (n = 8477), into positive and negative trends similar to the approach of Alcaraz-Segura et al.(2010a,b) to ensure regional trends are maintained for each of the three DHI indicators. We then tested the effect of land cover on the trend values using one-way ANOVAs, which account for spatial autocorrelation of the residuals with a spherical error term (Pinheiro and Bates 2000). Sequential Bonferroni post hoc test (Rice, 1989) ($p < 0.05$) of the ANOVAs were used for multiple comparisons of land cover types. We used generalised least square models to test the effects of environmental, anthropogenic drivers and their interactions, on trend values. Again, each positive and negative trends was modelled individually by DHI component and spatial autocorrelation of the residuals was modelled using a spherical error term.

Second, we focused on those cells which were deemed to be exhibiting a notable trend using the pre-defined, 20%, threshold. To assess if the proportion of cells with a notable trend was different than the proportion of land cover types, a chi-square analysis was used. To evaluate the impact of fire on the largest observed trends historical fire were grouped by burn date, i.e., 1970-1986, 1987-2003 and 2004-2008. We then examined to what extent these fire burn areas had a notable trend over the 6 year period again assessed using a chi-squared test.

All trend computation and analysis were performed using the zyp (Bronaugh and Werner, 2009), nlme (Pinheiro et al., 2010) and tree package (Ripley, 2010) in the R programming environment (R Development Core Team, 2010).

3 Results

3.1 Overall observed trends

Figure 1 shows the three averaged DHI components for 2003 – 2008 and as expected shows lower annual productivity in the northern plains, increasing in the central uplands and the southern latitudes. A similar pattern is found in the minimum cover component, except in the northern plains where minimum cover is higher. Seasonality also shows higher values in the north, but in contrast to the two other indicators, was higher in the central uplands and lower in the southeast. After normalisation, trend values across the three indicators also varied (Figure 2). The Hudson Plains are characterised by decreasing and increasing trends for annual productivity and seasonality, respectively. The central upland region is dominated by a decreasing trend in minimum cover, whereas in the south a combination of decreasing trends in annual productivity and increasing trends in seasonality is found.

Insert Figure 1 about here:
Insert Figure 2 about here:

3.1.1 Overall observed trends by land cover

Trends were highly variable between land cover classes (ANOVA, $p<0.001$; Bonferroni post hoc $p < 0.05$) (Figure 3). Of the three DHI indicators, the trend variability by land cover type was least for DHI seasonality and greatest for annual productivity and minimum cover. Across all land cover types, grasslands on average had the strongest increasing trend for annual productivity and minimum cover as well as the steepest decreasing trend for seasonality. Broadleaf forest, in contrast, exhibited on average the largest decreasing trend for annual productivity and minimum cover.

Insert Figure 3 about here:

3.1.2 Overall observed trends by environmental and anthropogenic drivers

Table 1 shows the slope of the regression line between the DHI component trends and the log-transformed distance from the nearest road, distance from nearest human settlement, elevation and their interactions. Again increasing and decreasing trend values were assessed for each DHI indicator and only absolute slopes significantly different from zero (p-value < 0.05) are displayed (Table 1). Results show significant relationships between the DHI trends and the three drivers, with elevation being the most significant driver for five out of six models. Regression analysis for the anthropogenic drivers indicated that average distance from roads had a negative slope with increasing seasonality and decreasing minimum cover. Average distance from human settlement exhibited a positive slope with decreasing annual productivity and negative with increasing seasonality. The interaction terms demonstrated some expected strong trends with distance to human settlement, and roads, interacting with elevation and positive trends in productivity. Less strong trends were found between the interaction of distance to roads and human settlement with decreasing trends in productivity. The distance to roads and human settlement interaction term was highly significant for decreasing minimum cover.

Insert Table 1 about here:

3.2 Notable trends

The second component of the analysis focused on those cells which observed a notable trend using the pre-defined, 20%, threshold. Figure 4 shows the areas with the largest 20% trend for each DHI component. In the case of annual productivity 89% of the notable area showed a decreasing trend occurring principally north of the 52nd parallel (Table 2). In the case of minimum cover, decreasing trends were observed principally in the central uplands and accounted for 63% of the notable trends in this component. In contrast, an increasing trend in seasonality was observed for 62% of the cells sparsely distributed around the 45th parallel.

Insert Figure 4 about here:
Insert Table 2 about here:

Land cover had a significant effect on the observed trends occurrence according to the chi-square test (X^2 = 1188.62, df = 50, p<0.001), with a number of cells per cover type differing significantly from the expected proportion in the landscape (Figure 5).

Insert Figure 5 about here:

3.2.1 Notable trend by fire history classes

Figure 6 shows that across the three fire classes, trends varied by DHI indicator. A decreasing trend in annual productivity was observed for cells in the earliest fire class (1970-1986). Those 10 km x 10 km cells experiencing fire from 1987 to 2003 exhibited an increasing trend in annual productivity (128% increase) and minimum cover (32% increase). Lastly, recent burned areas (2004-2008) exhibited a decreasing trend for annual productivity (42% increase) and minimum cover (60% increase).

Insert Figure 6 about here:

4 Discussion

4.1 Overall observed trend

In this research, we applied a novel remote sensing method to detect trends in vegetation productivity using MERIS fPAR time-series data. Our results indicate that across Ontario there is an increasing trend in seasonality and a decreasing trend in both annual productivity and minimum cover over the 6-year period, thus suggesting an overall decrease in vegetation productivity. In northern latitudes, direct anthropogenic pressure is unlikely to be a main driver of observed trends, especially in Hudson Bay ecozone, where the organic soil with poor drainage results in a lack of trees and valuable minerals, and subsequently lacks harvesting and mining activity (Baldwin et al., 2000). As a result, climatic factors are more likely to be driving these observed decreases in vegetation productivity. Climatic factors are also likely to be contributing to the negative trends detected in productivity in central uplands as discussed by Barber et al. (2000) who found that under recent climate warming, increases in temperature have restricted growth for a large portion of the North American boreal forest, due to drought stress. Conversely, we also detected positive productivity trends (i.e., increases in minimum cover and decreases in seasonality) north of Lake Superior, which have previously been recognised by NDVI time-series based on AVHRR in Canada (1985-2006) (Pouliot et al., 2009).

4.1.1 Land cover responses

Grassland patches, mostly located in the northwest boreal forests of Ontario, are mostly often associated with regenerating forest from old fire burns. These areas exhibit increasing trend in productivity and minimum cover and the decreasing trend in seasonality likely related to succession with reinvasion of woody plants following fire (Weber and Stocks, 1998).

In contrast, broadleaf forest followed by mixedwood forest land cover types, mainly located on the uplands following a SE-NW axis, observed the largest decreasing trend in annual productivity. Goetz et al. (2005) noted similar decreasing trends in photosynthetic activity across North America boreal forest between 1981 and 2003 and using a global circulation model, Bunn et al. (2005) predicted that this trend is likely to continue across this region until 2050. Summer droughts have also been recorded by Zhang et al. (2008) across most of the boreal forest region since the late-1990s and are likely to continue as the rate of warming also increases across Ontario's northern plains (Chapman and Walsh, 1993,Chapin III et al., 2005). Thus, our results correspond well with the observations of Zhang et al. (2008), Goetz et al. (2005) and predictions of Bunn et al. (2005) in that, despite the relatively short time period, significant decreasing trends in productivity were found for mixedwood and broadleaf forests.

4.1.2 Environmental and anthropogenic drivers

Elevation, average distance from roads and distance from human settlements show significant relationships with the DHI component trends. The most significant relationship was for elevation which was a significant driver for most of the three DHI indicators. In some situations elevation can be considered a surrogate to environmental conditions such as climate. However, this surrogate capacity may be distorted as climate in Ontario is principally driven by air sources which have a different impact on temperature and precipitation depending on the latitude, proximity to large water bodies, and to a lesser extent, topography (Baldwin et al. 2000). Thus, we believe that trends reported to be linked to the elevation gradient are, to some extent more likely to be land cover related. For example, most of the low elevation terrain that occurs in the Hudson Plains is dominated by wetlands which exhibits fewer trends when compared to other land cover types occurring in the uplands (i.e., broadleaf, mixedwood).

Of the anthropogenic indicators, cells closer to roads were predicted to observe an increase in seasonality and a decrease in minimum cover. Further distances to human settlements resulted in decreases in annual productivity. Conversely, cells closer from human settlements were predicted to observe increases in seasonality. As discussed by others, at broad spatial resolutions (1km or greater) forest harvesting and land clearing activities are difficult to capture due to smaller harvesting compartments, partial cuts, and selective harvesting management regimes all which minimise broad scale vegetation removal (Fraser et al., 2005,Coops et al., 2009c). As a result, relationships between the observed DHI trends and these anthropogenic drivers are limited at this spatial scale.

The interaction between elevation and the anthropogenic drivers observed for increasing annual productivity was highly significant confirming the observation that at higher elevations annual productivity increased over the time period. The distance to road interaction with distance to human settlement also exhibited high significance with decreasing minimum cover, suggesting that the variation in decreasing minimum cover with distance from road may be driven by variation in distance from human settlement along this same gradient.

4.1.3 Fire history classes

Overall, the pixels observing the highest 20% trend followed fire disturbance, as expected, with areas burnt from 1987 to 2003 exhibiting a higher proportion of increasing productivity cells, versus areas most recently burnt (2004-2008) showing a higher proportion of annual decreasing productivity based on their proportion in the landscape.

The only exception was for areas burnt in the earliest fire class (1970-1986) which experienced a higher proportion of decreasing annual productivity trends than expected.

4.1.4 Practicality of the approach

Monitoring vegetation productivity using remote sensing time-series has been examined in numerous studies. The majority of the studies have utilised NDVI however recent studies have moved towards the use of physically based indices, such as fPAR (Paruelo et al., 2005,Potter et al., 2007,Donohue et al., 2009,Garbulsky et al., 2010,Zhao and Running, 2010). Based on fPAR metrics, the DHI has the potential to be used as an indicator of environmental changes as, in addition to providing physically based information on vegetation productivity, it can provide biological insights on species richness and abundance (Coops et al., 2008). When coupled with the non-parametric Theil-Sen's test, which is robust against non-normality of the distribution, missing values, and outliers (Theil, 1950), the DHI allows for both the detection of trends in natural variability as well as the magnitude of those trends. Such trend test has already been applied over similar temporal remote sensing datasets and has shown to be well suited to capture long-term environmental change (Alcaraz-Segura et al., 2009, 2010a,b, Olthof and Pouliot, 2009).

Whereas previous work have mainly focused on trend validation using single datasets, (e.g., Fang et al. (2004) climate dataset, Alcaraz et al. (2006) land cover types, Alcaraz-Segura et al. (2010a) fire history), we found that a range of datasets provided additional insight on the underlying processes explaining the observed patterns for the studied time-series. In addition, the developed method presented in this paper is easily transferable to other datasets and has been applied to the long term historical AVHRR data over Canada (Fontana et al., submitted for publication).

5 Conclusions

The MERIS fPAR time-series, utilised in this study, provided metrics of photosynthetic activity over Ontario for a 6-year period. The aim of this study was to assess if indicators derived from the fPAR time-series allow the characterisation of broad scale vegetation condition across Ontario. Results indicate that time-series of fPAR, expressed as DHI indicators, is useful for effective assessment of the observed natural variability of vegetation, and highlighting areas which fall within, and beyond, the variability thresholds. The Theil-Sen's non-parametric statistical trend test provides valuable data to effectively track depletion and regrowth of vegetation which can aid in provincial or national monitoring activities and also can be used to focus more detailed analysis to local regions of specific interest. Trends in the DHI indicators imply that there is an overall decrease in vegetation productivity over the time period which aligns well with recent studies.

We acknowledge the limits imposed by the length of the 6 year time-series for establishing the natural variability baseline, however we believe that the approach is suitable to remote sensing data and can be applied to longer term datasets as these become available.

Continuing efforts to monitor vegetation change over time at a broad scale is critical for management of ecosystems, biodiversity, and monitoring climate change.

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Table 1. Slope of the regression line between the absolute trend values of the DHI components and the log-transformed average distance from the nearest road, distance from the nearest human settlement, average elevation and their interactions.

	Road dist.		Human settlement dist.		Elevation	
Annual productivity +	NS		NS		0.202	***
Annual productivity -	NS		0.031	*	-0.109	*
Seasonality +	-0.237	*	-0.023	*	-0.024	*
Seasonality -	NS		NS		0.106	***
Minimum cover +	NS		NS		NS	
Minimum cover -	-0.055	**	NS		0.205	**
	Road dist. x human settlement dist.		**Human settlement dist. x elevation**		**Road dist. x elevation**	
Annual productivity +	NS		0.015	***	0.010	***
Annual productivity -	0.002	*	NS		NS	
Seasonality +	-0.002	**	NS		NS	
Seasonality -	NS		0.005	**	NS	
Minimum cover +	NS		NS		NS	
Minimum cover -	-0.005	***	NS		NS	

***   P<0.05 indicate if the values are significantly different than zero.**
****   P<0.01 indicate if the values are significantly different than zero.**
***** P<0.001 indicate if the values are significantly different than zero.**
NS, not significant.

Table 2. Area in km^2 for each DHI indicator with a notable trend, using the 20% threshold, over the province of Ontario.

Trend	Annual productivity +	Annual productivity -	Minimum cover +	Minimum cover -	Seasonality +	Seasonality -
Area in (km^2)	19,100	150,400	62,900	106,600	105,900	63,600

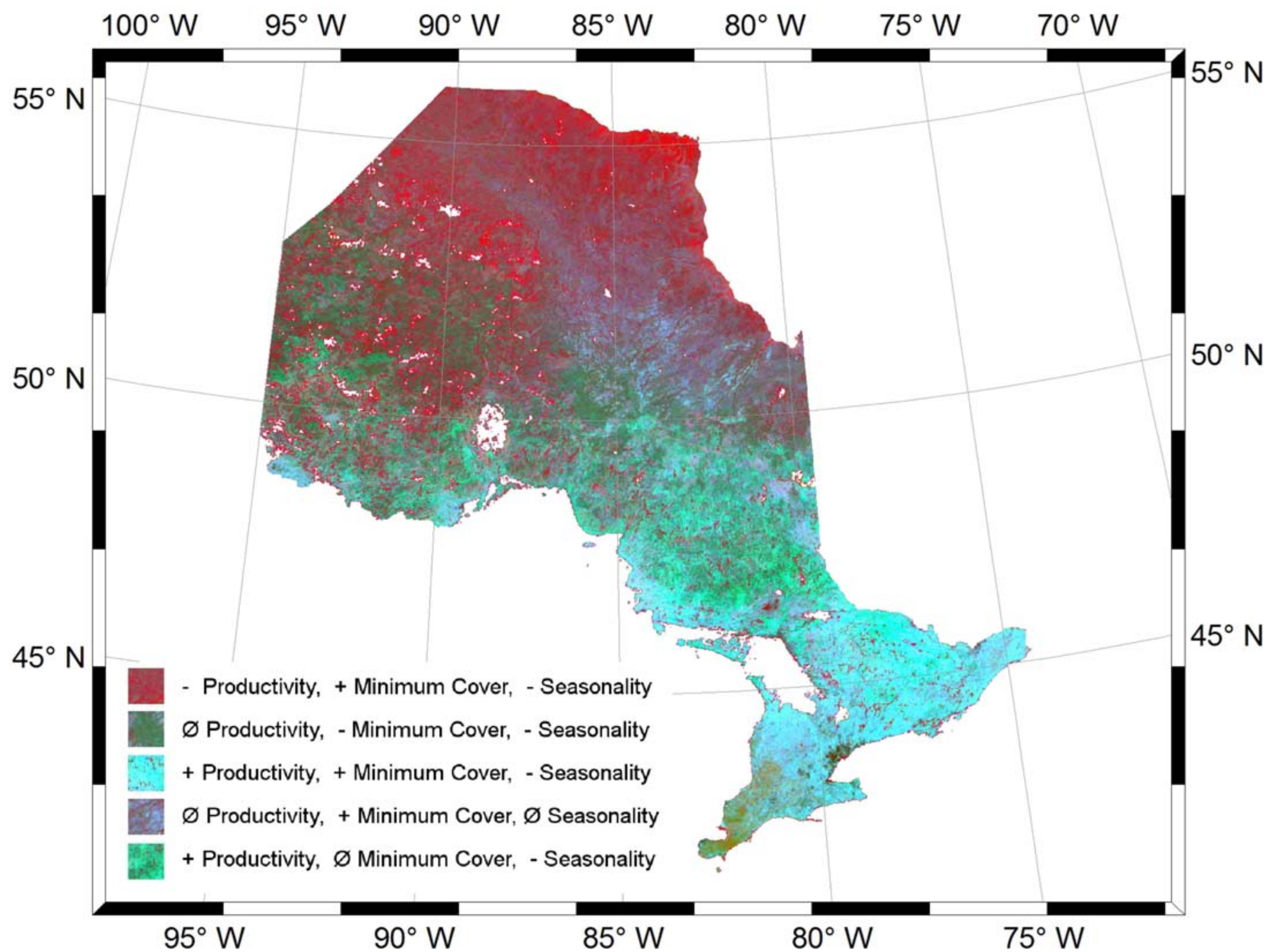

Figure 1. Combined components of the dynamic habitat index averaged over the 6 years of observations (2003-2008). This colour composite is elaborated by assigning the red band to seasonality, the green band to overall greenness and the blue band to minimum cover.

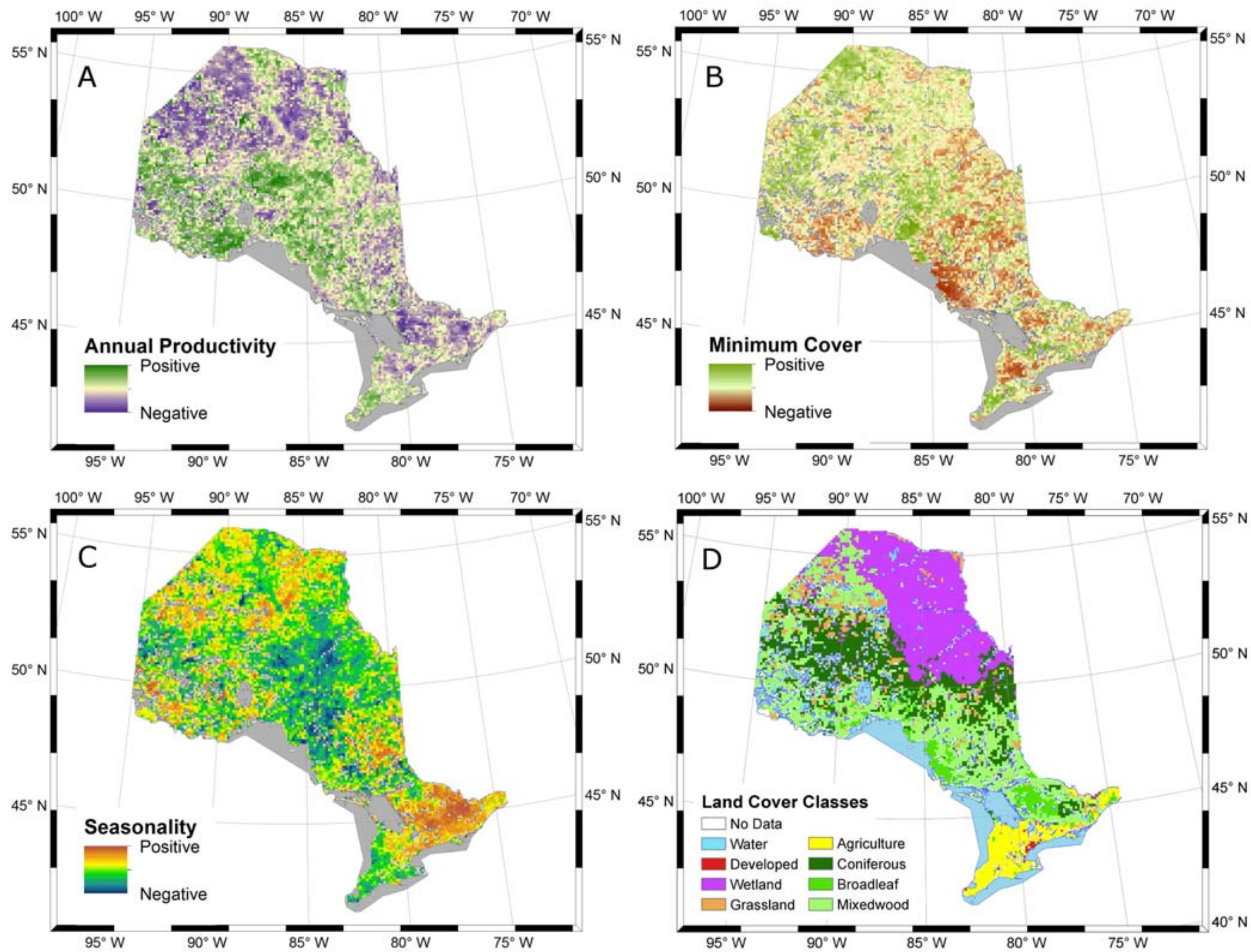

Figure 2. Ontario overall observed Theil-Sen's trend recorded over the 2003-08 period for each of the individual component of the dynamic habitat index (DHI): (A) annual productivity, (B) vegetative cover, (C) seasonality. Also shown is the EOSD land cover classification resampled to a 10 km x 10 km grid (D).

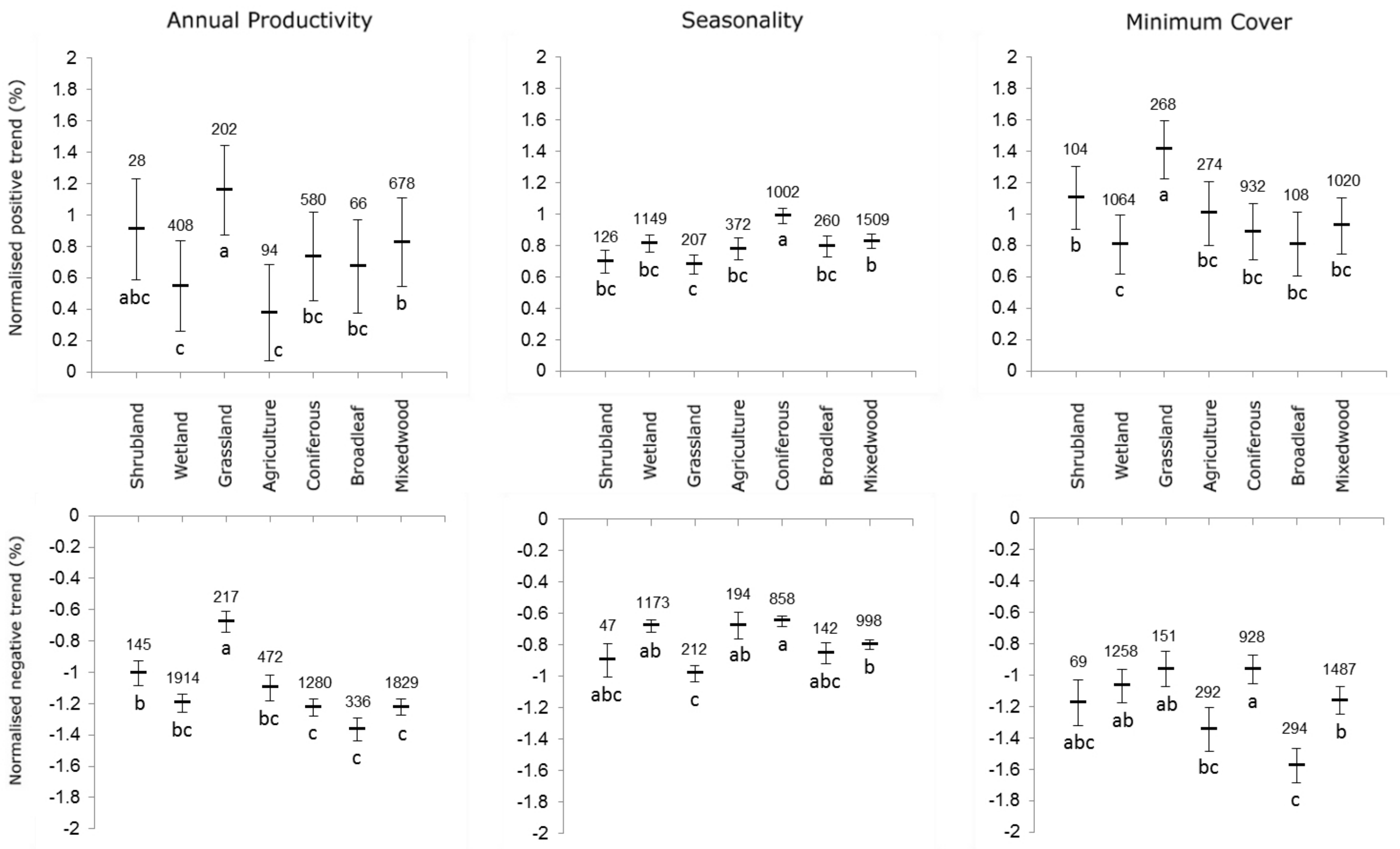

Figure 3. Increasing and decreasing overall observed trend per land cover type. Whisker shows the standard error. Data labels above the whisker indicate the sample size (no. of pixels). The same letter on different classes designates non-significantly different means as informed by a Bonferroni post hoc ($p < 0.05$) test of the ANOVA. For example, for annual productivity, with positive trends (top left figure), shrubland (abc) is not significantly different than any other land cover types, whereas wetland (c) is significantly different to classes with an "a" or a "b" designation.

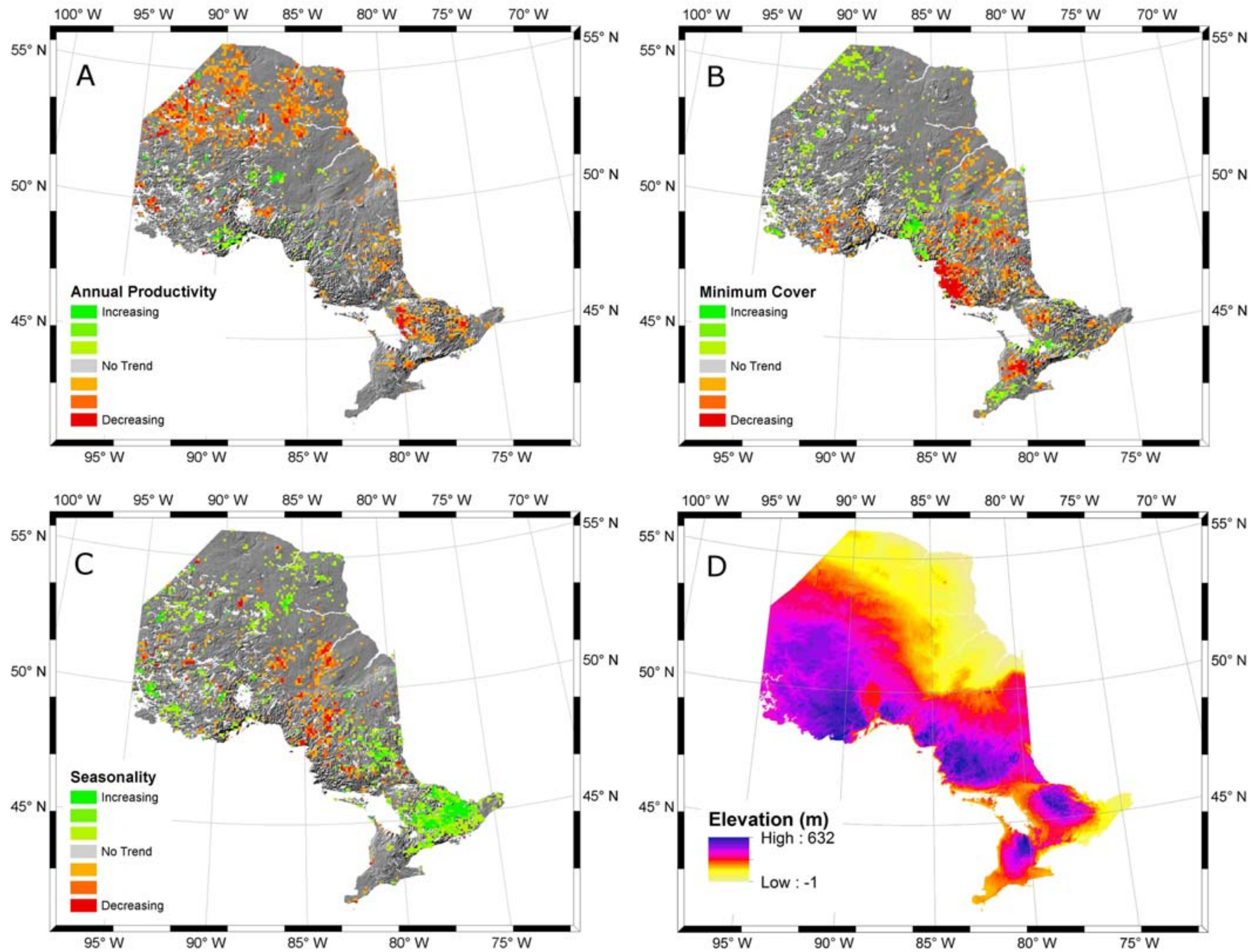

Figure 4. Areas of notable trends, using the 20% threshold, from 2003 to 2008 for each of the components of the dynamic habitat index (DHI): (A) annual productivity, (B) vegetative cover, (C) seasonality. Also shown is the SRTM elevation map (D).

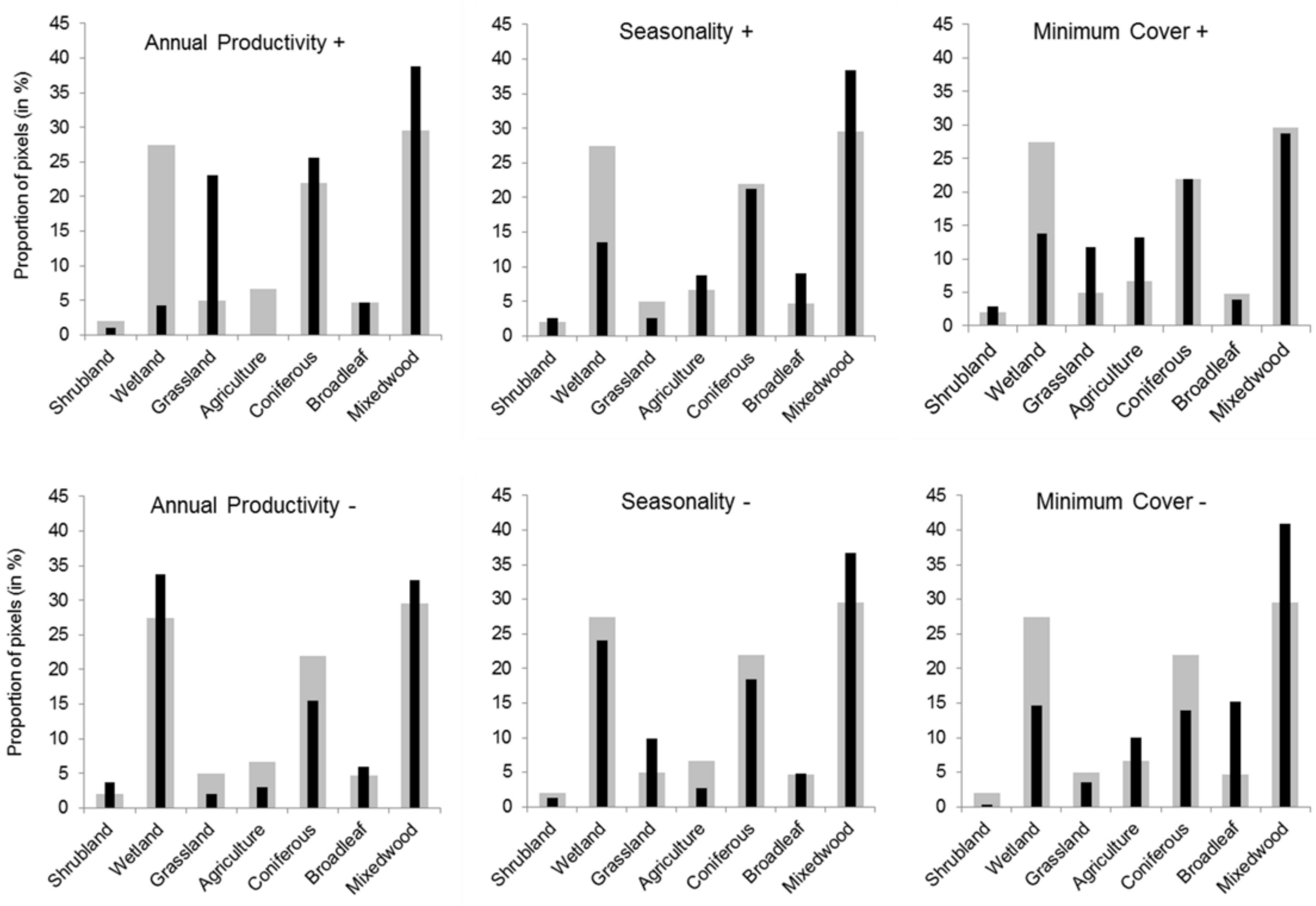

Figure 5. Bar plots show the proportion of pixels by land cover types for each of the DHI component. Pixels observing a notable trend are shown in thin black bars and all pixels in wide grey bars ((+) positive trend; (-) negative trend).

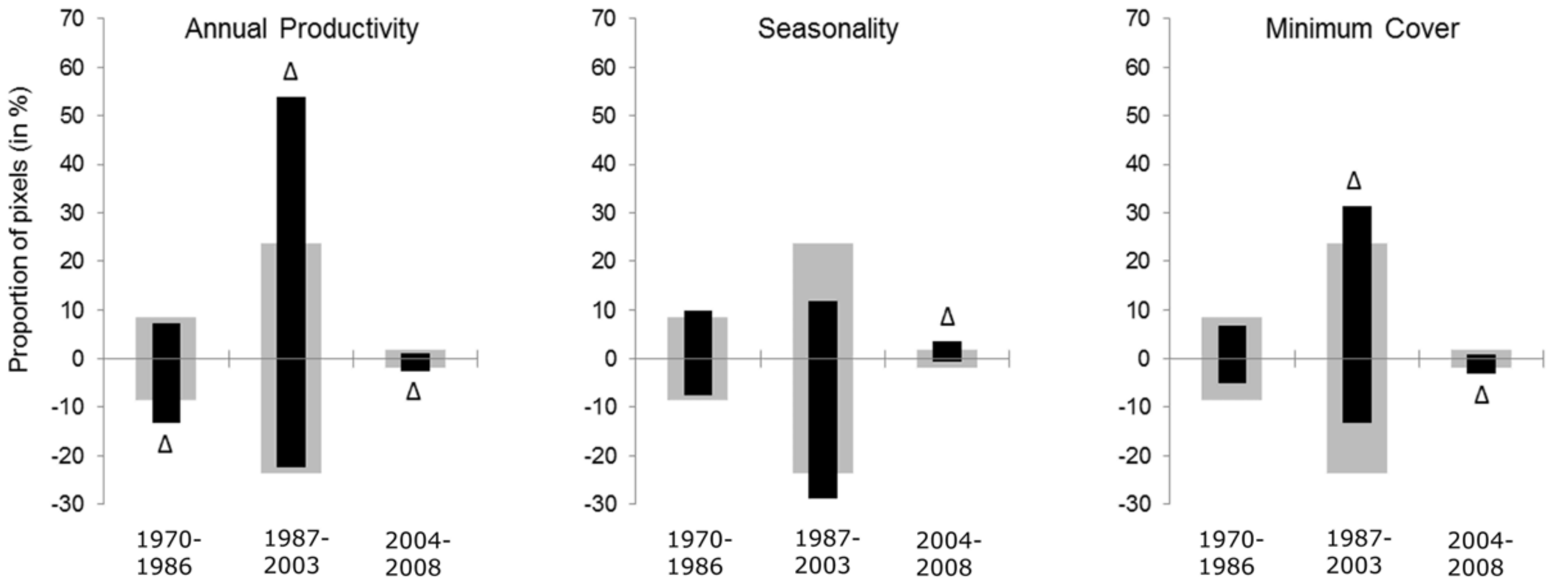

Figure 6. Bar plots show the proportion of pixels by fire years for each DHI component. Pixels observing a notable trend are shown in thin black bars and all pixels in wide grey bars. ***Delta*** **(Δ) indicates if the proportions of pixel are greater than 30% of what is observed in the overall landscape.**