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Comparison of a regional-level habitat index derived from MERIS and MODIS estimates of canopy absorbed photosynthetically active radiation

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ABSTRACT

Earth observation data and approaches are increasingly being utilized to improve our insights into the ecological processes that influence biological diversity. Physically based indices such as the fraction of absorbed photosynthetically active radiation (or fAPAR) intercepted by vegetation are particularly useful in describing variations in productivity and seasonality which can, in turn, be related to species abundances and distributions. The increasing availability of time series of fAPAR data from 2000 from the MODIS sensors, as well from other satellites, such as ENVISAT, has resulted in a motivation to extend techniques, originally developed for MODIS biophysical data, to other sensors. In this letter we investigate and demonstrate the application of the dynamic habitat index (DHI) methodology to the MERIS Global Vegetation Index (MGVI) across the over 1 million km^2 province of Ontario, Canada. To do so we briefly describe the DHI approach, the underlying basis of the MODIS and MERIS MGVI (fAPAR) indices, and then derive and compare the DHI from both sensors. Results indicate the three DHI components varied significantly in their magnitude, principally due to MODIS fAPAR estimates being larger than those observed by MERIS fAPAR. However the relationship was, in general, temporally stable across years and the residuals tended to be spatially consistent. We conclude that following inter-calibration the production of consistent indicators of habitat and biodiversity from different data sources is possible, thus supporting global terrestrial ecological research, policy support, and management.

Key words: Dynamic Habitat Index, Biodiversity, fAPAR, Vegetation

1. INTRODUCTION

Earth Observation (EO) satellites have been demonstrated as uniquely capable of synoptically covering the planet in a cost effective and repeatable manner, producing data which is ideal to monitor and assess changes in vegetation cover and condition across many spatial and temporal scales (Turner et al. 2003, Running et al. 2004, Duro et al. 2007). Typically the focus of terrestrial remote sensing activities is information acquisition related to leafy vegetation, which has arguably been described the single most vulnerable biotic component of terrestrial ecosystems (Potter et al. 2003). Vegetation is sensitive to anthropogenic and non-anthropogenic disturbance events, both of which drive global biological diversity patterns and are clearly discernable from remote observations (Fraser and Latifovic 2005, Coops et al. 2006). Data acquired from remote sensing has already improved our insights into the ecological processes that are understood to influence biological diversity (Turner et al. 2003) and can dramatically enhance traditional methods of inventorying and assessing biodiversity (Coops et al. 2008). This can be done through tracking changes in habitat, and other indirect biodiversity indicators, and through the assessment of changes in key indicators of vegetation productivity, such as the Normalized Difference Vegetation Index (NDVI), or more physically based indices, such as the fraction of absorbed photosynthetically active radiation (or fAPAR) intercepted by vegetation, which is analogous to greenness cover (Harestad and Bunnell 1979, Nilsen et al. 2005).

In order to condense high frequency (8 – 10 day) time series of fAPAR data, Berry et al., (2007) and Coops et al. (2008) derived the dynamic habitat index (DHI), which proposes three annual descriptors of the underlying vegetation dynamics: the total annual production, the minimum level of perennial cover, and the degree of vegetation seasonality. The index has been used to capture variations in habitat quality and quantity relevant for a number of species including birds (Coops et al. 2009b) and butterflies (Andrew et al. 2010). Initially, data from the MODIS sensor onboard TERRA and AQUA, which provide 1-km spatial resolution 8-day fAPAR estimates (Heinsch et al. 2006), were used to drive DHI estimates. The increasing availability of vegetation biophysical products from other sensors, such as MERIS (MEdium Resolution Imaging Spectrometer, from ENVISAT platform) (Gobron et al. 2007) and SPOT VEGETATION instruments onboard SPOT 4 / 5 satellites (Deng et al. 2006), has provided motivation to extend techniques originally developed for MODIS biophysical data to other sensors' data (Seixas et al. 2009) with the view to, despite these datasets being calculated using different algorithms and approaches, developing functionally equivalent data for terrestrial ecosystem modeling. In this letter we investigate and demonstrate the application of the DHI methodology to the MERIS Global Vegetation Index (MGVI) / fAPAR across the province of Ontario, Canada. To do so we briefly describe the DHI approach, the underlying basis of the MODIS and MERIS MGVI / fAPAR indices, and then derive and compare the DHI from both sensors, with the ultimate aim of producing seamless habitat layers from both sensors' datasets.

2. METHODS

2.1 The MODIS-fAPAR *Product*

A comprehensive description of the underlying fAPAR algorithms is beyond the scope of this letter. For a recent comprehensive comparison readers are referred to Seixas et al. (2009) and references therein. In brief, the processing stream from MODIS produces a suite of atmospherically corrected, geo-registered, data products on a routine basis, including fAPAR, which is calculated daily from surface reflectances (Tian et al. 2000) using a physically-based light propagation canopy model which takes into account sun and view angle and background reflectances (Tian et al. 2000). Model parameters are prescribed based on land cover, which limits the range that variables can vary in vegetation canopies (Myneni et al. 2002) and the retrieved fAPAR values are derived from a function of solutions using a lookup table (Knyazikhin et al. 1998, Seixas et al. 2009). The MODIS fAPAR estimates have been shown to be sensitive to error following recent fire (Steinberg et al. 2006), or where snow accumulates on the canopy (Yang et al. 2006) and recent comparisons have reported overestimation of fAPAR when compared to other remote sensing derived and field based datasets, principally due to atmospheric scattering overcorrection leading to low red reflectance retrievals (Cheng et al. 2006, Huemmrich et al. 2005). The spatial resolution of the MODIS fAPAR data is 1 x 1 km^2.

2.2 The MERIS GVI Product

The MERIS sensor, onboard ENVISAT which was launched in March of 2002, acquires data in 15 spectral bands which are programmable in position and width (Louet 2001).The MERIS global vegetation index (MGVI) is equivalent to fAPAR and is calculated using a combination of the blue, red and NIR bands (Bezy et al. 2000, Louet 2001). The blue band provides a dynamic correction to help reduce the impact of the atmospheric and angular effects and the reflectances are modelled to produce a top of canopy reflectance observed under standard illumination and observation geometries, as described in Gobron et al. (2008). The top of canopy reflectance is then optimized using a radiative transfer model to minimise additional influences such as soil background and values are constrained so that the MGVI is as close as possible to the fAPAR associated with the plant canopy, making the values functionally equivalent to other indices such as those computed from MODIS (Seixas et al. 2009). The original 1.2 x 1.2 km^2 spatial resolution MERIS fAPAR data was resampled using a nearest neighbour routine to 1.0 x 1.0 km^2.

2.3 Calculation of Dynamic Habitat Index

A full description and justification of the DHI methodology is available from Berry et al. (2007) and Coops et al. (2008). In summary, the index comprises three components: (i) annual primary production, (ii) seasonal greenness, and (iii) annual minimum cover. Annual primary production can be expressed as the integrated (or summed) greenness over an entire year, which has a strong theoretical and empirical justification in forests, crops and grasslands as an indicator of annual primary production (Goward et al. 1985). Annual minimum cover relates the potential of the landscape to support populations throughout the year (Schwartz et al. 2006). Locations bereft of significant snow cover following summer often maintain greenness into winter, and fAPAR remains above 0. In areas where snow covers the vegetation, fAPAR equals or approaches 0. Seasonal variation in greenness is an integrated measure of climate, topography, and land use. Forest and grasslands at northern latitudes having a much shorter growing season and higher seasonality, than those in more southern areas (Coops et al., 2009a). To assess variation in the fAPAR throughout the year, we computed the standard deviation of monthly values for each cell, and then divided that value by the mean annual fAPAR to attain the coefficient of variation (CV). High CV values signify seasonal extremes in climatic conditions or limited periods with agricultural production, whereas sites with low coefficient of variation typically represent irrigated pasture, barren land, or evergreen forests.

2.4 Data Collections

The MODIS data used in this comparison was downloaded from the “MODIS 4 NACP” web site which provides MODIS collection 5 (C5) data processed using a modified Timesat algorithm (Gao et al. 2008, Nightingale et al. 2009). 8-day composites are developed from daily data to ensure the best available quality assurance retrievals are utilized. The MERIS–MGVI products were provided by ESA through the “GRID processing on demand” web site following requests for the area of interest. MERIS products are available at different product levels. The highest level, 3, combines daily products into a time composite product that is more spatially uniform as it contains all valid data in a time composite over a defined period (Pinty et al. 2002). This time composite fAPAR algorithm selects the most representative valid value over a 10 day sequence

(Aussedat et al. 2006). In practice, it selects the nearest value to the arithmetic average over the composite period and remaps the daily Level 2 product at 1.2 x 1.2 km^2 spatial resolution using a nearest-neighbor method to preserve data integrity (Aussedat et al. 2006). We utilized data from 2003- 2007 to provide a range of annual conditions for the comparison. We modified the original DHI computation for minimum cover, due to sensitivities to snow in the very low fAPAR estimates (< 5%). As a result, rather than extracting the lowest fAPAR value for the annual sequence, which is strongly influenced by background responses in either of the fAPAR datasets, we summed the number of cells that were classified as snow over the non-growing season (defined as late September – early June for northern latitudes), which was then divided by the number of 8 or 10 day time periods. As a result sites with a number of 8 or 10 day time periods of snow had a higher fraction than those sites without snow. This index was then inverted to ensure it matched the original minimum cover calculation, with pixels with less days of snow cover having larger values (i.e. a larger number of 8 or 10 days periods without snow, akin to sites with a higher minimum cover) than those cells with longer periods of snow (and thus lower minimum cover).

2.5 Study Area

With an area of 1,076,395 km^2, Ontario is the second largest province in Canada, and has marked differences in productivity largely expressed along a latitudinal gradient. The highest annual seasonality in Ontario is found in the northern portions of the province where the vegetation is largely characterized by open fens and bogs with dry ground cover dominated by lichens. This region experiences extensive snow cover in the winter months resulting in significant phenological change, with greening of the fens and bogs in summer. In central Ontario, the landscape is increasingly variable topographically with coniferous and evergreen boreal forest species and a mosaic of forest conditions resulting from harvesting activities. The area also experiences less snow cover, persisting for a shorter time, and evergreen vegetation.

In the southern areas of Ontario, greater land cover diversity is found over mild topography and warmer temperatures, making the area suitable for agriculture that restricts forests to small, isolated woodlots. The intensive agriculture areas throughout this mosaic act to create patches of higher seasonality, low minimum cover, and lower overall production.

To capture and characterize regional variability across the Province we utilized the ecodistrict level of the National Ecological Framework of Environment Canada (Rowe and Sheard 1981). Stratification of ecodistricts is based on a classification system whereby each district is viewed as a discrete ecological system, considering interactions between geology, landform, soil, vegetation, climate, wildlife, water, and human factors with 87 ecodistricts delineated within the province.

2.6. Initial Statistical Analysis

In order to compare the DHI components derived from two different datasets, we initially assessed differences in magnitude using a paired t-test for dependent samples to establish if a statistically significant difference existed. Previously reported studies indicated that differences were likely (Seixas et al. 2009), which then led us to compare the indices using standard regression by component of the entire 2003-2007 dataset. Relationships between MERIS and MODIS DHI components were strongly nonlinear, and were accommodated by transformations (logit transform of all MODIS DHI values, scaled to (0,1); x^{-1}, log(x), and $(x+1)^{-1}$ transforms were used for the MERIS annual sum, coefficient of variation, and minimum cover, respectively). The temporal consistency of the MERIS-MODIS relationships was assessed by including year as a categorical term. To assess where differences in the DHI occurred spatially between the two datasets, we computed the residual from the line of best fit (using general or year-specific models, where necessary) of the 3 DHI components to visually locate where cells occur which were consistently different between the two datasets. We assessed the spatiotemporal consistency of MERIS-MODIS deviations for each factor both quantitatively, with a two-way ANOVA of the residuals by ecodistrict and year, and categorically, by coding residuals as negative (< 1 sd from line of best fit), positive (> 1 sd), or minor (within 1 sd). The breakdown of residual codes by ecodistrict was evaluated with chi-squared tests.

3. RESULTS

The three DHI components derived from the MODIS and MERIS fAPAR data from 2003, 2005 and 2007 were found to be significantly different both annually, and combined, using a paired t-test ($p < 0.001$). MODIS fAPAR values were higher overall than the values observed by MERIS MGVI, resulting in higher overall sum components. Despite the overall higher MODIS FAPAR values, the MERIS seasonality (the coefficient of variation of the fAPAR) was larger in magnitude than the seasonality derived from the MODIS fAPAR data. Correlation analysis confirmed that, whilst the magnitude of the different components was significantly different, the components from the two datasets were significantly correlated across the eco-districts. Of the three components, the combined annual seasonality was the most significantly correlated ($r = 0.89$), followed by the minimum cover and lastly the summed production component ($r = 0.71$) (Figure 1(a) – (c), Table 1).

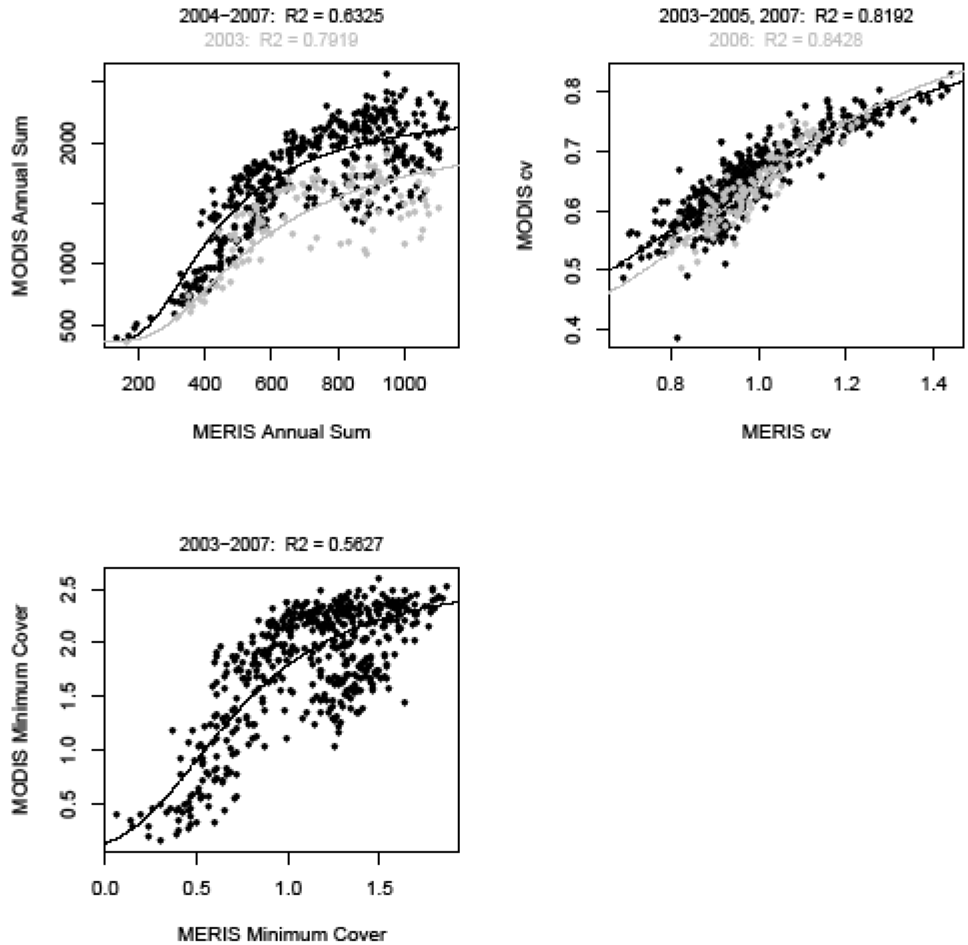

Figure 1: Scatter-plot of the three DHI components derived from MODIS fAPAR and MERIS MGVI data for 2003-2007; (a) Annual sum of fAPAR with 2004-2007 in black and 2003 in grey; (b) seasonality, with 2006 in grey and all other years in black and (c) minimum cover.

Table 1: Summaries of the mean, standard deviation (SD), correlation coefficient (r), and significance of the correlations of the MODIS vs MERIS DHI components.

DHI Component	**MERIS Mean**	**MERIS SD**	**MODIS Mean**	**MODIS SD**	**r**	***P***
Annual Sum	715.7	232.7	1587.4	462.1	0.711	0.000
Minimum Cover	1.103	0.374	1.753	0.5732	0.710	0.000
Seasonality	0.986	0.145	0.653	0.067	0.893	0.000

The relationships between MODIS- and MERIS-derived DHI components exhibited temporal stability. MODIS summed production values were anomalously low in 2003, requiring a year-specific calibration to MERIS values. For the seasonality component, only 2006 required a separate model, with MODIS values following a slightly steeper relationship with MERIS counterparts than in other years. There were no interannual differences in the relationship between minimum cover from MODIS and MERIS. Likewise, residuals were spatially consistent. ANOVAs revealed very strong effects of ecodistrict on residual values, particularly for summed production and minimum cover (not shown) and the distribution of residuals across ecodistricts was highly non-random (χ^2: $p < 0.0001$ for all DHI components). For summed production, seasonality, and minimum cover, 42, 28, and 62 ecodistricts respectively exhibited the same residual sign over all five years.

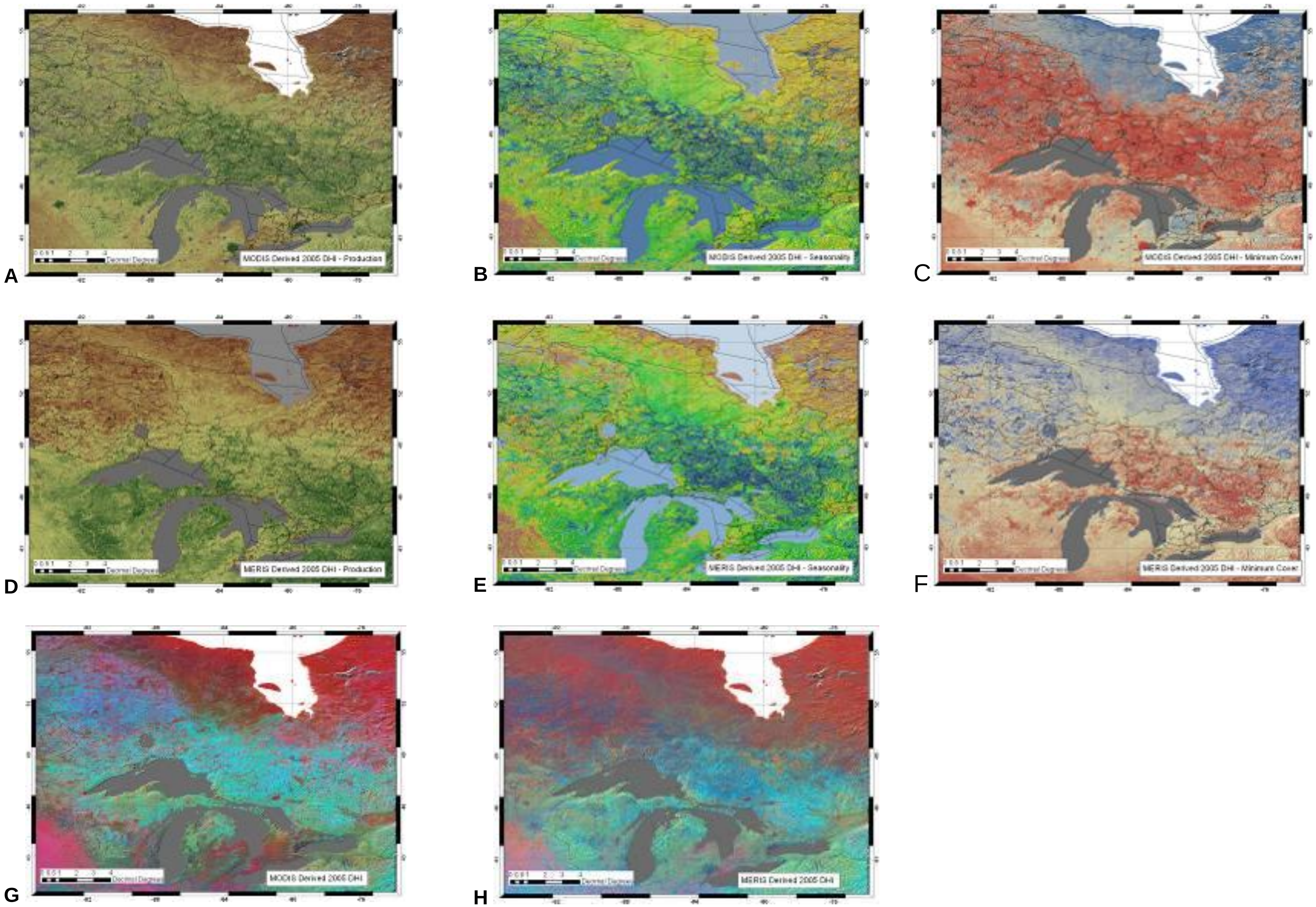

Figure 2: **The three DHI components derived from MODIS fAPAR and MERIS MGVI data for 2005; MODIS derived (a) Annual sum of fAPAR, (b) seasonality and (c) minimum cover; MERIS derived (d) Annual sum of fAPAR, (e) seasonality and (f) minimum cover; and composite DHI images derived from (g) MODIS and (h) MERIS. The composite DHI images were developed by assigning the annual integrated greenness to the green band, the annual cover to the blue band, and the seasonality to the red band. Bright red areas have low annual mean fAPAR, low annual minimum fAPAR and high seasonal variability. Bright cyan areas have a high mean, a high minimum and low variability. Darker blue indicates landscapes with a low mean, a high minimum, and low variability, orange areas indicate moderately productive vegetation that varied in productivity throughout the year and green areas are high annual production, a high annual minimum production and low seasonality**

The DHI images (Figure 2(g) and (h)) reveal consistent, spatially coherent patterns in the DHI components from both sensors. As follows from the ecodistrict analyses above, the differences between MODIS- and MERIS-derived DHI components also contain a strong spatial signal which follows the Canadian ecozones closely. All three components show consistently positive residuals (i.e., MODIS estimates above the line of best fit) in the Boreal Shield ecozone, with negative residuals in the Hudson Plain and Taiga Shield to the north. Further, residuals in the Mixedwood Plain of southern Ontario are generally negative for summed production and minimum cover, but positive for seasonality. Within the Boreal Shield, residuals for the different components show slightly different spatial trends. The greatest differences in summed production occur in central Ontario, while minimum cover estimates deviated the most in the west of the province.

4. DISCUSSION and CONCLUSIONS

The initial analysis presented here is designed to move towards a more comprehensive analysis between the inter-sensor use of MODIS and MERIS fAPAR products at regional scales. As discussed, throughout North America the MODIS sensor provides a key data source for much of the biophysical and biodiversity modeling. The increased availability of other datasets, with potentially increased benefits such as greater spectral and spatial resolutions, offers alternatives, however the capacity of these datasets to be used inter-changeably needs to be rigorously assessed. Analysis of the mean DHI values across the province of Ontario indicates that, as with other studies, MODIS fAPAR values are systematically higher than those derived from MERIS fAPAR. The implications of this, for the DHI, is that the annual sum fAPAR, an indicator of landscape productivity, and the presence of snow cover, which provides an indication of the area of land which has permanent green vegetative cover year round, will subsequently be higher than that observed by MERIS. Interestingly, in our analysis we found that the coefficient of variation (an indicator of seasonality) was higher from the MERIS derived fAPAR layers than the MODIS, indicating that the temporal variation in MERIS fAPAR is greater when compared to its annual mean, than that from the MODIS fAPAR values.

Despite these significant differences in the magnitude of the DHI components, the correlation between the two datasets was very high, ranging from 0.71 – 0.89, and relationships show a high degree of interannual stability. Given that the MERIS data collection is over a 10-day, and the MODIS an 8-day period, and the differences in the compositing methodology and spatial resolution, this high degree of correspondence is very promising. Deviations between the two products were strongly patterned spatially and this pattern was highly conserved over time, suggesting an underlying physical mechanism, such as the use of land cover in the calculation of MODIS fAPAR. In this analysis we have focused on the derivation of the DHI, which produces annual summaries of the fAPAR datasets. Obviously critical information is available for biodiversity and habitat at a seasonal and even monthly levels within these data, and biases and differences in these datasets at these finer temporal resolution time steps may be present. As a result, further analysis should be conducted to ensure that these finer scale variations are also matched in both datasets. This letter provides some confidence, however, that with the correct inter-calibration steps the production of consistent indicators of habitat and biodiversity from different data sources is possible, supporting research and management of global terrestrial ecological issues. This research indicates a cohesion between the information generated by differing sensors, with largely explainable and systematic differences present, indicating a capacity to extend the DHI logic and modeling framework over time and across sensors.

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