Spatio-Temporal Analysis Using a Multiscale Hierarchical Ecoregionalization

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Abstract

We address the need for spatio-temporally explicit analysis techniques linking the scales of ecosystem, observation, and analysis, using a hierarchical ecoregionalization to examine remotely sensed data at spatial scales of ecological and management significance. Long- and short-term changes in vegetation functioning are a key indicator of ecological processes. We predict net primary production (NPP) at monthly temporal resolution for 16 years (1981–1996) at an 8-km spatial resolution for the approximately 10^6 km^2 area of Ontario, Canada. We calculate landscape-level light use efficiency values that are tuned to monthly and long-term ecoclimates, and the Normalized Difference Vegetation Index from the NOAA-AVHRR sensor. Applying our spatio-temporal analysis tools, we show evidence for increasing NPP across most of the province. This increase varies seasonally and annually across Ontario, and its magnitude and distribution varies with the spatial scales of analysis. Bridging the gap between local and global studies, this research supports spatio-temporal monitoring and analysis of ecosystem functions.

Introduction

Recently, scientific and public interest in the better understanding and prediction of ecosystem functions has significantly increased (Cramer *et al.*, 1999), and linking global and local studies by scaling appears to be one of the major challenges. It is important to study changes in ecosystem functioning across multiple spatial scales because its spatial variability is due to the, frequently scale-dependent, variations in its controls. While the use of remotely sensed imagery allows data collection over regional and global extents, analysis techniques frequently ignore the link between the discrete spatial (e.g., leaf, tree, or forest) and temporal (e.g., day, season, or year) ecosystem scales, the spatial and temporal resolution of the observations, and the spatial and temporal scales of analysis. Spatially and temporally explicit techniques that link these scales of ecosystem, observation, and analysis have become essential in recent years with the availability of long time series of satellite data (e.g., NOAA Advanced Very High Resolution Radiometer (AVHRR)) with sub-annual (monthly, biweekly) time-steps and large regional extents. We address this need with analysis tools that use multi-scale spatial aggregation techniques for the spatio-temporal analysis of remotely sensed data.

The aggregation of spatial data, for example, within watershed boundaries or census tracts, allows the spatial scale of analysis to be fixed, and the local spatial heterogeneity to be controlled. Because ecosystems are hierarchical in nature, for studies of scale and scaling it is appropriate to aggregate within the boundaries of a hierarchical spatial partitioning scheme such as an ecoregionalization (Csillag, 1997; Goodchild and Quattrochi, 1997). Coarse spatial partitions (e.g., ecozones) correspond to coarse landscape characteristics such as climate. Coarse partitions are subdivided into nested finer spatial partitions (ecoregions or ecodistricts) based on more localized characteristics such as weather. The ecoregionalization therefore delineates cohesive ecosystem units (or *ecounits*), within which we expect similar ecological processes to occur that are appropriate for that spatial scale. In this study we use the ecoregionalization to fix the spatial scales of analysis and then examine spatio-temporal characteristics of the landscape within each ecounit (ecozone, ecoregion, and ecodistrict) boundary (Figure 1). Spatial patterns and trends calculated at varying temporal scales (e.g., annual or decadal) correspond to ecologically meaningful spatial scales, and can be assigned as new attributes to ecounits with management significance.

Because vegetation is a synthesis of the interactions of both geo-climatic factors (e.g., macro- and micro-climatic conditions, soil, and hydrology) and human and natural disturbances (e.g., agriculture, logging, fire, or disease), changes in vegetation species, distribution, amount, and spatial pattern are sensitive to environmental changes across various spatial and temporal scales. Vegetation functioning (e.g., measured by biomass accumulation, leaf-area, or photosynthetic activity) is detectable from remote sensing platforms, which makes vegetation a potentially highly visible indicator of ecosystem change. Dynamic vegetation characteristics are usually assessed using a continuous measure of vegetation growth such as net primary production (NPP) (Waring and Running, 1998). The requirement of landscape-level datasets of vegetation growth with a sub-annual time step, large spatial extent, and consistent methodology is problematic over large areas and long time periods because ground measurements of the composition and functioning of vegetation are not available.

Recently, remotely sensed satellite data have been used to study vegetation production using consistent and repeatable methods that allow changes in vegetation growth to be examined across large spatial extents (Prince, 1991; Potter *et al.*, 1993). We predict NPP based on the Normalized Difference Vegetation Index (NDVI) from the NOAA/NASA Pathfinder AVHRR Land (PAL) dataset, used to derive the fraction of absorbed photosynthetically active solar radiation (F_{APAR}), and a light use efficiency (LUE) model. We generate landscape level LUE (LUE_e) that integrates over the fine-scale spatial heterogeneity in the landscape, using a relationship that is tuned to monthly and long-term eco-climatic variables and LUE_e derived using

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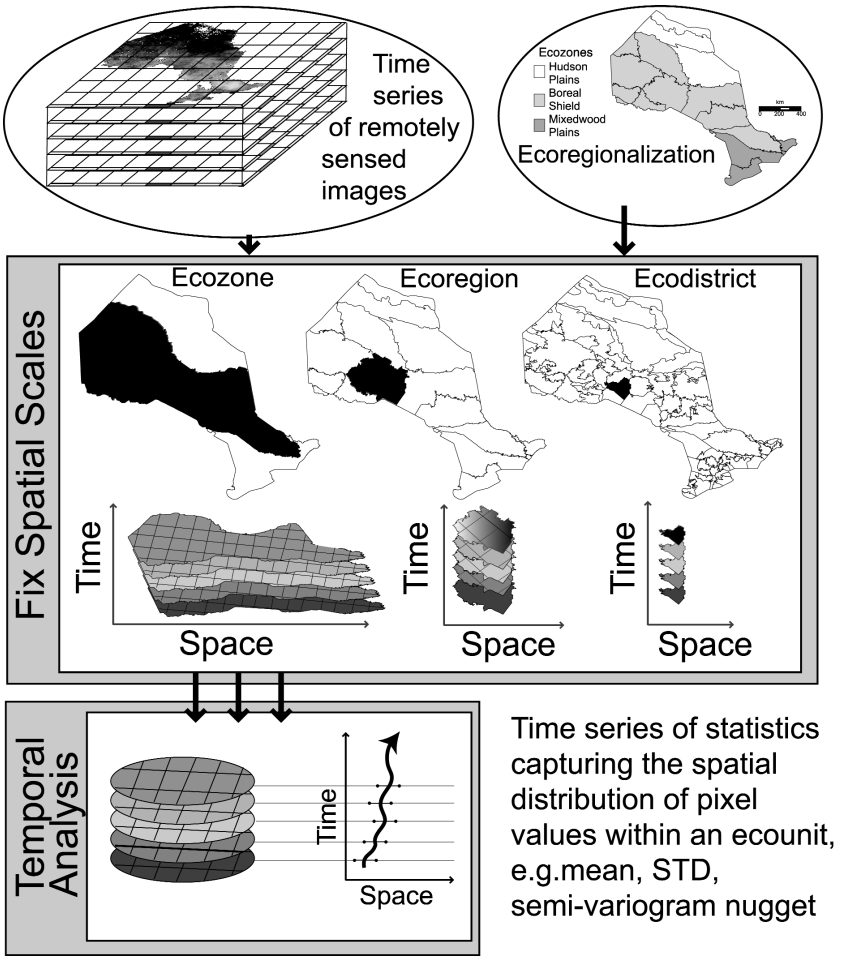

Figure 1. Spatio-temporal analysis of a time series of images using three spatial scales of a hierarchical nested ecoregionalization. At each spatial scale (ecozone, ecoregion, ecodistrict) a time series is created using the pixels within each ecounit, with statistics capturing the spatial distribution of values (e.g., mean, standard deviation). This time series can be further analyzed for trends.

the RHESSys spatially explicit simulation system for forest ecosystem processes.

In this paper we show that the fixed spatial scales of a hierarchical ecoregionalization can be used to analyze multi-temporal datasets at spatial scales with ecological and management significance. We apply these analysis techniques to 16 years (1981–1996) of monthly NPP calculated across Ontario, using predictions of landscape-level LUE values, and remotely sensed NDVI from the PAL dataset. At the fixed spatial scales of the ecoregionalization we show how spatio-temporal trajectories of NPP at different spatial scales vary seasonally and annually across Ontario.

Background

Spatio-Temporal Analysis Using an Ecoregionalization

While the time series of an individual pixel can be examined for cycles or trends, the spatial structure of these variations is often masked by local spatial heterogeneity of pixel values. Aggregation can be used both to characterize this spatial variability by describing the distribution of values within the partitioning unit, and to compare spatial patterns between spatial units.

The spatial extent, dimensions, and regularity of the spatial partitioning scheme used for aggregation will influence the prediction results (Handcock *et al.*, 1999). Regular spatial partitions such as grids do not have a direct physical correspondence with ecological variables, while specialized categories, such as from vegetation maps, do not encapsulate ecosystem processes. The use of an ecoregionalization to analyse a multi-temporal remotely sensed dataset allows spatial structure in the continuous image to be extracted from fine-scale spatial variability at fixed spatial scales of ecological significance. Spatial statistics, such as the ecounit mean and standard deviation, variograms parameters, or landscape metrics, describe the distribution of values within each ecounit (ecozone, ecoregion, or ecodistrict). At each scale of the analysis, the values within each ecounit can be further analyzed for temporal trends (Figure 1).

Predicting NPP

Non-destructive methods to determine stand-level NPP include using a statistical relationship with climate (Lieth and Whittaker, 1975), empirical relationships (Goetz and Prince, 1996; Cramer *et al.*, 1999), models of carbon and nutrient cycling (Goetz and Prince, 1996; Landsberg and Waring, 1997),

or LUE model (Monteith, 1977; Kumar and Monteith, 1981). These models are designed to capture processes (e.g., NPP or Gross Primary Production (GPP)) at a particular spatial scale and land-cover type, and are therefore limited in their ability to be scaled up to the landscape level, and by intensive data requirements for parameterization. Additionally, calculations of NPP are often applied only to a particular land cover (most frequently to trees to estimate harvestable timber), and ignore other components of landscape-level NPP (such as saplings, shrubs, moss) as well as variations in land use and land cover.

Various studies have shown that NDVI ((reflectance$_{INFRARED}$ − reflectance$_{RED}$)/(reflectance$_{INFRARED}$ + reflectance$_{RED}$)) is correlated with the amount of photosynthetically active vegetation (Tucker, 1979; Prince, 1991). Because NDVI does not scale directly with NPP at finer then annual time steps (Schloss *et al.*, 1999), for quantitative studies of vegetation processes in mature multilayered forest vegetation canopies, it is necessary to derive landscape-level NPP from the remotely sensed index. One method is to use a light use efficiency model (Monteith, 1977; Kumar and Monteith, 1981), which describes NPP (gCm^{-2}time-step^{-1}) as the product of time integrated APAR (MJ PAR m^{-2}time-step^{-1}) and LUE, which is the dry matter, or carbon yield of the ecosystem per unit APAR ($gCMJ^{-1}$APAR) (Waren Wilson, 1981; Landsberg *et al.*, 1995) (Figure 2).

The amount of energy that is absorbed by the canopy over a time period is dependent on the photosynthetically active (400- to 700-nm) radiation (PAR) incident over a time step (MJm^{-2}time-step^{-1}) and the fraction that is absorbed (F_{APAR}). Values of NDVI represent changes in the fraction of PAR that is intercepted (F_{IPAR}) in response to factors, including water availability, temperature, and cloudiness, that influence vegetation amount (Monteith, 1977). F_{IPAR} has been shown to scale linearly with NDVI (Goward and Huemmrich, 1992; Goward *et al.*, 1994; Ruimy, 1994; Gammon *et al.*, 1995). For vigorous vegetation it is assumed that all intercepted PAR (IPAR) is absorbed (Asrar *et al.*, 1989).

Predicting Landscape-Level LUE

LUE is a function of long-term and short-term constraints (e.g., ecosystem characteristics and weather conditions, respectively) (Monteith, 1977; Runyon *et al.*, 1994). Approaches to predicting NPP based on aggregated LUE data such as the CASA model (Field *et al.*, 1995; DeFries and Townshend, 1999) use a mean value of LUE within each modeling unit (e.g., a 1-km pixel), and are potentially biased due to the highly non-linear nature of spatio-temporal relationships with LUE. We approach this issue by generating landscape-level LUE (LUE_e) using a relationship between short- and long-term climate variables and LUE_e simulated using RHESSys.

RHESSys is a spatially explicit simulation system designed to predict forest ecosystem processes at the landscape level by integrating over the observed heterogeneity of the surface soils, topography, and canopy cover (Nemani *et al.*, 1993; Running and Hunt, 1993; Band, 1995; Coughlan and Dungan, 1997). The goal of RHESSys is to encapsulate the primary biotic and abiotic processes within specific landscape units (watersheds, forest patches, hill slopes), and to represent their spatial pattern within these landscape units. GPP, and NPP and LUE, derived using this method are, therefore, landscape-level predictions. RHESSys has been applied to different landscapes across Ontario (Band, 1993), and modeled outputs of observed runoff, forest growth, accumulated biomass, and snow depletion curves have been found to approximate well to field conditions (Band, 1993; Mackay and Band, 1997).

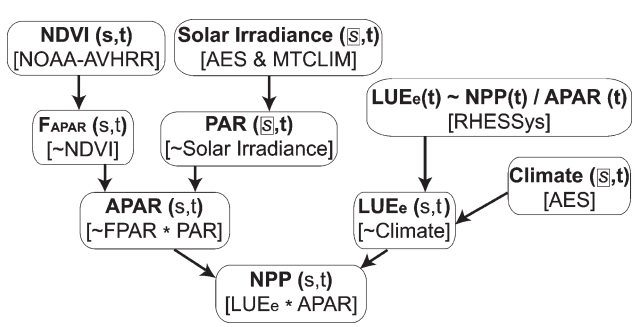

Figure 2. Flowchart for calculating landscape-level NPP. Each step shows the variable name (in bold on top) and the data source or computational model (bottom). The arguments s and t denote space and time; When s is present, then the variable is represented at all locations (**bold** denotes observed variables, *italics* surrounded by a box denotes interpolated variables). If t is present, then the variable is observed at all time steps.

Methodology

Data

Monthly meteorological data (average temperature and total precipitation) for 1981 to 1996 were extracted from the Environment Canada climate dataset for sites in Ontario, Quebec, and Manitoba (Environment-Canada, 1994), and interpolated using a kriging interpolation method to create monthly and yearly climate datasets for the province.

The ecoregionalization used in the present analysis is the National Ecological Framework (NEF) which is released in digital form as a part of the Canadian Soil Information System (NEF, 1999) for Canada (ESWG, 1996). The northern ecozone is dominated by fen and bog, the central ecozone by boreal coniferous and mixed forest, and the southern ecozone by agricultural land and mixed hardwood forest. Vegetation categories in Ontario were obtained from Agriculture and Agri-Food Canada, as a part of NEF, from the Canadian Soil Information System (NEF, 1999).

The PAL dataset (PAL, 1999) has been available for two decades, and is the only remotely sensed dataset with a long time series covering regional and global extents (DeFries and Townshend, 1999). We used a spatial subset across the province of Ontario, Canada, of 16 years (July 1981-December 1996) of monthly maximum composited (Holben, 1986) NDVI from this dataset.

All spatial analysis was performed on data stored as raster grid datasets within the ARC/INFO GIS (Environmental Systems Research Institute, Inc., Redlands, California). Software routines for analyzing time series of remotely sensed data were written using the ARC/INFO Arc Macro Language (Handcock, 1997) and SPLUS statistical software (Mathsoft, Seattle, Washington).

Predicting NPP Using NDVI and a LUE Model

We calculated monthly datasets of LUE_e and NPP across Ontario (Figure 2), by first predicting daily shortwave solar irradiance using the MTCLIM model (Running *et al.*, 1987) and daily climate data (Environment-Canada, 1998), at meteorological stations across Ontario, Quebec, and Manitoba. These data were temporally aggregated and spatially interpolated using a kriging interpolation method to create monthly datasets of surface solar irradiance for the province (Handcock, 2001; Wilson *et al.*, in review). Monthly PAR was calculated as 50 percent of the solar irradiance (Szeicz, 1974).

To calculate F_{APAR} from NDVI, we used published values for the parameters of their linear relationship, obtained for coniferous forest canopies across the Oregon transect (Goward *et al.*, 1994). These parameters were a first approximation for

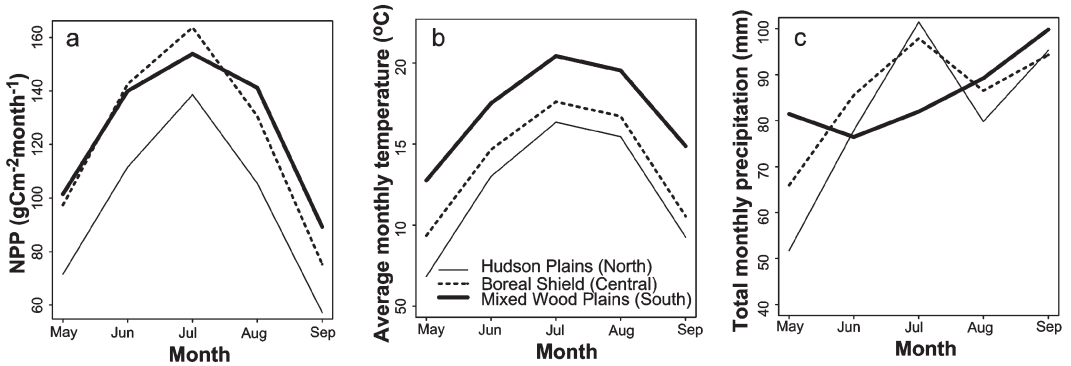

Figure 3. Sixteen-year averaged monthly values of NPP, temperature, and precipitation, aggregated across each of the three ecozones in Ontario. For clarity, the standard deviation of values within each ecozone is not displayed.

all land-cover categories across Ontario. Our LUE_e relationship (described in the following section) was also parameterized for forested regions. Future work is expected to refine this relationship because there is evidence that the coefficients for the F_{APAR} relationship vary over the growing season (Ruimy, 1994), and are sensitive to the amount of non-green biomass (Gammon *et al.*, 1995). There has also been recent work on parameterizing remotely sensed indices such as FPAR for various biomes, such as the NASA-MODIS validation (Running *et al.*, 1999).

Long-term average climate variables capture the biome effect *between* different ecosystems, and monthly climate variables capture the temporal variation in LUE *within* a spatially aggregated unit, across the growing season, and between years. We predicted monthly LUE_e at an 8-km by 8-km resolution across Ontario using a multiple linear regression relationship between monthly LUE_e, derived from RHESSys, and spatially extensive datasets of monthly mean temperature (T_{Month} in °C), total precipitation ($PRECIP_{Month}$ in mm), and the 16-year average of growing-degree-days above 5°C ($GDD_{30\text{-year-average}}$) in the following form:

$$LUE_e = c + d\,(T_{Month}) + e\,(PRECIP_{Month}) - f\,(GDD_{30\text{-year-average}}) \quad (1)$$

with $R^2 = 0.4987$ ($F = 0.0489$) (Band *et al.*, 1999). For these three sites, $c = 89.32$, $d = 0.0163$, $e = 0.0015$, and $f = 0.0022$, and all coefficients were significant at the 95 percent confidence level. This relationship was based on predictions of GPP and APAR for five growing season months (May-September) for a limited number of intensively studied forested watersheds in central Ontario (Rinker Lake, Temagami, Petawawa) (Band *et al.*, 1999; Band, 2000). Further research is expected to refine the fit of this relationship and expand the extent analysis to include more sites that are representative of ecosystems in the north and south of the province.

We derived monthly NPP ($gCm^{-2}month^{-1}$) by reducing GPP by 36 percent to account for maintenance respiration (Landsberg and Waring, 1997; Band *et al.*, 1999). Annual NPP (ANPP) was calculated as the time-integrated monthly NPP during the active growing season from May to September. ANPP for 1981 is missing because the PAL dataset started in July 1981, and ANPP for 1994 was not calculated because of missing data due to sensor problems from September to December 1994.

Because variability in temporally aggregated LUE has been shown to decrease with coarse time scales (Medlyn, 1998), the monthly time step we use to predict LUE and NPP is a trade-off between choosing longer time steps to reduce variation, and the utility of having finer time steps for examining phenological changes using NPP.

Spatio-Temporal Analysis

Within each ecounit we calculated the mean and standard deviation of monthly NPP values as a simple measure of the spatial distribution of values across the ecounit. We calculated multiyear averaged ecounit normals of ANPP and monthly NPP at the three spatial scales of the ecoregionalization hierarchy (Figure 3), similar to long-term average annual precipitation and biomass (Penner *et al.*, 1997; Band *et al.*, 1999) commonly associated with ecounits for management purposes. As spatio-temporal trajectories (Henebry, 1993), these ecounit summaries characterize both the magnitude and seasonal pattern of monthly NPP, and could be combined with other ecosystem variables to create spatio-temporal signatures (Handcock, 2001). Additionally, these summaries provide a base-line for variables derived from remotely sensed data that can be compared to new data.

Because the analysis of the time series of NPP is performed on ecounits with fixed spatial scales, geographical variation (trends and local association) can also be analyzed across the hierarchy at any given time, as well as across time. Following Leach (1979), we use Kendall's (τ) correlation coefficient (Snedecor and Cochran, 1967) to evaluate the significance of trends in NPP within each ecounit at three spatial scales: ecodistrict (fine), ecoregion (medium), and ecozone (coarse) (Handcock, 2001; Handcock and Csillag, 2002).

Results and Discussion

Comparison of NPP Predictions

The main obstacle to using site data for validating landscape-level NPP predictions is that plot-resolution data cannot be used to validate heterogeneous 8-km-resolution pixels. Other difficulties include differences in measurement and reporting strategies, and the difficultly in estimating NPP from ground data. Despite these limitations, we assessed our NPP predictions using two methods. Ecodistrict averages of predicted ANPP were generally higher than measured ANPP at field locations in southern and central Ontario, and at the upper end of the range of values reported for comparable forested sites in northeastern Minnesota (Goetz and Prince, 1996). The range of our NPP predictions was also within the range of other spatially averaged NPP predictions (Goetz *et al.*, 1999), although at the upper end of the range. A detailed discussion of this validation can be found in Handcock (2001).

Some of this overestimation in NPP can be explained by the LUE_e relationship, which should be refined by running RHESSys for sites in the southern agricultural areas, as well as for the largely un-forested areas of northern Ontario. Another consideration is the use of only positive-value growing-season NPP to generate ANPP, because some months will have negative productivity as GPP shuts down but there is still a low level of maintenance respiration. This is especially true in May and October when temperatures can still be warm, or at least above freezing in some locations. While these relationships will be refined in future research, this fine-tuning would not alter the seasonal structure of the data because all of the relationships that make up the methodology are linear. For spatio-temporal analysis of vegetation dynamics, it is the relative magnitude of differences that is important, so our monthly NPP dataset is still suitable for further spatio-temporal analysis of landscape-level NPP. Because we look at how trends and other ecounit summary statistics vary across space, the absolute magnitudes of NPP values are not directly compared.

NPP and LUE_e for Ontario 1981–1996

Spatio-temporal summaries of NPP using the NEF ecoregionalization boundaries support exploratory analysis across space and time (Figures 3 through 7). Analysis of monthly 16-year aggregates of NPP and climatic variables for the growing season months (May to September) (Handcock, 2001) confirms our general understanding and expectation about controls of vegetation functioning at all scales of the ecoregionalization (Figure 3). The most northern ecozone (Hudson Plains) has lower monthly NPP values than do other ecozones; this is because of a shorter growing season, which reflects the short cool summers and the very cold winters of a cold continental climate. In the Boreal Shield ecozone of central Ontario, the ecozone average monthly NPP values are noticeably higher than in the northern ecozone, and the growing season is longer. This reflects the large areas of predominantly coniferous and mixed forest, and the warmer summers that are mitigated by the lake effect from the nearby Great Lakes. The largest values of ecozone average monthly NPP, and the longest growing season, are found in the southern Mixed Plains ecozone. This area is characterized by warm summers, abundant precipitation throughout the year, and relatively rich soil. The southern ecozone also has the most human influence in terms of urbanization and land cleared for agriculture.

At the annual time step, ecozone-averaged time-integrated NDVI (TINDVI) values share the same temporal trajectory as ANPP (Figure 4a), but, at the finer temporal scale, monthly NDVI does not correspond directly to monthly changes in NPP (Figure 4b) (Schloss *et al.*, 1999) and is relatively "flat" over the growing season compared to monthly NPP. In the autumn, for example, deciduous leaves may still be green and NDVI values relatively high, but the production efficiency of the vegetation (i.e., LUE) is decreasing, and IPAR is not equal to APAR (Asrar *et al.*, 1989). These results show the necessity of using a measure such as NPP, which has direct biophysical comparison for sub-annual analysis of vegetation dynamics.

Inter-Annual Variation

An advantage of using an ecoregionalization to examine spatio-temporal patterns is that the aggregation process encapsulates fine-scale variation in the spatial dimension of the dataset, and allows IAV in the temporal domain to be examined separately, for example, the lower than average values in 1992 ANPP due to the June 1991 eruption of Mt. Pinatubo (Figures 4a and 5f). Examination of the monthly datasets for these years (Figures 5a through 5e) shows that these lowered temperatures affected the 1992 June and July NPP values the most, with all ecozones having lower NPP (and NDVI) values for these months. ANPP for 1991 shows a peak value due to high values of NPP for the months prior to the June eruption, which highlights the utility of multitemporal datasets, rather than the snap-shot views often used in remote sensing.

IAV in the time series of NPP may be the result of natural disturbance such as fires or disease, human influences such

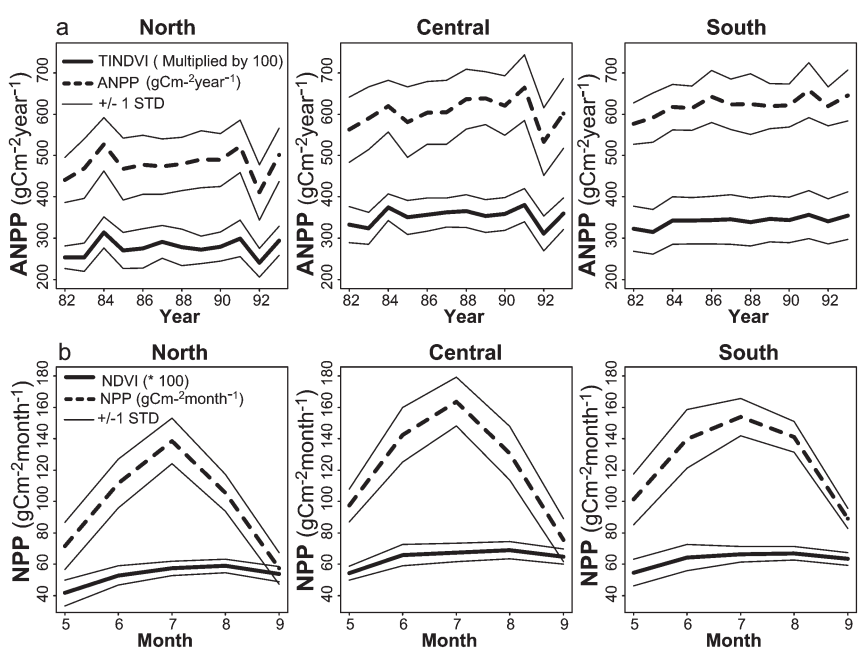

Figure 4. (a) 16-year annual NPP (ANPP) and TINDVI. (b) 16-years monthly average NPP and NDVI, aggregated across each of the three ecozones in Ontario. The standard deviation of values within each ecozone is also displayed.

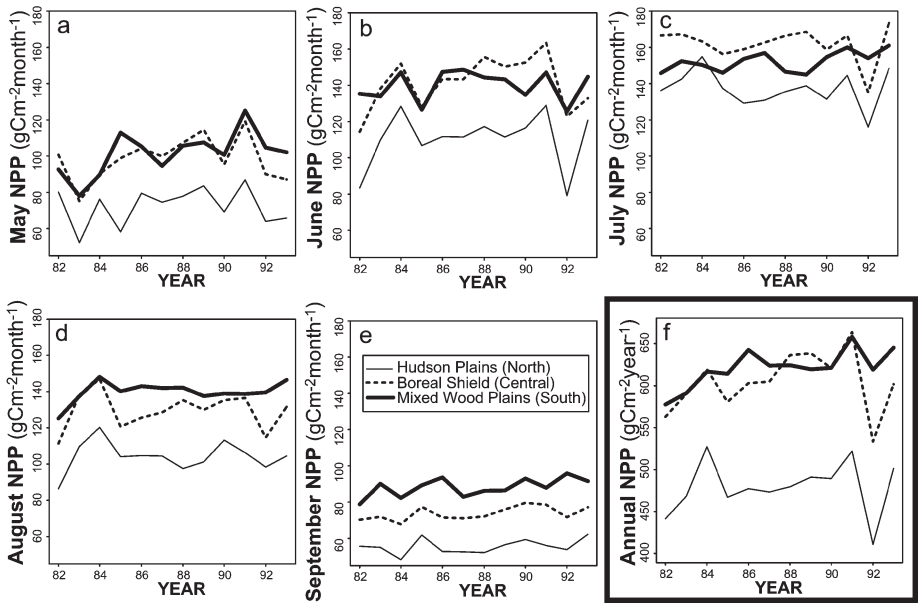

Figure 5. Temporal profiles of monthly NPP and annual NPP (ANPP), aggregated across each of the three ecozones in Ontario. IAV in values can be seen. For clarity, the standard deviation of values within each ecozone is not displayed.

as changes in agricultural practices or urban expansion, variations due to noise in both the spatial and temporal dimensions, or errors in processing and sensor effects. An advantage of using an ecoregionalization for analysis is that the quantitative and qualitative auxiliary characteristics associated with ecounits at each spatial scale, such as geo-climatic and anthropogenic variables, can be associated with the trends and IAV of NPP or other remotely sensed data within each ecounit. For example, the frequent natural fires in central Ontario are often supplemented by human induced fires, whether set for fire management purposes or the accidental or deliberate results of human expansion into the northern part of the

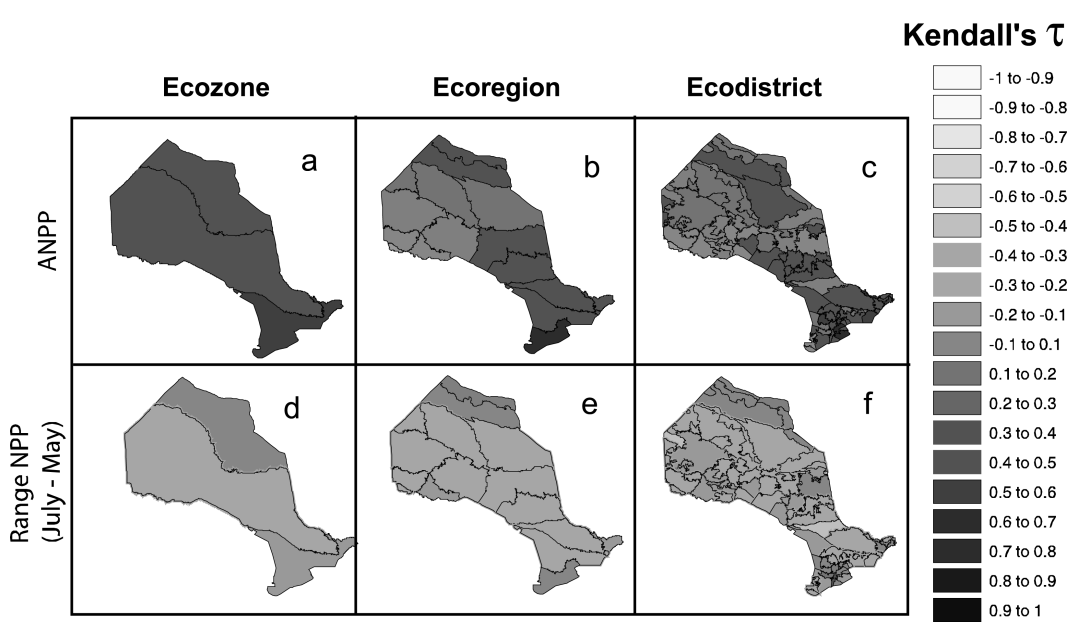

Figure 6. Sixteen-year (1981–1996) trends in ANPP across Ontario, shown at various levels of spatial aggregation: (a) three ecozones, (b) seventeen ecoregions, (c) eighty-five ecodistricts. The mapped statistic is Kendall's τ, which is used to measure the significance of the ANPP~time relationship; high positive and negative values (shown respectively as extremes of dark and light shading) denote significant increase or decrease over the 16 years.

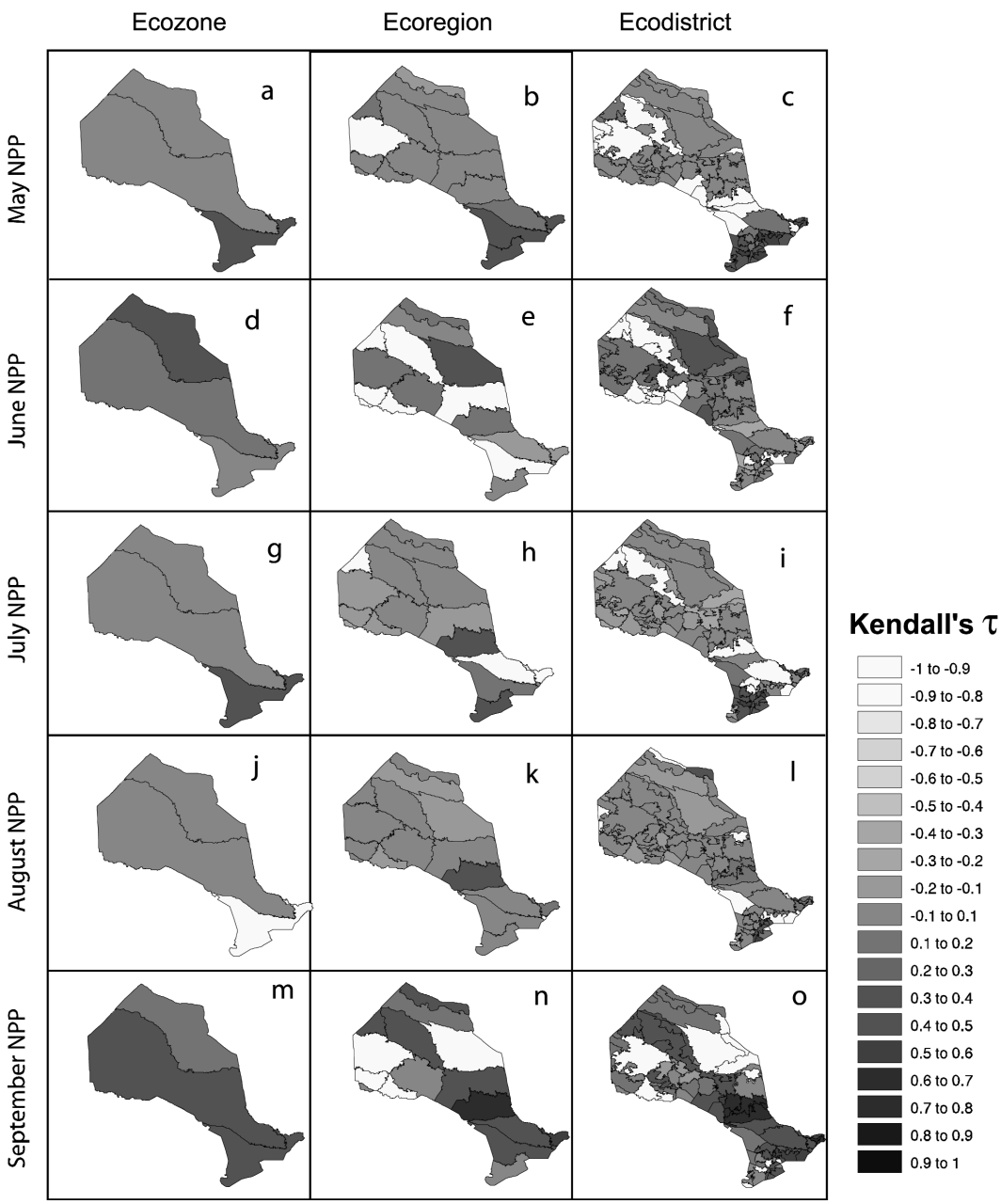

Figure 7. Sixteen-year (1981–1996) trends in monthly NPP across Ontario, shown at various levels of spatial aggregation. The mapped statistic is Kendall's τ, with the same description as Figure 6.

province. The effect of this burning persists in reduced values of the remotely sensed NPP signal. To separate out the effects of a single driver such as climate would require the extraction of the effects of these fires from the NPP signal using fire records and correlations with roads and other records of urban expansion.

The effects of disease and infestations such as spruce budworm are also common in central Ontario, with large areas of forest being defoliated in a spatially variable multiyear cycle (Candau *et al.*, 1998). Some of the variation in the time series of NPP between individual ecodistricts in the central ecozone (Figure 6c) may also be due to east-west spatial variation in this disease cycle, although the 36-year oscillation of outbreaks is only partially covered by the 16-year length of our NPP series.

Temporal Trends

Figures 6 and 7 show temporal trends in NPP within individual ecounits at the three fixed spatial scales, quantified using Kendall's (τ) correlation coefficient. ANPP for ecounits across the province displays increasing trends (Figures 6a, 6b, and 6c), and the spatial distribution of these increases varies with the spatial scale in the ecoregionalization hierarchy. At the coarsest spatial scale (Figure 6a), ANPP aggregated by ecozone is shown to be increasing everywhere, with the largest increases in the southern ecozone. At the finer scales (Figures 6a and 6c), the increases are concentrated in the northern and southern-central parts of the province.

The range in monthly NPP from July to May (Figures 6d, 6e, and 6f) is decreasing over much of the province. This captures

the pattern of monthly NPP trends (Figure 7), which are not distributed evenly through the growing season, across the province, or between spatial scales. The southern part of the province shows the largest increasing trend in May NPP and almost the entire province shows increasing values of NPP in September and June, but generally stable or decreasing values in August. These 16-year trends shows that there are different changes occurring at different times in the seasonal structure of the growing season, and that the magnitude and temporal distribution of these changes varies with the spatial scale of the ecoregionalization analysis.

Because these changes will affect different stages of the growing cycle of vegetation, such as the response to summer water stress, this could have a greater effect on the vegetation's resilience to disturbance than would a consistent trend over the year. The 16-year time period of the NPP is long enough to identify areas where change is occurring, but not to determine the cause at each spatial scale of analysis. Some of these changes may be due to medium-duration human and naturally cyclical disturbances such as the successional cycle of vegetation growth after a fire.

The seasonal variability in our observed trends, repeated across the province at the three spatial analysis scales, is in accordance with other empirical as well as modeling evidence that the impact of long-term climatic changes on net primary production are not distributed evenly over the year (Myneni *et al.*, 1997; Mitchell and Csillag, 2001).

Summary and Conclusions

We presented hierarchical tools for the analysis of multitemporal remotely sensed datasets with large spatial extent, and used these tools to examine trends and patterns in NPP at three discrete spatial scales. The use of an ecoregionalization for spatio-temporal analysis allowed fine-scale heterogeneity in the data to be controlled by aggregating across the spatial domain at partitioning scales that have direct correspondence to scales with ecological significance. We studied dynamic landscape processes by examining temporal trends within these fixed ecounit boundaries. Regional summaries were created at scales with management significance by removing IAV using temporal aggregation.

We presented a simplified approach for generating landscape-level NPP over large extents and many years, which may be extended to include a range of land-cover types not covered by this initial study. Landscape-level LUE was generated over large extents and monthly time steps using a method that integrates finer-scale spatial heterogeneity in the landscape. This approach bridges the gap between local and global studies, and allows vegetation dynamics to be assessed using a remotely sensed measure (NPP) that has a direct biophysical interpretation. Recent work with biophysical models and 1-km-resolution remotely sensed data from the MODIS sensor shows the applicability of this type of methodology to large areas and new sensors with medium spatial resolution (Running *et al.*, 1999), although the newer sensors do not have the long time series of the global PAL dataset. Clearly, further research is needed to develop relationships between site and landscape-averages predictions of NPP, and to refine the NPP methodology.

Our results show that across three spatial scales in Ontario there are distinct differences in the spatial and temporal patterns of NPP. Over our study period annual NPP was shown to be increasing, with the greatest increases being located in the southern part of the province. While all months showed some increasing trends, the magnitude of the increases was not uniform across all months in the growing season. It is significant that the magnitude and spatial distribution of these temporal trends varied with the spatial scale of the hierarchical partitioning level. These results highlight the utility of using a hierarchical ecoregionalization for analyzing spatially and temporally extensive data. Further work is needed to relate these results to driving variables that act at the equivalent spatial scales, and to extend the analysis with a longer time series of data.

Acknowledgments

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