Comparison of Single-Year and Multiyear NDVI Time Series Principal Components in Cold Temperate Biomes

Mryka Hall-Beyer

Abstract—Standardized principal components analysis (SPCA) is performed on normalized difference vegetation index (NDVI) time series of a 10° latitude by 10° longitude area of western Canada including grassland, parkland, and forest ecosystems. When used with input from a single growing season (April–October), early components correspond closely to ecoregional mapping based on long-term vegetation composition. Later components isolate areas showing agricultural practice or climatic stress particular to the year. When three years’ growing seasons are input together into a multiyear SPCA, similar patterns occur in the first component. However, components occur early in the series that discriminate areas having different seasonality patterns associated with plant phenology. Deciduous-dominated areas are well distinguished from grasslands. Multiyear SPCA includes an early component apparently related to latitudinal variation in day length, which does not appear in single-year component series. An early component unrelated to any known geographical or climatological pattern or event appears, which may relate to sensor degradation. Both single-year and multiyear SPCA isolate NDVI variability in higher numbered components that is limited in space and/or in time. This allows interpretation of transient or localized events using detailed local data, separating them from regional trends that occur in earlier (lower numbered) components of the series. These results demonstrate the possibility of refining ecoregion mapping based on selected early components to incorporate actual interannual variability for selected time periods as well as the long-term stable elements of biogeoeclimatic regions. Longer time series could potentially quantify observed unidirectional trends resulting from climate change.

Index Terms—Advanced Very High Resolution Radiometer (AVHRR), ecoregions, normalized difference vegetation index (NDVI), principal components, time series.

I. INTRODUCTION

NORMALIZED difference vegetation index (NDVI)-based time series have been used to track global vegetation dynamics, notably in Africa [8] and on the North American Great Plains [23]. Vegetation phenology is the timing of various life-cycle events of the plants in an area, one of which is the change in leaf density through seasonal cycles of warm/cold or wet/dry. In areas of natural vegetation, phenology is a useful surrogate for annual climate trends. This is true particularly in temperate climate spring when multispecies plant leaf-out responds to accumulated heat [7]. Although response is more complicated in wet/dry areas, leafout with a delay can be a surrogate for rain onset [11].

Data needed to calculate NDVI has been available for nearly two decades on a regional scale through the Advanced Very High Resolution Radiometer (AVHRR) sensors aboard National Oceanic and Atmospheric Administration (NOAA) satellites [6]. Various products have been available since the mid 1980s with pixel sizes from 16 through 1 km [14]. Since 2001, 250-m resolution red and near-infrared data have been added through the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, with a repeat cycle for temperate areas of one day.1 MODIS also includes data in blue, green, mid-infrared (500 m), and many thermal bands (1000 m). The extended wavelength capabilities of MODIS permit much improved atmospheric characterization and the preparation of many specialized land-cover products [21]. It will be extremely useful for change detection and analysis when its archive becomes long enough. Both AVHRR and MODIS data are available free of charge, greatly facilitating time series research that requires large numbers of images.

Data preprocessing techniques have varied during the life of these programs. Sensor degradation has been a problem, and correction for atmospheric interference and bidirectional effects has changed over time [4]. These facts are particularly bothersome when performing time series analysis. The short time series reported on in the present paper takes advantage of uniform processing to minimize these problems, but extension to longer series requires careful attention to them. For Canada, a six-year series (1993–1998) with improved calibration has become available [5] and will be further extended in time [1]. These data are under analysis by the author.

The primary method used to track regional phenology has been to calculate “NDVI metrics” such as the date of greenup (sudden increase of NDVI or NDVI surpassing a threshold value), date and magnitude of maximum NDVI, integrated NDVI over time, and rates of NDVI change [15], [17], [19], [23]. Metrics allow progressive greenup and dieback to be traced on a continental scale and comparisons to be made between one year and another [17], [23]. However, algorithms used to extract many of these metrics, and their interpretation, are biome-specific. For example, the onset of NDVI greenup in deciduous forests corresponds to leafout and is relatively independent of remnant snow cover under the trees, whereas evergreen forests’ apparent “greenup” in the boreal area may

really be snowmelt date [17], [22]. Grasslands present particular problems, as NDVI greenup occurs when green grass surpasses the height of standing or flat-lying dead grass. It may also be sensitive to the amount of snow cover trapped by dead grasses. These factors lead to a gradual greenness increase, which may not be detected by algorithms based on sudden changes in the slope of the NDVI versus time plot. The greenup date derived thus may reflect grassland grazing practice in different areas and not only regional climatological patterns.

Principal components analysis decorrelates multivariate data by translating and/or rotating the axes of the original feature space, so that each data point receives a value in the new component space. The first component, or new axis called PC1, is defined by the direction of greatest variance in all input data. The second, PC2, is orthogonal to it and accounts for the maximum remaining variance not accounted for by component 1. Each subsequent axis is defined in the same way. The process first computes the covariance matrix \( S \) among all input bands (in the case of time series, dates). \( S \) is symmetric and of dimensions \( k \times k \) where \( k \) is the total number of input bands. Each element of \( S \) is calculated

\[
\text{cov}_{k1,k2} = \frac{1}{nm} \sum_{i=1}^{n} \sum_{j=1}^{m} (P_{i,j,k1} - \mu_{k1})(P_{i,j,k2} - \mu_{k2})
\]

where
\( k1, k2 \) two input bands;
\( P_{i,j} \) brightness value of a pixel in row \( i \) and column \( j \);
\( n \) number of rows;
\( m \) number of columns;
\( \mu \) mean of all pixel values in the subscripted input band.

\( U \) is defined as an orthogonal matrix that diagonalizes \( S \), such that the diagonal elements are by in descending order, fixing the order of columns in \( U \). In other words computing \( U'SU \) results in a diagonal similar to \( S \), whose diagonal elements are eigenvalues (\( \lambda_i \)) of \( S \). The columns of \( U \) (\( U_i \)) are eigenvectors of \( S \). The percent of total dataset variance explained by each component \( i \) is [13]

\[
\%_i = \frac{100 \times \lambda_i}{\sum_{i=1}^{k} \lambda_i}
\]

A value is calculated for each pixel to produce a series of image layers, called “eigenchannels” or “components,” by multiplying the eigenvector for that component by the vector of original pixel values in the input bands

\[
P_i = \sum_{k=1}^{n} U_{ik} P_k
\]

where
\( P_i \) indicates a brightness value in component \( i \);
\( U_{ik} \) eigenvector element for component \( i \) in input band \( k \);
\( P_k \) brightness value in band \( k \);
\( n \) number of input bands [13], [16].

A loading, or correlation \( R \) of each component \( i \) with each input band \( k \) can be calculated

\[
R_{ki} = \frac{u_{ki} \sqrt{\lambda_i}}{\sqrt{\text{var}_k}}
\]

where \( \text{var}_k \) is the variance of input band \( k \) (obtained by reading the \( j \)th diagonal of the covariance matrix) [13].

If the eigenvalues and eigenvectors are computed from the correlation matrix rather than the covariance matrix, the loadings are simply the \( u_{ki} \) values.

PCA can be used to reduce dimensionality of the dataset. Because of the way they are selected, each successive component contains less of the total dataset variance. Usually, later components will contain information that is essentially noise with respect to the phenomenon analyzed, and so can be disregarded. However, in time series PCA as in multispectral PCA, it is always possible that some later component, containing a very low proportion of total dataset variance, might represent informational variance for a small area.

Principal components analysis of NDVI time series provides an alternative to NDVI metrics for tracking vegetation response to climate variability and to changes in agricultural practice such as irrigation. Since eigenvectors are extracted from the series itself and have no universal meaning, each series must be interpreted through a combination of geographical knowledge, climatological data, and loadings. Nevertheless, common patterns occur in different time series for the same area. Individual components early in the series correspond to pervasive and durable geographic differences and temporal variability, whereas those occurring later in the series highlight variability more limited in space and/or time. Noise elements such as long-duration cloud events or sensor and processing problems are likely to be isolated in their own components, and so may be more easily separated from the desired signal.

This paper examines the first three components and the geographic pattern of component values, when computing SPCA for single-year growing seasons. These were compared with the first six components resulting from a single analysis including three growing seasons. The data for Alberta covers 11° of latitude and over 4000 m of elevation, and includes ecotones between grasslands, deciduous, mixed, and coniferous forest, and the eastern ranges of the Rocky Mountains. Fig. 1 shows a simplified version of the mapped ecoregions for Alberta and will be used for comparison with all time series results.

The years 1992, 1993, and 1995 were used, thus including the unusual 1992 pattern caused by climatic variation associated with both a strong El Niño event and with volcanic upper atmosphere dust. The global 1-km dataset did not produce images for 1994 because of platform orbit degradation leading to very large viewing angles for many pixels and the resulting difficulties in applying standardized calibration procedures. Corrections for this problem are becoming available, so that 1994 is included in some time series datasets now being produced for specific areas [1].
II. METHODS

A. Data

One-kilometer resolution NDVI AVHRR datasets were acquired over the western Canadian prairies (latitudes 49 to 60 N, longitudes 110 to 120 W) for 1992, 1993, and 1995 (Fig. 2). The images were processed by the EROS Data Center and are freely available to researchers.\footnote{See http://edcwww.cr.usgs.gov/landdaac/1KM/comp10d.html.}

The images were composited at ten-day intervals; compositing selects individual pixels for the largest NDVI over each period. This eliminates most clouds and biases in favor of pixels closer to sensor nadir. Further processing provided partial correction of bidirectional effects and atmospheric scattering [9], [24].

B. Principal Components

Unlike the most common technique for deriving components of multispectral datasets, extraction of eigenvectors for time series commonly is based on the correlation matrix (“standardized” or SPCA), rather than the covariance matrix. SPCA eliminates heavy weighting of summer images caused by their inherently much larger dynamic range [8]. Because of this, SPCA allows interseasonal variability and short-term fluctuations to be readily visible in the resulting images. However, the PCI software used is based on the covariance matrix [18]. Therefore, before processing the pixel values in each input band were transformed into z scores [8]. Eigenvectors were calculated for all 16 (1993) or 18 (1992 and 1995) or 52 (multiyear) potential image components. Output images were prepared for the first six (single-year) and 12 (multiyear) components. Loadings were calculated for each output component.

SPCA was performed using images from early April (still in the dormant season) through late September (leaf senescence for almost all species). The same dates were used for all years with the exception of September 11–20 and 21–30, 1993, which had extensive areas of visible anomalies. Plants are dormant and usually snow covered during the October–March period. Winter images at these latitudes suffer from very low light, but in these climates are not necessary to interpret vegetation dynamics.

III. RESULTS AND INTERPRETATION

A. Single-Year SPCA

The years 1992, 1993, and 1995 are appropriate for comparing single-year time series. The year 1992 was a strong El Niño year, and weather records show a very early spring warming. However, unusually cold weather occurred later in the growing season, as the result of atmospheric ash from the eruption of Mount Pinatubo in summer 1991 [2], 1993 did not deviate significantly from long-term normal. The year 1995 also followed an El Niño event, less intense than in 1991 and 1992; however, Alberta in 1995 was slightly cooler and dryer than 1961–1980 normal [2]. The presence or absence of El Niño has been shown to affect the growing season and precipitation on the Canadian prairies [3].

SPCA was performed separately for each of the three years. Each component was interpreted using a combination of loadings for each date and geographic pattern.

Fig. 3 shows the loadings for 1993 and 1995. They perform similarly, with high correlation between component 1 and all dates; the 1992 spring exception to this is discussed below.

High component 1 pixel values correspond to areas with the maximum integrated yearly vegetation density, grading to low values in areas of permanent nonvegetated cover such as the exposed rock on high mountains in the southwest. Fig. 4 illustrates this geographical pattern for component 1, using the 1995 image as an example. The legend for Fig. 4 serves for all other images. Colors are not associated with particular values, but rather illustrate the gradation between minimum and maximum for each individual image. The other years are similar. PC1 patterns are those expected from ecoregion mapping, which is based on long-term stable climate and topography (compare Fig. 1). Highest component 1 values are in central and northern forested areas, where little land has been converted to agriculture. Slightly lower values occur over
less dense forest, in northern areas (especially in the Porcupine Hills, the ovoid structure at center extreme north) and at higher elevation in the southwest. There is little distinction between primarily deciduous and primarily coniferous forest. PC1 values become lower still where forest is sporadic and where much land has been converted to annual crops, in the south central area (parkland). Lowest values occur in the high mountains along the southwest border, and in dry grasslands of the south and east. Some extensively irrigated districts in this area have a contrastingly higher value.

Loadings for 1992 are anomalous, showing low correlation with spring dates. The first component shows a similar geographical pattern, (Fig. 5), but it is derived only from summer and fall vegetation density. Spring values do not follow this variance pattern.

The main element loaded into component 2 is the contrast between spring and summer NDVI values. Fig. 6 illustrates 1995; it shows high pixel values in mainly deciduous forest or in predominantly annual crop areas where bare ground in spring and fall contrasts to uniform vegetation in summer. Coniferous forests are intermediate, and grasslands low. The date of loadings transition from positive to negative corresponds to general deciduous leafout, which varies surprisingly little over the latitudinal range of the area.

Once again, PC2 for 1992 (Fig. 7) is different, picking up the anomalous spring behavior that was missing from PC1. What is shown in PC2 in the other years, occurs in PC3 in 1992. Bright 1992 PC2 pixels are those with particularly high NDVI values in spring: an early spring related to El Nino and confirmed by weather records [2]. The spatial pattern shows a marked greening of the northern areas, the Athabasca River valley cutting diagonally across the northwest. There is some early greening in the southern grassland, but little effect in the dark band of the central mixedwood area.

Components 3 and later for “normal” years, and PC4 and later for 1992, are more date specific (loadings Fig. 2; images not illustrated). They capture the contrast between certain dates and
those values that are more stable over the long term. The loaded
dates include unseasonable snow cover or cloud cover of un-
usual duration or short-term drought. As such they are of par-
ticular interest for local applications, particularly in forestry and
agriculture.

The following sums up single-year SPCA.

- Early components allow the definition of areas whose veg-
etation development behaves similarly. This corresponds
to biome (ecoregion) or, to some extent, to land use.
- Later components single out areas that deviate from the re-
gional value either in magnitude of greenness or in timing
of events.
- A widespread climatic anomaly is isolated into a particular
component.

B. Multiyear SPCA

Widespread anomalous events occurring in a single year will
contribute significantly to the total variance occurring over sev-
eral years. Since they are likely to have a unique location in mul-
titemporal feature space, they are expected to be isolated in in-
dividual components.

PC1 images and loadings are shown in Fig. 8. As in
single-year analysis, PC1, accounting for 81% of total dataset
variance, correlates strongly with all dates across all years,

Multiyear PC2, unlike single-year PC2, does not represent
seasonality. Instead its bright areas show where there is a great
deal of contrast between two groups of dates: all of 1993 plus
spring 1995 on the one hand, and the rest of the dates on the
other. This occurs over much of the Province, with the excep-
tion of dry grasslands of the southeast. No natural phenomenon
has been found that would account for this type of variance, ac-
counting for 6.6% of total dataset variance. Instrumental vari-
ation is being investigated as an explanation. The omission of
the two 1993 September images would not readily explain this
pattern.

Fig. 9 shows data for PC3 (3.6% of dataset variance) and PC4
(1.4%). PC3 represents the intensity of seasonality, i.e., con-
trast between summer and other seasons, which was expected
to show up in PC2 [8]. Loadings alternate between positive for
spring and fall and negative for summer. The crossover between
positive and negative varies somewhat with the year, and is as-
sociated with particular climatic conditions. Note especially the
rise to positive in early August 1995, corresponding to a no-
toriously cool and wet August in that year. This caused early
plant maturation [2]. Brightest pixels, meaning areas of max-
imum contrast between summer and spring/fall, occur in the
central mixed-wood and in the foothills regions, which are cov-
ered with similar vegetation. These represent areas of Alberta
with a high proportion of deciduous forests.

It is somewhat surprising to see a zone within the southeastern
grasslands that is moderately bright in PC3, even though this
area is devoted more to pasture than to the annual crops; the
latter might be expected to show greater seasonal contrast. Iri-
rigated areas show low values in PC3. PC3 can, thus, be inter-
preted as isolating the scene variance due primarily to deciduous
leafout and senescence, rather than to seasonality in general.

PC4 loadings are highly erratic and the geographic pattern
shows mainly latitudinal variation with no evidence of topo-
graphic or biome influence. It is interpreted as showing variance
due to sun angle differences across the image. It was expected
that some components would effectively isolate noise as far as
vegetation patterns are concerned. PC4 is the first of these components to appear.

PC5 (0.9% of variance) and PC6 (0.7%) loadings (Fig. 10) both exhibit seasonal cycling, with a slightly different periodicity than PC3. Within anomalous 1992, PC5 records a strong contrast between the warm April and the cold later spring. Geographically, bright areas occur in the central mixedwood zone as for PC3, but also in the central mountains and the high elevation western grasslands, which showed little contrast in PC3. These areas exhibit the greatest seasonal advance in spring 1992 followed by greatest effects of the cold snap.

PC6 is bright primarily in high elevation areas, plus the driest southeastern grasslands. Loadings show seasonal periodicity, but with crossovers from positive to negative loading in mid August and late June. PC6, thus, highlights areas with a short growing season. In the grasslands, this “late” spring season relates to the late appearance of green material above the dead grass litter. The “early” fall means the senescence of grass in response to the normal end of the rainy season in July.

Components beyond PC6 were examined, and primarily show events localized in time and/or space. Detailed analysis would rely on local data, not feasible in this regional synthesis. However, later components may isolate small regions meriting such close scrutiny when attempting to track localized weather or crop anomalies such as insect infestation. They have the potential to even show political and economic events’ influence on vegetation, e.g., changes in irrigation allocations to agriculture.

The following sums up multiyear SPCA.

- Component 1 allows the definition of areas whose vegetation defines a single biome or ecoregion. This is no different from single-year PC1.
- Later components single out areas that have in common a particular pattern of seasonality. Areas with common timing of greenup and senescence appear together in a single component, whereas those dominated by different timing appear in a different component. The order of each seasonality component in the sequence depends on the areal extent of its influence. Causes of this timing difference may be degree of dominance by deciduous trees or by grasses and elevation differences. This information is not available from single-year SPCA.
- Components appear early in the sequence that relate to interyear contrast or to sun angle variation. These are not apparent in single-year analysis. They constitute noise for most purposes of vegetation interpretation and, thus, may be used to remove potentially confusing data from analysis.
- Later components relate to vegetation events limited in time and/or space, that must be interpreted using detailed local knowledge. This is the same as later single-year components.

IV. DISCUSSION

A drawback of SPCA is that eigenvectors are derived exclusively from the input data. It is, therefore, impossible to assert that a given component in the sequence will be interpretable in the same way from one year to the next or from one geographical area to the next. The anomalous 1992 single-year data demonstrated this. Multiyear SPCA has the potential to lessen the impact of this factor, since particular anomalies will tend to be isolated in individual components. Also, a multiyear image is less likely to be compared with an image of another time period since all times under consideration would be considered in a single analysis. The primary drawback with multiyear SPCA is the requirement that it include a very large number of input dates (variables). This demands a large amount of computing power or time, and in some operational software may result in algorithm instability [18]. This can be partially offset by using fewer images per year, as has been done for the tropics [8]. For higher latitudes, using fewer images risks eliminating vegetation events that are compressed into short time periods.

Data clustering (unsupervised classification) techniques also yield a geographical pattern related to ecoregions [10]. However, it has the same dependence on input data as does SPCA, without having SPCA’s ability to separate noise from signal. In addition, SPCA provides much more information on individual elements contributing to the geographical pattern observed.

These considerations point out the need for ongoing research into cyclicity analysis that is less dependent on the idiosyncrasies of the input data. Other approaches such as Fourier analysis are ongoing [12].

Time series of cyclical processes allow interpretation of not only broad regional patterns but also of temporal anomalies. The present work has demonstrated that, at a 1-km resolution, a detailed landscape pattern emerges that closely resembles existing ecoregion mapping. The ecotones separating mapped ecoregions are particularly sensitive to perturbation, and their position and extent may well vary from year to year. This variability would not be apparent when mapping ecoregions relying only on long-term averages and “climax” vegetation. With imagery, it is also possible to discern isolated areas within ecoregion core areas that behave markedly differently from their surroundings. The potential exists to follow these from year to year to see if they are indeed consistently different, and if so to figure out why.

Thus, image time series analysis permits fine tuning of both the definition of ecoregions and mapping their boundaries. In
conventional mapping these are highly generalized and based on few field sampling points. Potentially, early time series components could allow introduction of a temporal element into ecoregion definition. For example, it might be feasible to separately map areas showing quantifiable degrees of interannual variability. Under climate change scenarios, this could be important for agricultural and water policy, and designation of protected areas and corridors to preserve biodiversity. The present study only indicates that this is a possibility, that the components do indeed correspond to expectations. Implementation would require inclusion of more years and development of definitions.

The interpretation must be carried out with a high degree of knowledge of the region being interpreted. This study includes a number of biomes, and demonstrates that the principles and interpretation hold true across them. Nonetheless, this entire area may be characterized as cold-temperate continental. Results remain to be demonstrated for subtropical, tropical, and maritime regions.

The research reported here uses only three years’ data, mainly to avoid image calibration problems. If these problems, and those posed by large numbers of input dates, are solved, a much longer time sequence can be analyzed. Inclusion of a longer time sequence can be expected to yield additional components having to do with areas subject to unidirectional changes such as climate change or agricultural change.

V. Conclusion

Principal components analysis of NDVI time series provides a way to map geographical variation of cyclical vegetation behavior. The most prominent variation, spatially and temporally, is related to elements of long-term interregional differences. These, in turn, are related to variables associated with ecoregion mapping at the subcontinental scale. In an area including the grassland–forest transition, later components highlight 1) seasonality and 2) differences between years that are caused by large-area influences such as climatic anomalies. Still later components indicate small-area or shorter duration anomalies. Interpretation of broad trends is not hampered by the problems of curve smoothing inherent in NDVI metrics, since principal components isolate short-term anomalies into separate components. Inclusion of several years in the time series allows tracing of interyear contrasts. The judicious selection of components may provide a means of mapping ecoregional boundaries based on dynamic as well as long-term factors.

REFERENCES

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Since 1996, she has been an Assistant Professor of geography at the University of Calgary, Calgary, AB, Canada. She teaches undergraduate courses in physical geography, cartography, remote sensing, and biogeography and is involved in both teaching and mentoring students in the MGIS program. She is undergraduate advisor for the Department of Geography and is an active participant in attracting young people, particularly young women, to geography. Her research focuses on understanding large-area vegetation cycle dynamics using time series of low-resolution satellite imagery. She also works extensively on developing image classification techniques in the service of habitat mapping and environmental impact analysis. A major research concern is developing course material at an advanced level in digital image processing, and she is also active in interpreting remote sensing capabilities to experts in other domains who need to use satellite data. She has had a varied 30-year teaching career, instructing elementary outdoor education, high school earth science, physics, and mathematics; community college geography, geology, and statistics; and undergraduate and graduate remote sensing, cartography, and biogeography. She has participated in teacher training in Remote Sensing through the Canadian Council for Geographic Education and the GLOBE project. While employed by for Canada’s National Museums and Parks Canada, she developed exhibits and provided staff training internally and for other organizations involved in natural history interpretation. Recently, she has adapted several advanced undergraduate courses for “paper-free” online delivery using WebCT and has worked with a graduate student to prepare ArcView tutorials for nonexperts.

Dr. Hall-Beyer is a Board Member of several professional organizations, including the Alberta Geomatics Group (an industry association) and the Alberta Native Plant Council. She has served as Technical Co-Chair of the Canadian Remote Sensing Society annual conference in 1998.