A global framework for monitoring phenological responses to climate change

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[1] Remote sensing of vegetation phenology is an important method with which to monitor terrestrial responses to climate change, but most approaches include signals from multiple forcings, such as mixed phenological signals from multiple biomes, urbanization, political changes, shifts in agricultural practices, and disturbances. Consequently, it is difficult to extract a clear signal from the usually assumed forcing: climate change. Here, using global 8 km 1982 to 1999 Normalized Difference Vegetation Index (NDVI) data and an eight-element monthly climatology, we identified pixels whose wavelet power spectrum was consistently dominated by annual cycles and then created phenologically and climatically self-similar clusters, which we term phenoregions. We then ranked and screened each phenoregion as a function of landcover homogeneity and consistency, evidence of human impacts, and political diversity. Remaining phenoregions represented areas with a minimized probability of non-climatic forcings and form elemental units for long-term phenological monitoring.
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1. Introduction

[2] Vegetation phenology, the study of the timing of recurring vegetation cycles such as canopy emergence and senescence, is an emerging field of climate change science. Yet many ground-based and modeling studies are biased towards biomes (deciduous broadleaf forest) and regions (western Europe) that, from a global perspective, are nearly irrelevant. Additionally, in remote sensing studies focusing on global patterns, observed trends are subject to multiple and often unknown non-climatic forcings and technical problems.

[3] In spite of these difficulties, there is a clear need for continued phenological monitoring. Observational [*Menzel et al.*, 2001], modeling [*Schwartz and Reiter*, 2000], and remote sensing evidence [*Bogaert et al.*, 2002; *Myneni et al.*, 1997; *Slayback et al.*, 2003; *Zhou et al.*, 2001] suggests that vegetation phenology is changing in response to warming climates, principally through an earlier start of season (SOS) and later end of season (EOS). Through these types of studies, vegetation phenology can be used as a sensitive barometer of terrestrial responses to short- and long-term climate variability.

[4] Climate change usually is assumed to be the primary forcing of trends or turning points in SOS and/or EOS timeseries; while this may be true in many cases, especially when analyzed over large regions [*Zhou et al.*, 2003], a variety of factors may influence observed trends. Non-climatic forcings of observed shifts in vegetation phenology include urbanization [*White et al.*, 2002; *Zhang et al.*, 2004], the collapse of political systems [*de Beurs and Henebry*, 2004a], and disturbances. Further, while independent lines of evidence tend to show similar overall trends, geographically coincident data are often weakly correlated [*Badeck et al.*, 2004; *Schwartz et al.*, 2002], complicating attempts to extract a clear vegetative signal from potentially confounding factors (variation in soil wetness, trends in snow cover, degradation of remote sensing platforms, variable within-pixel phenological trends).

[5] In response to the need for a monitoring strategy that targets climate change impacts and provides geographical units for trend attribution and fine resolution remote sensing studies, we propose the use of a limited number of phenologically and climatically self-similar clusters. There are four central features of our proposed strategy: (1) identification of pixels with a strong annual cycle; (2) creation of clusters with similar vegetation phenology and climate; (3) removal of clusters dominated by human-related landcover; (4) selection of remaining clusters with homogeneous landcover, low evidence of human impacts, and low diversity of political units. This approach, which identifies clusters of pixels with an easily identifiable seasonal signal, is designed to maximize the potential for detecting climate forcings while minimizing the influence of landcover, human, and political influences. As such, these identified phenoregions can form the basis for a global phenological monitoring network.

2. Definition of Elemental Clusters

[6] We obtained the 1982–1999 (1994 not used because of sensor failure) 10-day composite 8-km Pathfinder Advanced Very High Resolution Radiometer Land (PAL) Normalized Difference Vegetation Index (NDVI) dataset. The PAL dataset contains extensive artifacts related to within- and among-sensor calibration, volcanic eruptions, and water vapor. Post-corrected datasets exist [*Nemani et al.*, 2003], but by intentionally selecting the PAL dataset, we implemented an extremely conservative approach: only

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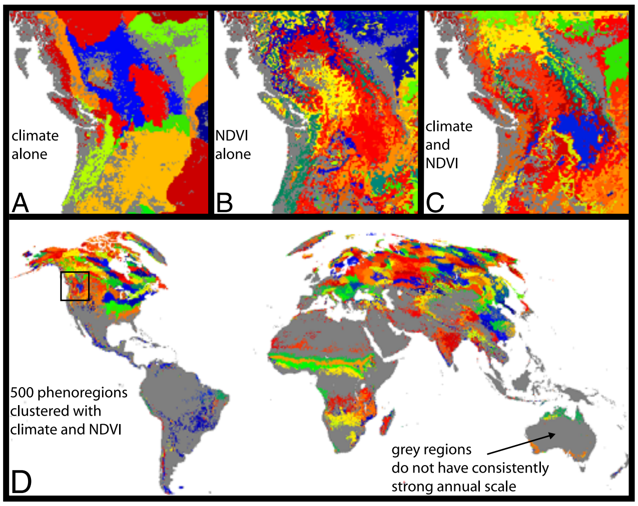

Figure 1. Generation of the 500 phenoregions. Examples based on: (a) eight-element climate alone; (b) NDVI alone; and (c) climate + NDVI, which captured overall climate and vegetation dynamics without creating large numbers of sparsely represented clusters. In (d) the global climate + NDVI phenoregion map (colored randomly using a repeating color table) used in the remainder of the analysis, areas for which the dominant NDVI time scale is not annual are shown with light grey shading (deserts, barren, shrublands, and moist tropical forests).

those pixels whose annual cycle is stronger than the inherent PAL noise passed our initial filter (next section). Use of PAL data is most problematic when assessing trends [*de Beurs and Henebry*, 2004b], which we do not present here.

[7] Next, we conducted a continuous wavelet transformation [*Torrence and Compo*, 1998] of the 612-element NDVI timeseries for each pixel. We calculated annual time-averaged local wavelet spectra and identified pixels in which the annual time scale was dominant in at least 15 of 17 possible years. This step identified the 1,012,866 pixels for which the annual scale was consistently strong and therefore tractable for coarse resolution phenology monitoring. Nearly all arid shrublands, deserts, and moist tropical forests were eliminated (Figure 1; please see online supporting material for discussion on the use of PAL data[1]).

[8] We then used an iterative k-means clustering approach [*Hargrove and Hoffman*, 2005] of the PAL NDVI and an eight-element global 1961 to 1990 10′ monthly climatology [*New et al.*, 2002] reprojected to the 8 km PAL Goode's Interrupted Homolosine projection to identify the groups of pixels forming the elemental monitoring units. The clustering approach, performed on an Oak Ridge National Laboratory parallel supercomputer, generated n initial cluster centroids spaced evenly in the 708-axis hyperspace (all data were normalized to a mean of zero and a unit variance, individually by axis). Each pixel was then assigned to the centroid with the nearest Euclidian distance. Mean centroid locations were recalculated based on the assigned pixels and the process was repeated until less than 0.05% of pixels were reassigned. Although techniques exist to reduce the dimensionality of clustering inputs, the inclusion of correlated axes does not strongly affect final grouping. Given that sets of axes without perfect correlation (as will occur with landcover changes or disturbances) can add discriminatory information and that axes used here represent either a climate descriptor or NDVI at a particular date, we chose to retain all axes.

[9] We experimented with a range of clusters from 10 to 1000 and found that 500 clusters provided an optimal separation such that clusters tended to exist on only one continent and the distribution did not contain a high frequency of minimally represented clusters. We created three clusterings: (1) climate alone, (2) NDVI alone; and (3) climate and NDVI. Climate alone produced large homogeneous clusters (Figure 1a); NDVI alone produced large numbers of clusters with only one or a few pixels (Figure 1b); NDVI and climate provided good representation of distinctions in landcover and topography without creation of numerous sparse clusters (Figure 1c). We adopted use of the NDVI and climate clusters (Figure 1d), which we term phenoregions. The phenoregions capture well-known vegetation features, such as precipitation gradients in Sahelian Africa, the mesic periphery of Australia, and extensive crop-dominated regions of the Midwestern United States. Use of the PAL data will tend to create phenoregions with similar satellite contamination, a useful characteristic for assessing long-term trend attribution between corrected and uncorrected NDVI datasets.

3. Selection of Clusters

[10] At this stage, the 500 climatically and phenologically self-similar phenoregions represented groups of pixels appropriate for the formation of spatially composited timeseries. We then used a four-step process to identify phenoregions, by landcover, with characteristics likely to maximize their utility for climate-response monitoring.

[11] First, to minimize the incidence of sparse clusters and consequent potential for georegistration/georectification difficulties, we removed all clusters with fewer than 100 pixels. Second, we removed clusters if the categorical landcover [*DeFries et al.*, 1998] with the highest percent cover was crop, barren, or urban, all of which are likely to be responsive to non-climatic forcings. Third, we implemented a ranking system designed to represent quantitatively the suitability of the remaining 211 clusters for climate-response monitoring. Simply, the abundance of the dominant landcover and consistent information from a vegetation continuous fields product increased rankings whereas cropland, barren, or urban landcovers, evidence of human impacts, and political diversity reduced rankings. See Table 1 for details. Fourth, we used elements of the same ranking system in a filter to eliminate clusters with low scores in one or more categories.

[12] The remaining 136 phenoregions existed almost exclusively in mid to high latitudes of North America and Eurasia (Figure 2). In this final selection, the dominant biomes were evergreen needleleaf forest and woodlands. Grasslands, mixed forests, and deciduous needleleaf forests were well represented whereas evergreen broadleaf forests, deciduous broadleaf forests, and wooded grasslands were sparse. The selected evergreen broadleaf forest phenore-

[1]Auxiliary material is available at ftp://ftp.agu.org/apend/gl/2004GL021961.

Table 1. Ranking and Screening of Phenoregions[a]

Variable	Ranking Impact	Cluster Acceptable If
pixels	NA	>100
dominant landcover[b]	NA	Not crop, urban, or barren
percent dominant landcover[b]	+	>30%
percent urban + crop + barren[b]	-	<30%
mean percent bare cover[c]	-	<30%
mean percent tree cover[c]	+ for forests	forests >30% 10% > woodland < 60% 10% > wooded grassland < 40%
mean percent herbaceous cover[c]	+ for grassland	grasslands >40% woodlands >20% wooded grasslands >40%
mean human footprint[d]	-	<30
political diversity[e]	-	<50

[a]For ranking, variables were calculated or averaged for the phenoregion and added (+) or subtracted (−). Note that for woodlands and wooded grasslands, the vegetation continuous fields were not used. All rankings were scaled from 0 to 100. Clusters were accepted as a valid phenoregions if the listed conditions were met. Acceptability criteria are not absolute; users are encouraged to develop customized screenings using the archived supporting materials (M. A. White et al., Phenoregions for monitoring vegetation responses to climate change, available at http://www.daac.ornl.gov, 2004). All data existed or were reprojected to the 8 km global Goode's Homolosine projection.

[b]Categorical landcover [*DeFries et al.*, 1998] with the highest percent cover.

[c]From vegetation continuous fields product [*Hansen et al.*, 2003].

[d]Based on population, land transformation, accessibility, and stable electrical light sources [*Sanderson et al.*, 2002]. Dimensionless from 0 (no human footprint) to 100 (highest possible human footprint).

[e]Based on Center for International Earth Science Information Network (Gridded population of the world (GPW), version 2, 2000, available at http://sedac.ciesin.columbia.edu/plue/gpw) and Simpson's diversity index [*Simpson*, 1949]. Ranges from 0 (phenoregion contains only one country) to 100 (infinite number of countries).

gions existed in seasonally dry regions; no equatorial moist tropical forest was selected. No arid shrublands were selected. Given that much of the NDVI amplitude in northern forests is related to annual snow cover patterns, monitoring in these abundant phenoregions should focus on trend attribution to snow versus vegetation dynamics. This decoupling of low canopy amplitude in many boreal forests from a strong snowmelt signal is challenging with AVHRR records and should be a focus of future ground campaigns linked to multi-resolution remote sensing.

[13] With the exception of a phenoregion in southeastern Madagascar (barely visible in Figure 2), Africa was removed, usually as a result of high political diversity within the longitudinally extensive phenoregions. Small dry evergreen broadleaf forest phenoregions existed in South America but the continent, in general, did not pass our screening criteria. The single wooded grassland phenoregion spanned nearly the entirety of northern Australia. The deciduous broadleaf forest and western European regions were minimally represented.

[14] Our approach, which is designed only to select optimal regions, not to represent the possible distribution of biome/climate combinations, strongly suggests that a limited region of the globe is suitable for climate response monitoring with coarse resolution sensors. Other regions, especially those dominated by precipitation variability, are also likely to be highly responsive to climate change and are not included here. For these critical regions in which coarse

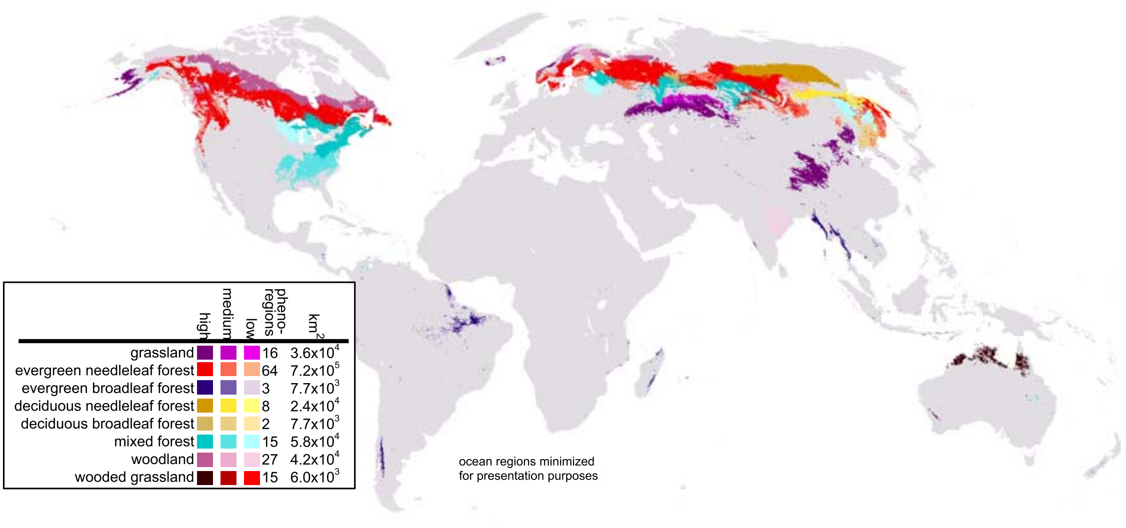

Figure 2. Selection of monitoring phenoregions. Phenoregions with fewer than 100 pixels or dominated by crop, urban or barren landcover removed. Remaining phenoregions are those passing the screening factors in Table 1 and are shown with normalized rankings by landcover.

resolution monitoring is not optimal or in which other factors are likely to confound results, we advocate the use of finer resolution sensors and ground observations coupled with landcover and landuse histories, and the comparison of protected and non-protected regions.

4. Conclusions

[15] We submit that our strategy is an appropriate method with which to identify clusters of pixels with self-similar climate and phenology and to prioritize the collection of ground-based validation data. Within these phenoregions, the possible influence of mixed phenological signals, urbanization, human infrastructure, shifts in cropping practices, and variation in politically controlled land management is minimized. Critically, the strategy provides a quantitative method with which to focus global phenological studies on a limited number of regions that are most likely to respond to the presumed forcing: climate change. If phenological trends or shifts are detected, the phenoregions are the geographical unit within which finite resources for finer resolution remote sensing should be allocated.

[16] We have designed a conservative approach to select regions with a maximal probability of displaying a climate response signal. Further stratification could be accomplished based on climatic zonations. For other applications, selection of crop- or urban-dominated phenoregions may be desired. To accommodate these and other needs, users may obtain the 500-phenoregion image (Figure 1), the selected phenoregion image (Figure 2), and related ancillary information (see data set by M. A. White et al., Phenoregions for monitoring vegetation responses to climate change, available at http://www.daac.ornl.gov, 2004).

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