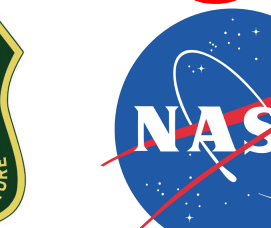


A Statistical Methodology for Detecting and Monitoring Change in Forest Ecosystems Using Remotely Sensed Imagery



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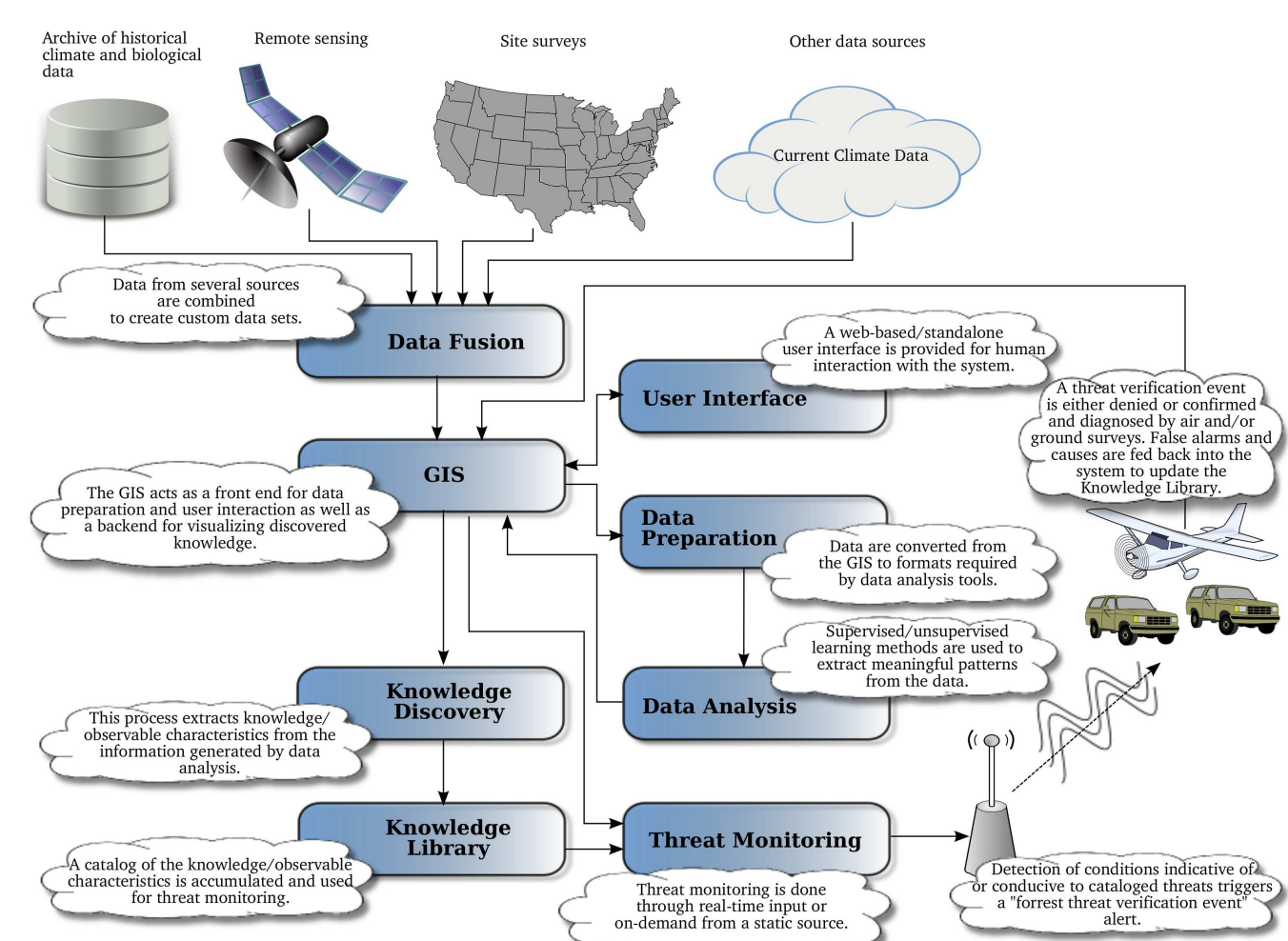
Introduction

The USDA Forest Service, NASA Stennis Space Center, and DOE Oak Ridge National Laboratory are creating a system to monitor threats to U.S. forests and wildlands at two different scales:

Tier 1: Strategic — An Early Warning System (EWS) that routinely monitors wide areas at coarser resolution, repeated frequently — a *change detection system* to produce alerts or warnings for particular locations that may be of interest.

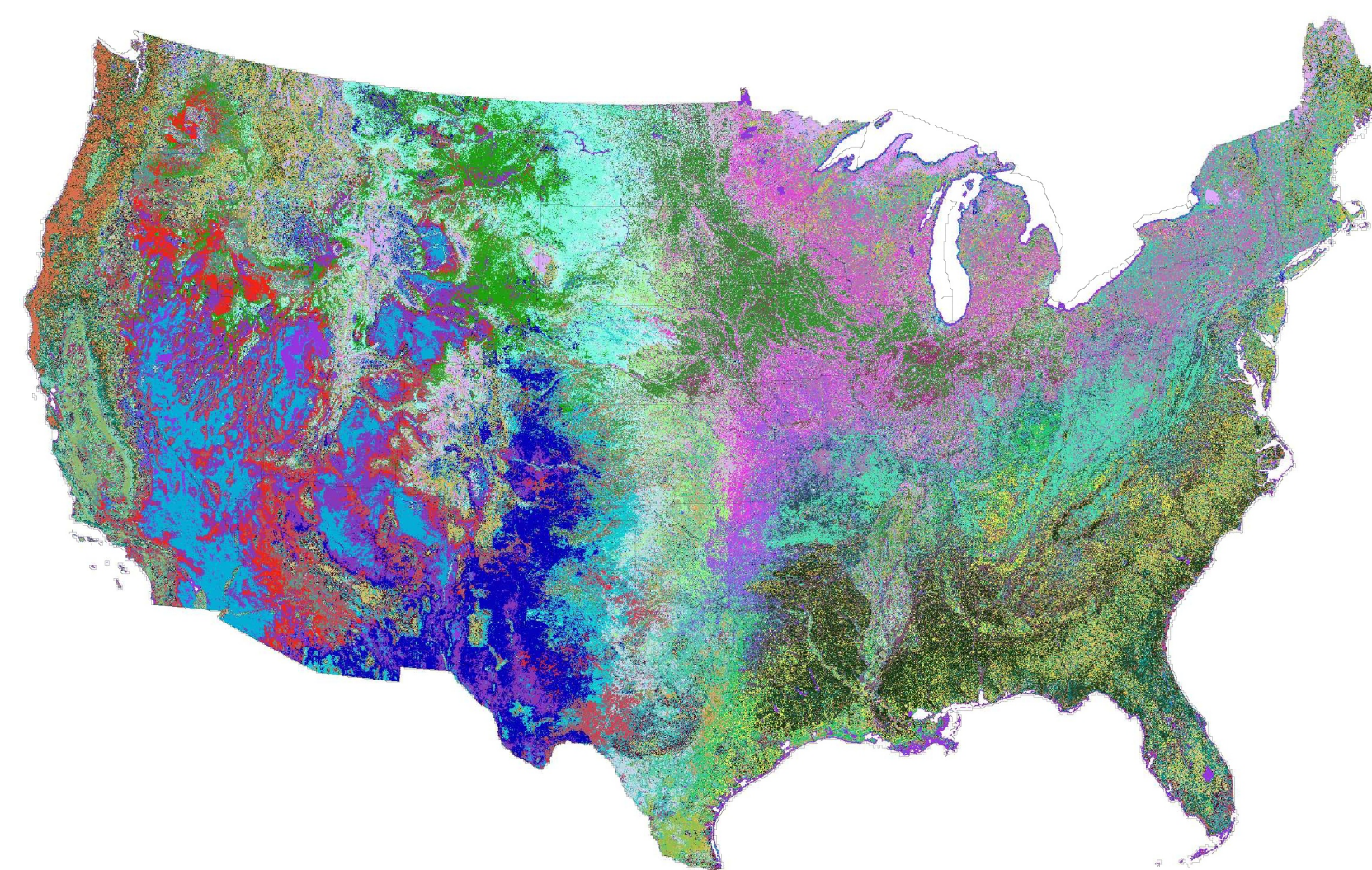
Tier 2: Tactical — Finer resolution airborne overflights and ground inspections of areas of potential interest — *Aerial Detection Survey (ADS)* monitoring to determine if such warnings become alarms.

Tier 2 is largely in place, but Tier 1 is needed to optimally direct its labor-intensive efforts and discover new threats sooner.



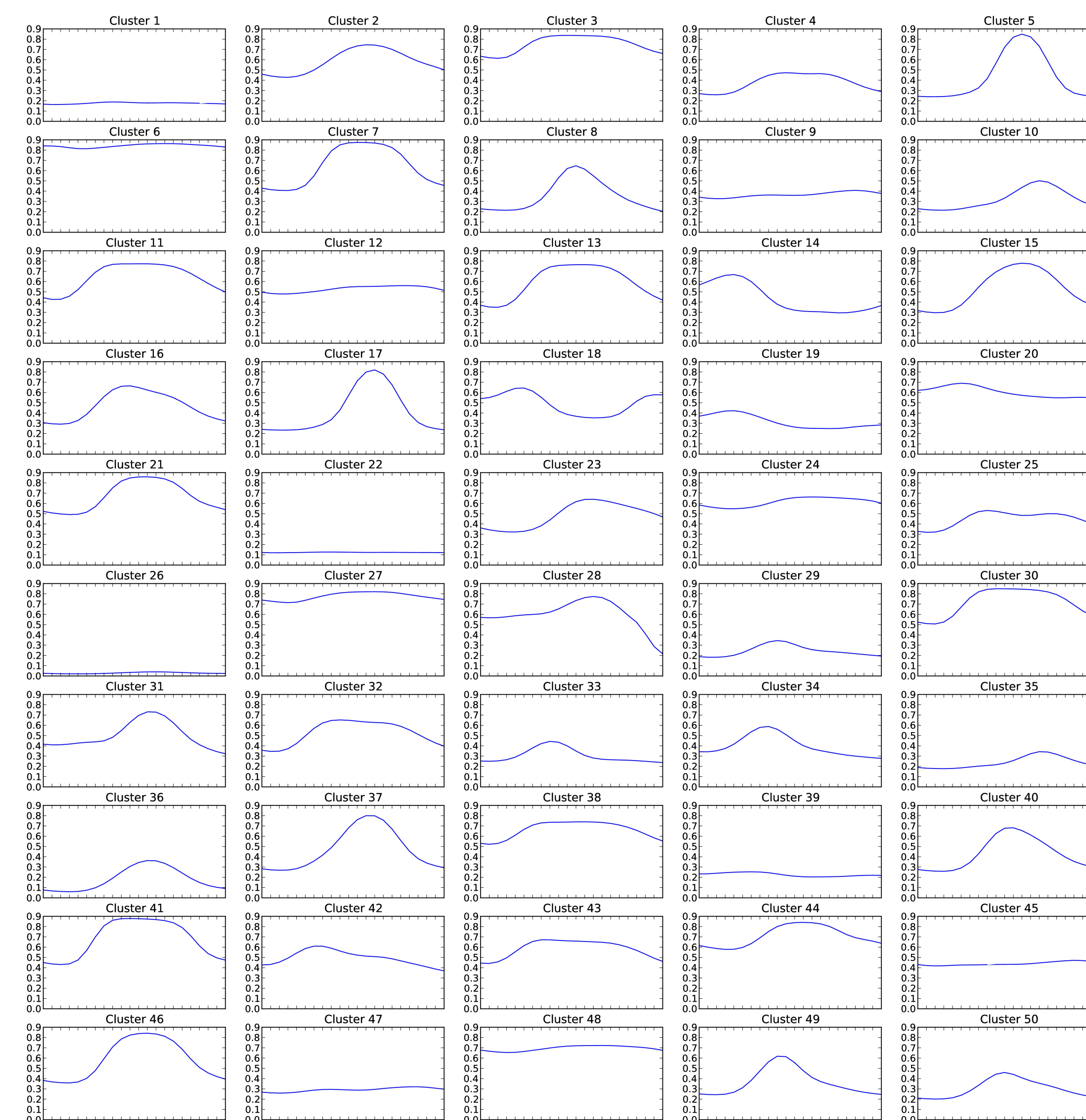
Developing Phenoregions with Clustering

Cluster analysis yields six maps, one for each year, that classify each cell into one of $k = 50$ phenological classes or phenoclasses. The time evolution of phenoclass assignment, or phenostate occupation, indicates a trajectory of change in the phenological behavior due to natural or anthropogenic disturbance plus the ecosystem's responses to climate variability and long term trends.



The 50 most different phenological regions, or phenoregions, for the year 2008 created by clustering the 16-day MODIS NDVI data at a resolution of 250 m² for all the years 2003–2008.

50 Phenoregion Prototypes



These plots show the mean annual phenological behavior of each of the 50 phenoclasses defined by the cluster analysis process. Clusters 6 and 27 have high NDVI all year, so they are dominated by areas of highly productive evergreen vegetation. Clusters 5 and 17 are examples of areas dominated by deciduous vegetation, while clusters 7 and 41 appear to represent a mixture of evergreen and deciduous vegetation. Very low and flat phenology curves, like clusters 22 and 26, represent very low productivity areas, like deserts and water bodies. The other phenoclasses represent various combinations of vegetation types with different growing season lengths and timing. For example, clusters 14 and 18 are probably dominated by drought-deciduous vegetation.

Normalized Difference Vegetation Index (NDVI)

NDVI exploits the strong differences in plant reflectance between red and near-infrared wavelengths to provide a measure of "greenness" from remote sensing measurements.

$$NDVI = \frac{(\sigma_{nir} - \sigma_{red})}{(\sigma_{nir} + \sigma_{red})}$$

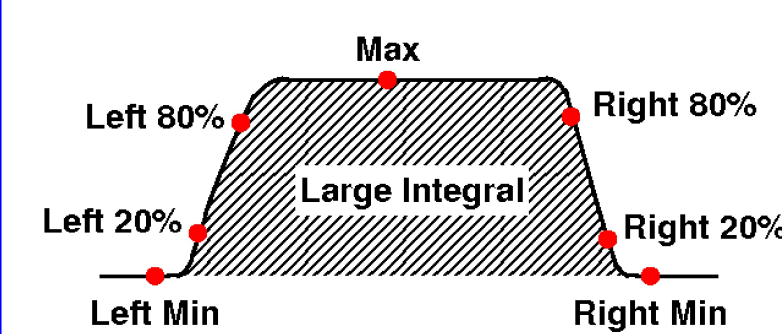
These spectral reflectances are ratios of reflected over incoming radiation, hence they take on values between 0.0 and 1.0. As a result, NDVI varies between -1.0 and +1.0. Dense vegetation cover is 0.3–0.8, soils are about 0.1–0.2, surface water is near 0.0, and clouds and snow are negative.

Phenology from Remote Sensing

Phenology is the study of periodic plant and animal life cycle events and how these are influenced by seasonal and interannual variations in climate. We are interested in deviations from the "normal" seasonal cycle of vegetation growth and senescence. NASA SCS has developed a new set of National Phenology Datasets based on MODIS MOD 13 NDVI at 250 m² resolution. Outlier/noise removal and temporal smoothing are performed, followed by curve-fitting and estimation of descriptive curve parameters.

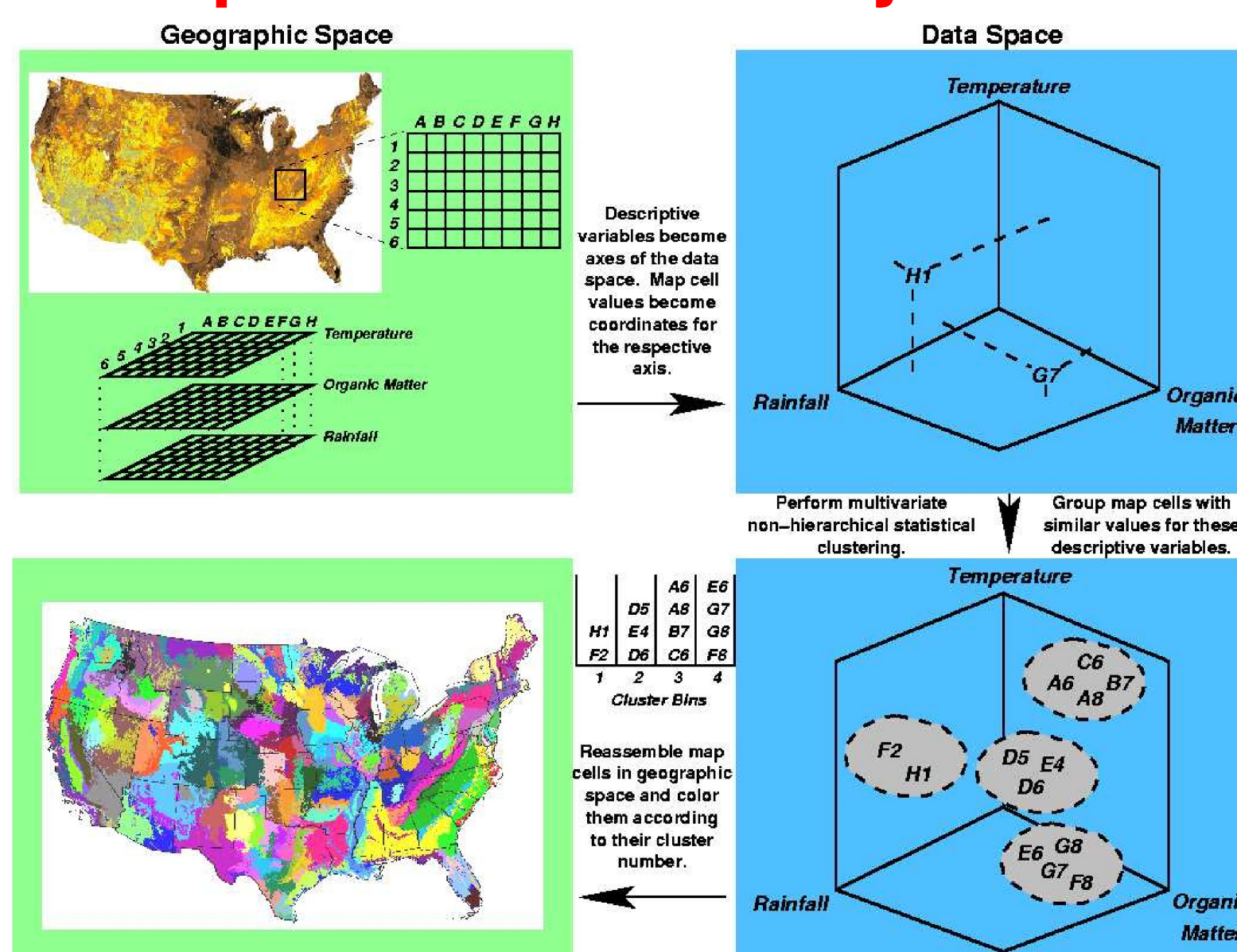


An idealized seasonal NDVI curve is fit through data for each MODIS cell, and seven parameters are extracted. Each parameter results in one map for NDVI value and another for the time of occurrence.

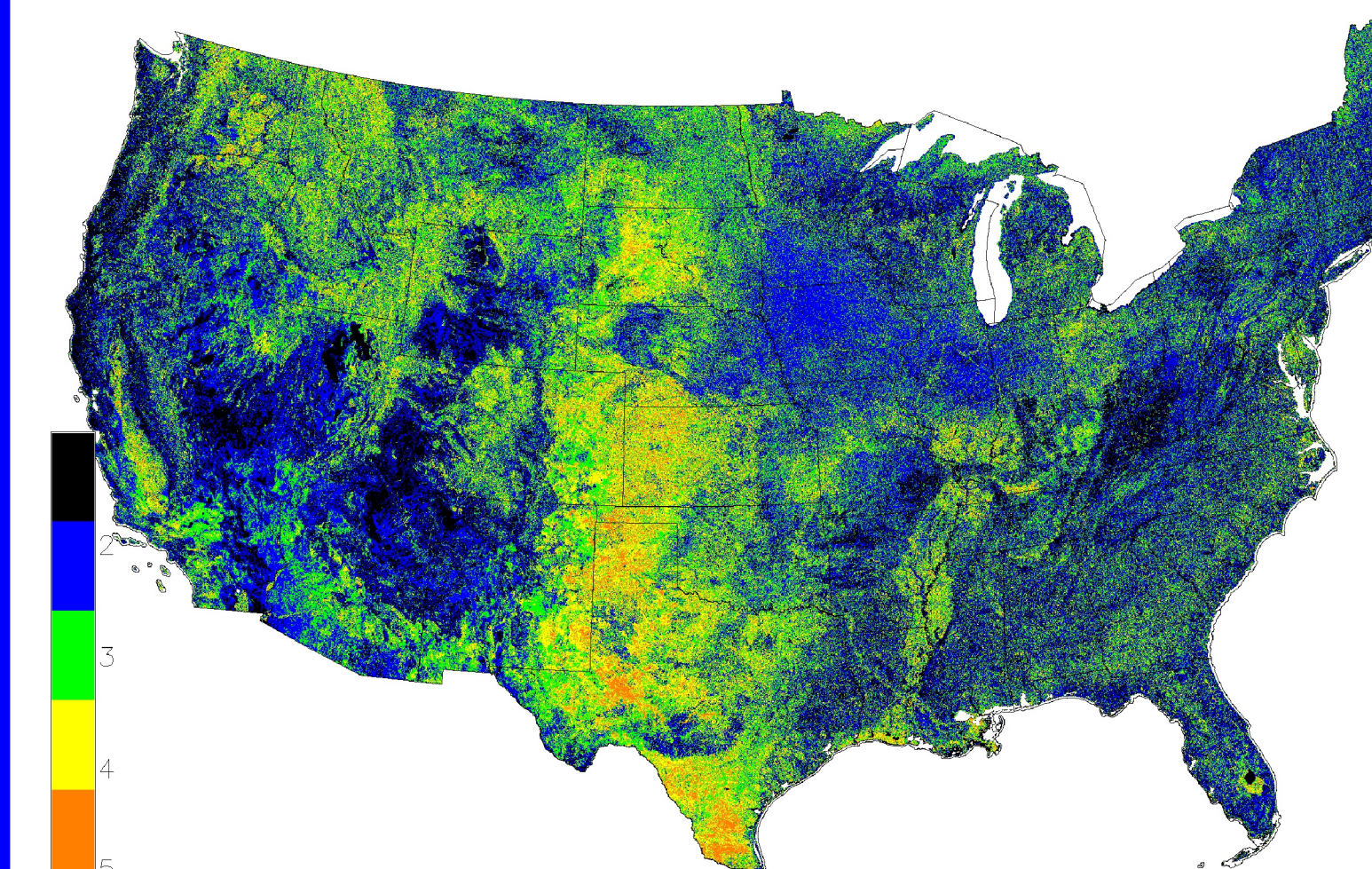


Multivariate Spatio-Temporal Cluster Analysis

A data mining approach, utilizing high performance computing (HPC), for the entire MODIS history of NDVI provides a basis for determining normal phenological behavior. Hoffman and Hargrove previously employed a scalable k -means algorithm, shown at right, to automatically detect brine scar disturbances from hyperspectral imagery (Hoffman, 2004) and for phenology from AVHRR NDVI (White et al., 2005). The 2003–2008 NDVI represent 77 GB of data.

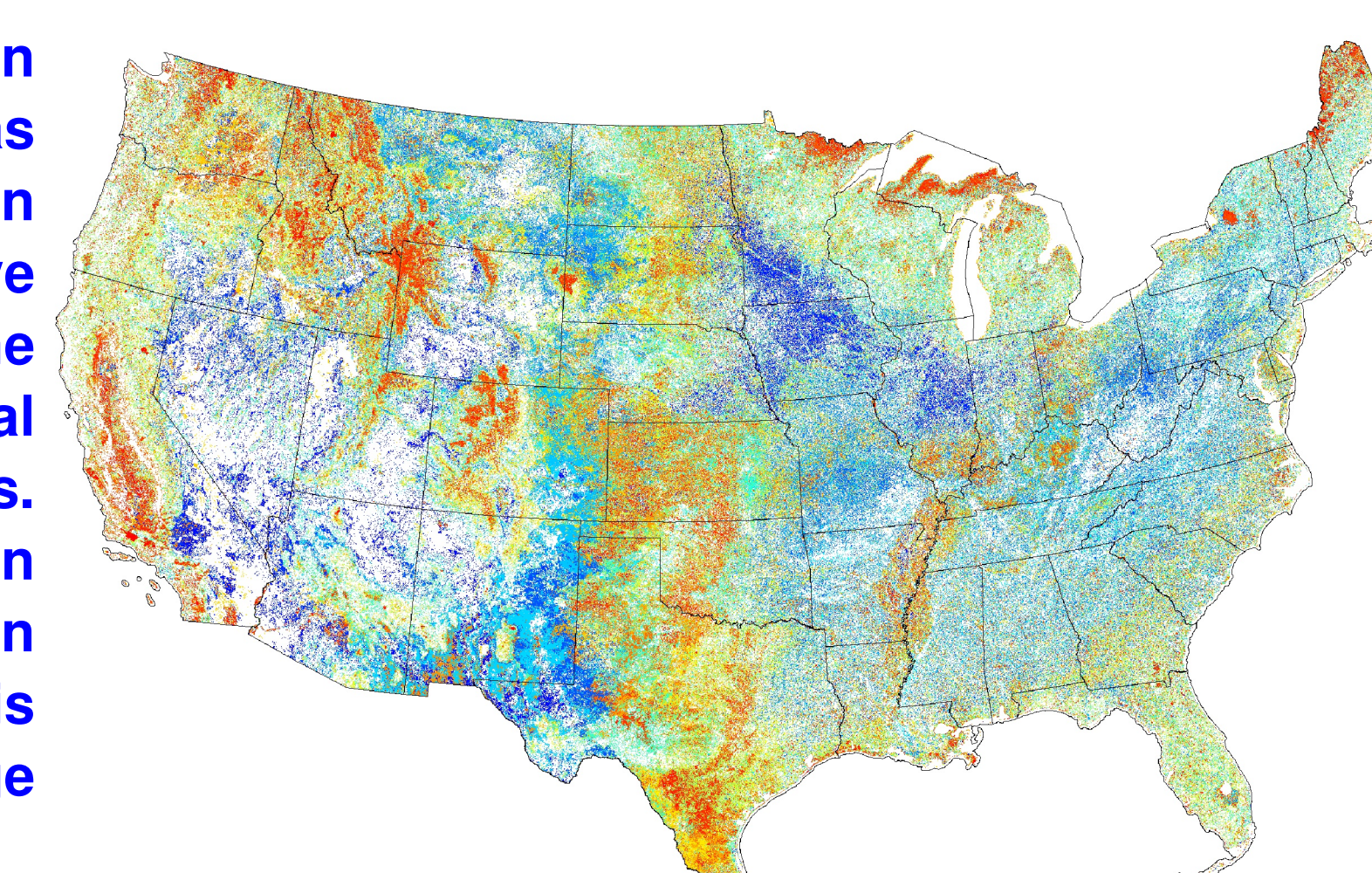


Cluster Persistence and Transition Distance Maps

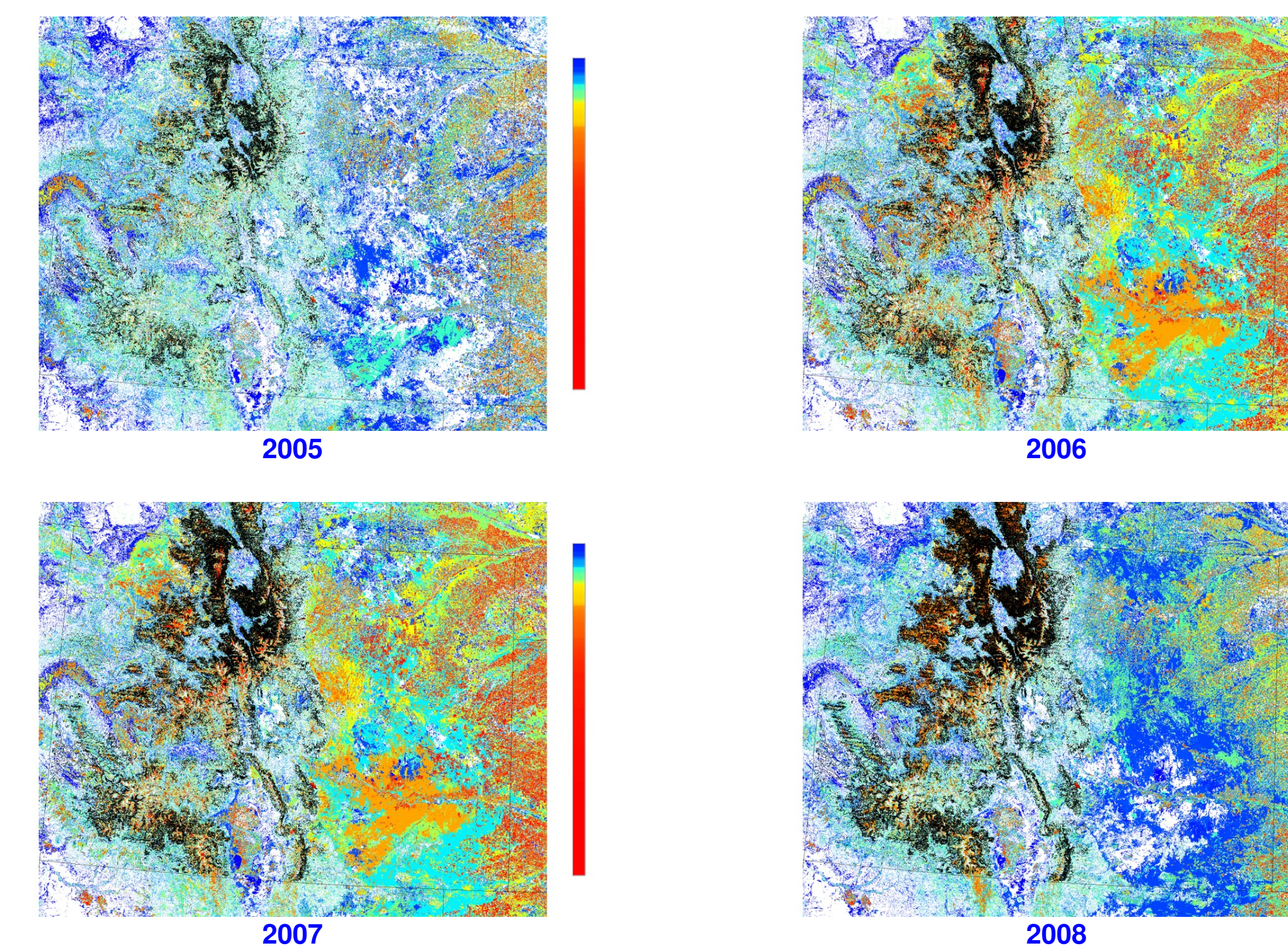


The frequency of phenostate occupation for each map cell across all years provides insights into the phenological persistence or variability at every location in the CONUS. This map shows the number of years in which each map cell was classified into the same phenoclass. Black cells exhibit nearly identical behavior each year, while orange cells show large interannual variability.

The Euclidean distance between cluster centroids can be taken as the transition distance between phenostates. It provides a relative measure of the strength of the observed change in phenological behavior between any two years. This map shows the transition distance between phenostates in years 2008 and 2003, where blue is small changes, red is large changes, and white is no change.



Progressive Mountain Pine Beetle Damage in Colorado



These annual transition distance maps are zoomed in on the state of Colorado, where significant progressive mountain pine beetle damage has been observed over the MODIS period of observation. The areas in and around the Rocky Mountains appear to have increasing orange to red colors from 2005–2008, indicating large changes in phenological behavior from year to year. The black vectors are from sketchmaps collected by the Forest Service, where human observers have identified areas of forest disturbance from aerial and ground-based surveys.

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