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Spatiotemporal dimensionality and Time-Space characterization of multitemporal imagery

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ABSTRACT

Spatiotemporal dimensionality refers to the continuum of spatial and temporal patterns in an image time series. Time-Space characterization refers to a way of representing this continuum of patterns as combinations of spatial and temporal constituents — with a minimum of assumptions about the forms of the patterns. Patterns can be related to processes through modeling. By combining characterization and modeling, two complementary analytical tools can be used together so that each resolves a key limitation of the other. This study describes a straightforward extension of Principal Component Analysis and Spectral Mixture Analysis to multitemporal imagery and illustrates how characterization of the dimensionality and eigenstructure of the data can inform modeling of the processes represented in the data. The relationships among spatiotemporal processes can be represented as combinations of temporal endmembers in a temporal feature space where the dimensions represent different components of the temporal patterns present in the data. The topology of the feature space and the processes being modeled together inform the selection of temporal endmembers and the structure of the model chosen to represent the processes. The dimensionality revealed by the characterization can also provide a partial solution to the problem of endmember variability. The characterization and modeling process is illustrated with the vegetation phenology of the Ganges–Brahmaputra delta using a MODIS vegetation index time series. Additional applications and limitations of Time-Space characterization and mixture modeling are further illustrated by comparing the eigenstructures and temporal feature spaces of Landsat vegetation fraction and DMSP-OLS night light time series.

1. Introduction

Over the past 30+ years, broad interest in Earth surface processes has led to a variety of approaches to quantify remotely sensed change. The diversity of approaches has resulted in multiple review papers which have developed categorizations of the different approaches for change detection and their relative strengths and weaknesses. (Coppin & Bauer, 1996; Coppin et al., 2004; Lu et al., 2004). However, most of this work has focused on discrete change detection. The more general problem of quantifying continuous spatial and temporal changes has received less attention. The relatively recent availability of large volumes of multitemporal imagery at hectometer (e.g. MODIS) to decameter (e.g. Landsat) resolutions now makes it more feasible to consider the related problem of spatiotemporal (ST) analysis. Spatiotemporal analysis can be considered distinct from discrete change detection in the sense that it simultaneously quantifies both temporal patterns and their spatial distribution. Proposed approaches for spatiotemporal analysis include logistic function fitting (Zhang et al., 2006), wavelet decomposition (Galford et al., 2008), Independent Component Analysis (Ozdogan, 2010), trend and change decomposition (Verbesselt et al., 2010), and temporal mixture modeling (Lobell & Asner, 2004; Piwowar et al., 1998; deBeurs & Henebry, 2006). Most of these approaches involve some assumptions about the temporal patterns in the data. However, with image time series the "Curse of Dimensionality" (Bellman, 1957) often arises in the challenge of determining what spatial and temporal patterns are actually present in the data and what method is best suited to quantifying them. Characterization of high dimensional data in terms of its dimensionality provides a way to represent the high dimensional information content of multitemporal imagery while managing the challenges modeling the underlying processes.

Characterization of data can be considered the complement of modeling. Modeling involves the representation of observations or processes with a conceptual or mathematical simplification. (Gershenfeld, 1999). Forward modeling simulates a process given a set of parameters while model inversion seeks optimal estimates of model parameters or structure corresponding to a set of observations (Parker, 1994). Modeling generally involves assumptions about the functional form of the processes represented by the data. The implicit assumptions are usually that the functional form of the processes is known *a priori* and that the model parameter estimates convey something about the processes. Forward modeling of atmospheric effects with a radiative transfer model is

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an example of deterministic modeling (e.g. (Tanre et al., 1979)). Estimation of phenological parameters by fitting logistic functions to time series of vegetation indices is an example of model inversion (e.g. (Zhang et al., 2006)). In contrast, characterization of data can take the form of an exploratory data analysis and thereby makes less rigid assumptions about processes and their representation in the data. (Tukey, 1977). The assumption of a specific functional form is not required for characterization. Identification of uncorrelated modes of variability using Principal Component transform is a common example of data characterization. (von Storch & Zwiers, 1999) The analogy to supervised and unsupervised classification used by (Verbesselt et al., 2010) to describe change detection methods can also be applied to spatiotemporal analysis. Data characterization can be considered analogous to unsupervised classification in that it identifies patterns in data with few assumptions from the analyst. Data modeling is analogous to supervised classification in that the result is strongly dependent on assumptions and input from the analyst. Both modeling and characterization have strengths and limitations. When used together they can complement and inform each other.

The idea of spatiotemporal dimensionality provides a basis for characterization of multitemporal imagery and the development of spatiotemporal models. In the context of this study spatiotemporal dimensionality refers to the structure of the continuum of spatial and temporal patterns present in an image time series. The spatiotemporal dimensionality of an image time series is related to the number and combination of processes that can be distinguished at different geographic locations through time. Before using data to quantify or infer spatiotemporal processes, it is important to know if and how these processes are represented in the data. Characterization of multitemporal imagery can provide insights into how different processes are represented by the spatial and temporal sampling of the imagery. The purpose of characterization is not only to identify specific features but also to determine what can and cannot be distinguished in the data — with a minimum of assumptions. While characterization can inform any of the modeling approaches referenced previously, the continuous representation of spectral mixture models is particularly well-suited to characterization in terms of Principal Components.

This study presents an approach to characterizing and modeling spatiotemporal processes in multitemporal imagery. The combined approach of Time-Space characterization and spatiotemporal modeling is developed using Empirical Orthogonal Function analysis and Temporal Mixture Models. The approach follows a strategy developed for spectral mixture analysis (Adams et al., 1986) but addresses some important differences between spectral and spatiotemporal dimensionality and the physical processes they represent. The Principal Component (PC) transformation and resulting Empirical Orthogonal Functions (EOFs) provide a tool for representing the spatiotemporal dimensionality of an image time series in the form of uncorrelated temporal patterns (EOFs) and their spatial distributions (PCs). The dimensionality and structure of the temporal feature space reveals the dominant temporal patterns and the relationships among them. The Temporal Mixture Model provides a tool for modeling and mapping spatial relationships among the temporal patterns as processes. When used together, each tool resolves a key limitation of the other. The characterization of the dimensionality informs the design of the mixture model while the use of the mixture model eliminates the difficulty of direct interpretation of the individual EOFs. The spatiotemporal (ST) dimensionality determined from the EOF analysis also provides a potential solution to a principal challenge of mixture modeling: endmember selection and variability. This is achieved through a separation of high and low order variance as indicated by results of the EOF analysis.

This study illustrates the combined use of characterization and modeling with a combination of theory and application. The intention is to illustrate both strengths and limitations of the approach by comparison of examples. The common theoretical basis and mathematical similarities of EOF analysis and linear mixture modeling are discussed first. This is followed by a worked example of characterization of the relatively well-posed problem of phenology mapping with a time series of MODIS-derived vegetation index images. This example is followed by a brief comparison of two more challenging examples intended to highlight some effects of differences in dimensionality and eigenstructure. The use of three contrasting examples illustrates both the generality of the characterization approach and the diversity of spatiotemporal structure of different image time series. It also illustrates some limitations of the use of purely statistical transformations in the representation of high dimensional data.

2. Principal components and empirical orthogonal functions

PC transformations are commonly used to represent uncorrelated modes of variance in high dimensional data. Different types of PC transform are used to reduce the dimensionality of multispectral imagery (e.g. (Green et al., 1988; Lee et al., 1990; Singh & Harrison, 1985)) and to represent the topology of spectral feature spaces (Adams et al., 1986; Crist & Cicone, 1984; Johnson et al., 1985; Kauth & Thomas, 1976; Smith et al., 1985). Because spectral bands are often correlated, PC transforms provide an efficient low dimensional projection of the uncorrelated components of the spectral feature space. The same property applies to temporal dimensions. PC transforms have also been used to represent uncorrelated patterns in multitemporal imagery (Richards, 1984) (Eastman & Fulk, 1993; Townshend et al., 1985) and for change detection (Byrne et al., 1980; Fung & LeDrew, 1987). In meteorology and oceanography the PC transformation provides the basis of Empirical Orthogonal Function analysis; a standard tool for analysis of spatiotemporal patterns and processes. (see (Bretherton et al., 1992; Preisendorfer, 1988; von Storch & Zwiers, 1999) for overviews).

The PC transform provides a very convenient tool for identification of spatiotemporal patterns. By rotating the coordinate system to align with orthogonal dimensions of uncorrelated variance, any location-specific pixel time series P_{xt} contained in an N image time series can be represented as a linear combination of temporal patterns, *F*, and their location-specific components, *C*, as:

$$P_{xt} = \sum_{i=1}^{N} C_{ix} F_{it} \tag{1}$$

where C_{ix} is the spatial Principal Component (PC) and F_{it} is the corresponding temporal Empirical Orthogonal Function (EOF) and *i* is the dimension. The EOFs are the eigenvectors of the covariance matrix that represent uncorrelated temporal patterns of variability within the data. The PCs are the corresponding spatial weights that represent the relative contribution of each temporal EOF to the corresponding pixel time series P_{xt} at each location *x*. The relative contribution of each EOF to the total spatiotemporal variance is given by the eigenvalues of the covariance matrix. *N* is the number of discrete dimensions represented by the data; which may be greater, or less, than the true physical dimensionality of the process(es) imaged. Principal Components are uncorrelated but not necessarily independent — unless the data are jointly normally distributed. In systems where the same deterministic processes are manifest at many locations, but stochastic processes are uncorrelated, the variance of the spatiotemporal structure of the deterministic processes can be represented in the low order PC/EOF dimensions while the stochastic variance is represented in the higher order dimensions (Preisendorfer, 1988). When a clear distinction can be made, this can provide a statistical basis for separation of deterministic and stochastic components of an image time series. However, the