# CREATION OF TEMPORAL IMAGES FROM SEQUENCES OF REMOTELY SENSED IMAGES

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**KEY WORDS:** Remote Sensing, Image Processing, Temporal Image Data, Temporal Image Analysis, Hypertemporal Data.

## ABSTRACT

A sequence of remotely sensed images of an area captures information on the dynamic processes that are occurring in the area, as snapshots in time. At present such sequences can be run as a movie sequence, to gain some appreciation of the dynamic processes that are at work. Whilst such sequences are valuable in gaining a subjective appreciation of the dynamics of the processes at work, they are not amenable to detailed image analysis, because of the transitory nature of the display. For detailed analysis and interpretation, other ways of displaying the dynamic record need to be found.

This paper describes seven approaches to the construction of temporal images, or images that capture the temporal changes that occur in the surfaces being sensed. Since the temporal information is in a fourth dimension, the display of temporal change requires that other information be surrendered in creating these images. The different approaches surrender different types of information. The paper describes the seven approaches to the display hypertemporal image data, discusses the information that is surrendered in using each type, and shows early results in the analysis of Global NDVI data using five of the seven approaches.

## RESUME

*Création d'images temporaires par l'emploi des séries d'images capturées à grande distance*
Une série de téléphotos d'une superficie montrent les actions dynamiques, qui se présentent à la superficie, comme des instantanés du temps. A présent les series de cette espèce peuvent être montrées sous forme d'un film pour mieux comprendre les actions dynamiques travaillantes. Bien qu'elles soient précieuses quand il s'agît d'obtenir une interprétation subjective de ces actions dynamiques, ces séries ne sont pas applicables pour les analyses detaillées des images à cause de leur nature transitoire. Par conséquent, pour les analyses detaillées ainsi que pour l'interprétation il est necessaire de chercher une autre manière quand il faut montrer les informations dynamiques.

Cet article décrit sept essais de construire des images temporaires ou des images, qui montrent les changements temporaires des superficies en question. Etant donné que l'information temporaire est dans la dimension quatrième, il est necessaire que les autres informations soient abandonnées pour montrer la changement temporaire en créant ces images. Les maniéres differentes donnent des informations differentes. L'article décrit sept manières pour montrer les donnés d'images hypertemporaux, fait une discussion des informations rendues en utilisant les types differents et montre les resultats précoces dans l'analyse des donnés de NDVI global en se servant de cinq des sept manières.

## 1    BACKGROUND

The use of satellite remote sensing images for monitoring was quickly recognized as one of the major potential benefits of this technology. This benefit was perceived to arise because of the ability of satellite borne sensors to provide repetitive coverage at low cost, acquiring data that would be both internally and externally more consistent than scanner data acquired from an airborne platform. Despite this promise, only

AVHRR data has been extensively used in this way. Long term data sets derived from AVHRR data are freely available on the Internet, primarily from a NASA based source, such as;

- The Pathfinder Program of NASA produces long-term data sets that have been processed in a consistent manner for global change research. http://daac.gsfc.nasa.gov/DATASET_DOCS/avhrr_dataset.html.

- Sea surface temperature data sets constructed from AVHRR thermal data, available through http://podaac.jpl.nasa.gov/order/order_sstemp.html.

As well as these products, many others based on AVHRR and other satellite data, are available through the Distributed Active Archive Centre (DAAC) of NASA.

A number of groups have developed the use of AVHRR data for long term monitoring purposes. Since 1975, the Food and Agriculture Organisation (FAO) Global Information and Early Warning System on Food and Agriculture (GIEWSE) has used AVHRR data to monitor Global vegetative conditions. The purpose of this monitoring program is to provide policy-makers and policy-analysts with up-to-date information on all aspects of food supply and demand and to provide a warning of imminent food crises so that timely interventions can be planned (GIEWSE website at http://www.fao.org/giews/english/giewse.htm). The data has also been used in the preparation of improved vegetation maps of the different continents, and the globe (DeFries and Townshend, 1994 and http://cstars.ucdavis.edu/projects/indexfr.html, "Mapping the Land Surface for Global Atmosphere- Biosphere Models: Toward Continuous Distributions of Vegetation's Functional Properties" by Ruth DeFries et al,).

The reasons for this situation are not hard to find. The costs of medium (10 – 100 meter) resolution image data are prohibitive for the accumulation of frequent data sets. In contrast, AVHRR data sets are cheap. There is also the issue of being able to acquire frequent coverage. Most medium resolution satellite systems have an orbit revisit time that is in excess of 14 days, with only SPOT able to avoid this long interval by its ability to point its sensors off axis. Consequently, these satellites cannot acquire data at a frequency that allows it to be categorised as hypertemporal image data, where hypertemporal data are those acquired at a much higher frequency than the processes being sensed, and accumulating a large set of temporal data.

The importance of being able to monitor earth resources has also been well recognised. This recognition has led to the establishment of various international research oriented organisations with roles in the development of methods to acquire information on the long term trends of resources and processes on, over and under the earth's surface. Such initiatives include the US Global Change Research Program with home page at http://www.usgcrp.gov/, the Intergovernmental Panel on Climate Change (IPCC) at http://www.ipcc.ch/, and the Centre for International Earth Science Information Network (CIESIN) at http://www.ciesin.org/. The World Meteorological Organisation (WMO) and the United Nations Environment Programme (UNEP) established the Intergovernmental Panel on Climate Change (IPCC) in 1988. The role of the IPCC is to assess the scientific, technical and socio-economic information relevant for the understanding of the risk of human-induced climate change. CIESIN promotes the use of satellite remote sensing to study the human dimensions of global environmental change.

Despite the widespread recognition of the importance of monitoring critical environmental parameters, and the recognition of the role of Remote Sensing in this task, few tools have been developed for this purpose. Many existing tools operate in blissful ignorance of the needs of long term monitoring, so that these tools are very difficult, or impossible, to use for this purpose. The need to develop tools for the analysis of long sequences of image data is because;

- There is a need to understand the dynamic nature of environmental processes, as this will improve our understanding of the processes themselves.
- This understanding is crucial to the modelling of these processes.
- Understanding of these dynamics is important in the management of the resources.

Depiction of temporally dynamic processes in a manner that is suitable for analysis is particularly challenging because of the need to collapse three or four dimensions of data into two for depiction and analysis. The approach that has been taken to this challenge is to identify those dimensions of the data set, that are either known in some other way, or which are irrelevant to the analysis, and remove them from the data set, so as to reduce the dimensionality of the data set. Some of the dimensions of the data that can be derived by other means include;

- The landcover/landuse classification of the data, so that the analyst may just look at one or at sets of landcovers and not at all of the landcovers that are represented within the image area.
- The condition of that landcover can be estimated by other means. Thus multispectral data may be collapsed into an indicator of condition; if vegetation is that cover of interest then NDVI, LAI or biomass may be suitable indicators.

In addition to these methods of dimensionality reduction, further methods can be based on information that can be retained by the analyst in other forms, and integrated into the analysis by the analyst, as long as the imagery is conducive to this activity. Thus in standard visual interpretation, the analyst brings with him/her a lot of information about the area, and about those disciplines that are relevant to the interpretation. The same concepts will apply in the interpretation of temporal image data sets, except that further information sets need to be stored mentally and used by the analyst. The most obvious of these additional information sets are those relating to the dynamic characteristics of different cover types. Conceptually we have a good understanding of the broad dynamic characteristics of many earth processes, even though we do not understand these processes in detail, nor indeed, may we understand how they interact and thus evolve over time. If we have a conceptual understanding of the characteristics of dynamic processes, then we should try to build image data that uses and allows the analyst to improve on, these conceptual models.

## 2    GOALS OF THE WORK

The goals of this work are to develop tools to analyse long sequences of image data and to investigate how such hypertemporal image sets can be used to derive environmental information.

## 3    DEVELOPMENT OF TOOLS

Raw hypertemporal image data is four dimensional data, I(Pixel, Line, Band, Time). Since it is not possible to display such data sets using standard display facilities, some form of dimensionality reduction has to be applied. There are a number of ways by which this dimensionality reduction can be applied;

- **Statistical Techniques**. There is a significant level of correlation between each of these dimensions in the data, so that statistical methods of dimensionality reduction should enable us to collapse these four dimensions into the two required for display.
- **Use known subsets of the image domain**. Images can be classified, and then estimates derived of parameters from the image data, using more conventional remote sensing techniques. By doing this, the body of relevant image data to be analysed is significantly reduced. Thus the analyst may concentrate on the one landcover of interest, and use parameters derived from the hyperspectral data in the analysis.
- **Use other forms of information in the analysis**. Such other forms include both conceptual and numerical models of the dynamic processes being displayed in the image data. It should not be forgotten that the simplest model will be that there are no changes, so that the system can then show the types of changes that are actually occurring. At some stage a subset of this depicted change will then become the new conceptual model of the dynamics of that surface type or condition. In this way both the conceptual and numerical models can be refined using the temporal image data set.

Given these concepts, at present six different approaches are being investigated. It should be emphasised that these approaches are not being considered in isolation; it may well evolve that combinations of these approaches are better than the approaches on their own. It is also assumed that as we develop our understanding of the nature of the issues that we are tackling, so other approaches will suggest themselves. In

this way the work is very dynamic; it is expected that only some of the current approaches will be retained. The seven current approaches being investigated include;

- Statistical Transformation of the image data using Principal Components analysis.
- Statistically based classification.
- Temporal Semi-variograms.
- Temporal Panoramas.
- Fourier Analysis.
- Temporal Distance Images.
- Temporal Enhancements.

## 2.1 Statistical Transforms

The Principal Components transform has been used for this, simply because it is the most readily available in image processing software. Imagery in one waveband has been selected. The image data has then been transformed using conventional Principal Components transform software within the Erdas Imagine image-processing package.

## 2.2 Image Classification

Unsupervised classification of the temporal data sets was conducted using the standard unsupervised classification facilities in Erdas Imagine image-processing software.

## 2.3 Temporal Semi-variograms

Software has been developed to compute both three-dimensional Semi-variograms and just the temporal semi-variograms for image data sets in three dimensions. To reduce the image data stack to three dimensions, only one waveband, or one derived spectral parameter, can be analysed at a time. The temporal semi-variograms produce a semi-variogram through time for each pixel in the image data.

## 2.4 Temporal Panoramas

An image is collapsed into a line of data, by joining the lines end on end. Each subsequent image is then laid, as one line, adjacent to the prior line, so that a two dimensional image is constructed with one axis being (Pixel, Line) and the second axis being time. In this way up to three bands of temporal information can be displayed as blue, green and red. Because such a transformation destroys spatial relationships, two windows are employed; one to hold the temporal panorama and one to hold one original image. The windows are linked, so that by pointing at one, the location is shown in the other window. Because such a display will create very long, often narrow, images, other techniques may be used to reduce the length of the (Pixel, Line) axis. Such techniques would include;
- Selecting only areas of interest in the image data.
- Pixel resampling to increase pixel size.

## 2.5 Fourier Analysis

Temporal panoramas will initially be used to investigate whether Fourier analysis helps us to understand the nature of dynamic process as depicted in those image data.

## 2.6 Temporal Distance Images

The analyst retains a conceptual model of how the cover that he is interested in, changes over time, even though the initial model that he holds may be of no change. A temporal distance image depicts the distance of the pixel for which the distance has been calculated from this model. Thus pixels that are close to the model will have short distances in a Temporal Distance Image. Pixels that have large distances in the

Temporal Distance Image are unlike the model in the image data. Calculation of the distances is based either on values derived from numerical versions of the model, or by adoption of a training area in the image as being representative of that model. In practice a training area is defined for the surface type of interest. Using the statistics for this area in each image, either Euclidean or Mahalonobis type distances can be computed for each pixel in that image. The same process is repeated for each image. The distances for a pixel in each image can then be combined in some way to give an integrated distance through time. At present average distances are being used. However this version of the distance will mask significant short-term variations that may be of great interest to the analyst. Consequently, other forms of distance, or derivations from the distance, are being considered.

## 2.7 Temporal Enhancements

For each pixel, there is a depth of data at each time in the temporal image set, or a depth of wavebands in Hyperspectral data. Conventionally three wavebands of hyperspectral data are selected for display, so that none of the other wavebands can be shown at the same time. In a Temporal Enhancement the information in all temporal images, or all wavebands, contribute to the displayed image. This is done by constructing a table depicting the weighting to be given to blue, green and red for each value through the temporal sequence, or through the set of wavebands (see Figure 1). The intensity of each colour for that pixel is the sum of the products of the value in the temporal image or in the wavebands and the weighting to be given to that image in the temporal sequence or that waveband.

For the simple enhancement shown in Figure 1, the weightings are ;

$$
\begin{aligned}
\mathbf{W}_{blue} \quad &= 1.0 - (2 * I) / len & \text{for } I < (len / 2) \\
&= 0.0 & \text{for } I >= (len / 2) \\[2mm]
\mathbf{W}_{green} \quad &= 1.0 - 2 * absolute((I / len) - 0.5) & (1) \\[2mm]
\mathbf{W}_{red} \quad &= ((2 * I) / len) - 1.0 & \text{for } I > (len / 2) \\
&= 0.0 & \text{for } I <= (len / 2)
\end{aligned}
$$

where    $len$ = number of images in the temporal sequence or number of wavebands, and
         $I$   = image or waveband within this sequence.

If the data for a pixel is in array(len), then the pixel value for blue, green and red are given by;

$$
\begin{aligned}
\mathbf{V}_{blue} &= \Sigma\ array(I) * \mathbf{W}_{blue}(I), & \text{for } I = 1 \text{ to } len \\
\mathbf{V}_{green} &= \Sigma\ array(I) * \mathbf{W}_{green}(I), & \text{for } I = 1 \text{ to } len & \quad (2) \\
\mathbf{V}_{red} &= \Sigma\ array(I) * \mathbf{W}_{red}(I), & \text{for } I = 1 \text{ to } len
\end{aligned}
$$

## 3    EVALUATION OF THESE TOOLS

Initial work to evaluate these tools is being done using the Global NDVI data set available through NASA at website http://daac.gsfc.nasa.gov/CAMPAIGN_DOCS/LAND_BIO/GLBDST_Data.html. The Global NDVI 1 degree by 1 degree data is extensive, with continuous monthly coverage from April 1981 until July 1994. It is a relatively small data set, consisting of 360 pixel by 180 line, one byte per pixel images for each month through this period. The period covers a total of 158 months. There was a gap with no acquisition during late 1994, with acquisition being resumed in 1995. However these subsequent images have not been used in this study, because of the gap. The images have been registered so that rectification is not a problem. The imagery was imported into Imagine, and then an image stack was created consisting of all 158 images in the sequence. Imagine uses the word stack to mean the construction of new images using existing images as layers in these new images. In this paper the word stack is used in a specific way that can be compatible with its usage within Imagine. An image stack is defined as a registered sequence of hyperspectral and hypertemporal images stored within the one file. At present one image format is being used for these images. In this format the data is stored such that the pixels, lines, bands, images change at a decreasing rate. Thus

pixels change most rapidly, and images change least rapidly in the format. The construction is identical to Band Sequential (BSQ) if either only one band is stored, or one image, as is the case in this study where only NDVI data are used at each date. Analysis of the image data showed that some of the images contained errors at high latitudes, so the data set was subsetted to contain 360 pixels by 101 lines for 154 images. The last four images in 1994 were dropped because the errors in these images were significant over parts of Australia and South Africa, covered satisfactorily in the remainder of the data set.

Software has been developed to display the sequence, create and display temporal panoramas and temporal distance images. In addition to this software, other software has been developed to create temporal and 3_D Semi-variogram stacks and temporal enhancement images.

To date the analysis has commenced to investigate the use of statistical analysis, temporal distance images, temporal Semi-variograms and temporal enhancements. The other techniques are still to be evaluated.

## 4       RESULTS ACHIEVED

A composite of three NDVI images, for February, July and October 1984 are shown in Figure 2. The range of colour variations in the image are indicative of the range of conditions that can be met. Profiles for seven typical sites, representing seven different climatic regions are shown in Figure 3. All of the covers, with the exception of the desert and the rainforest sites, show strong cyclic patterns.

The NDVI image stack was then automatically classified. The initial classification was set to accept 200 classes with 20 iterations. This classification produced what appeared to be unsatisfactory results. They appeared to be unsatisfactory because many classes were allocated to low NDVI values and few to high NDVI values, in comparison with the variability seen in the NDVI data. A further classification, setting 100 classes and requiring the software to select seed locations using the first principal component, gave better results, yielding 78 classes (Figure 4). The classification has yielded similar levels of class variability within the rainforest end of the spectrum as in the desert end, contrary to what happened in the first classification.

The cyclic nature of most covers is illustrated very well in the temporal semi-variograms, depicted in Figures 5 and 6. The very regular nature of the global cycles yields very regular cyclic patterns, as shown for the profiles of the same sites used to get NDVI profiles (Figure 6). Classification of this semi-variogram data (Figure 7), depicts areas that are similar in terms of their cyclic variability.

The original data was processed into Principal components as shown in Figure 8. Whilst the eigen vectors (Figure 9) show that most of the variability has been placed in the first component, the images show that there is little noise in the first 6 components, and after that there is both noise and information. The Principal components appear to display more variability and hence more information, than any of the methods discussed so far. However the components seem to also make it hard to appreciate the temporal dynamic characteristics of the different colours in the principal component images. This form of orthogonal transformation seems to loose the dynamic information content of the data in the transformation.

Figure 10 shows a colour composite of three temporal distance images. Training areas for desert (Sahara), rainforest (Amazon), and Mediterranean (Australia) climatic regions were used to compute distance images for each cover type. These images were then enhanced and combined in Figure 10. The images clearly delineate areas that are similar to each of the cover types in NDVI values. The images are easy to interpret, and each distance image is linked to a conceptual model, so that the analyst can readily perceive the conditions for areas with similar distance values. Areas of intermediate distances will create their own colouring in the image; it is not yet clear how to interpret these colours in relation to the parent classes.

The final form of temporal analysis conducted so far is shown in Figure 11. This temporal enhancement uses the enhancement scheme shown in Figure 1 to enhance sequences from January through to December as blue, through green, to red. The images from the period January 1983 until December 1993 were used in the construction of the image, with the images in each year contributing to the same part of the enhancement.

The enhancement is thus a form of average over twelve months, using the eleven years of data to construct "typical" response distributions for a twelve-month period.

This image shows areas that are green early in the year as blue, in the middle of the year as green, and late in the year as red. The image shows as green, the greening up that occurs in northern latitudes in the northern summer period. The areas of monsoonal activity late in the year in India and South East Asia show very clearly as red. There are areas of blue in South Africa and South America that will correspond to greener vegetation early in the year, or during summer/autumn in those areas.

## 5    CONCLUSIONS

The work shown in this paper represents early work in the evaluation of tools to assist in the analysis of long sequences of temporal image data, or hypertemporal imagery. The work has been hampered by the difficulty of dealing with such data sets in conventional image processing systems. For example, conventional systems do not have easy ways to create temporal stacks that contain more than one waveband of data. Nor can they display such data sets. Finally, the methods of image rectification and image calibration that is resident in most existing software systems is suitable when only a few images have to be dealt with, but they are very inefficient when many images have to be processed. The work has shown that many conventional image processing techniques are of limited value in the analysis of hypertemporal data. It may be that new algorithms for image classification and the development of better orthogonal transformation will be necessary. The distance and enhancement images seem to offer useful tools for the analysis of temporal images. But more work has to be done to see how these tools can be adapted, improved and then utilised.

## REFERENCES

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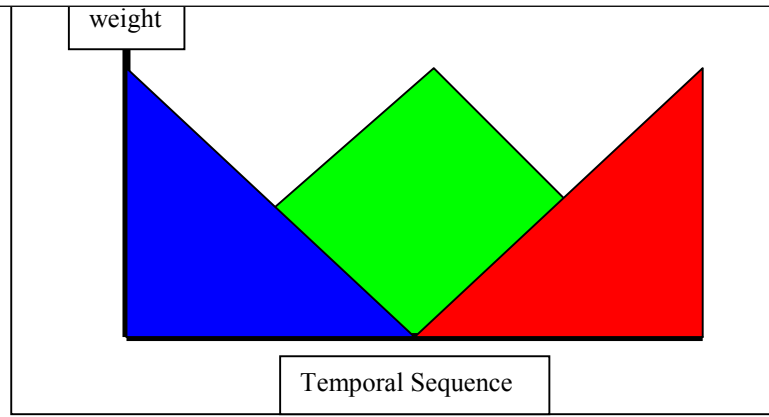http://cstars.ucdavis.edu/projects/indexfr.html.

Figure 1: Weighting that could be given to blue green and red for each image through the temporal or hyperspectral sequence. Such a weighting will give blue- cyan- green - yellow - red in the sequence, but no magenta. Other weighting functions could be adopted that include magenta.
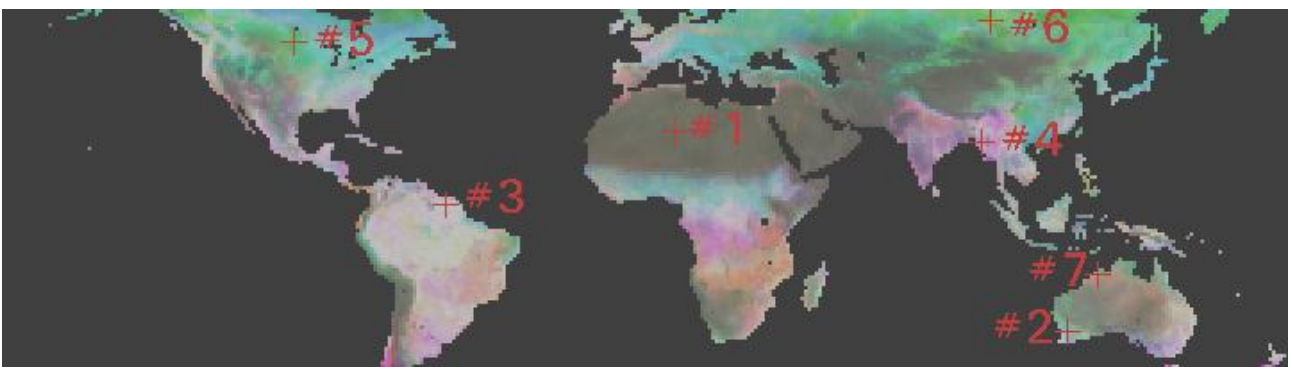


Figure 2: Composite of NDVI images for February, July and October 1984, with the locations of the profiles shown in Figure 3. These are common climatic regions, but the image shows clearly that they do not represent all of the climatic zones that exist around the globe.
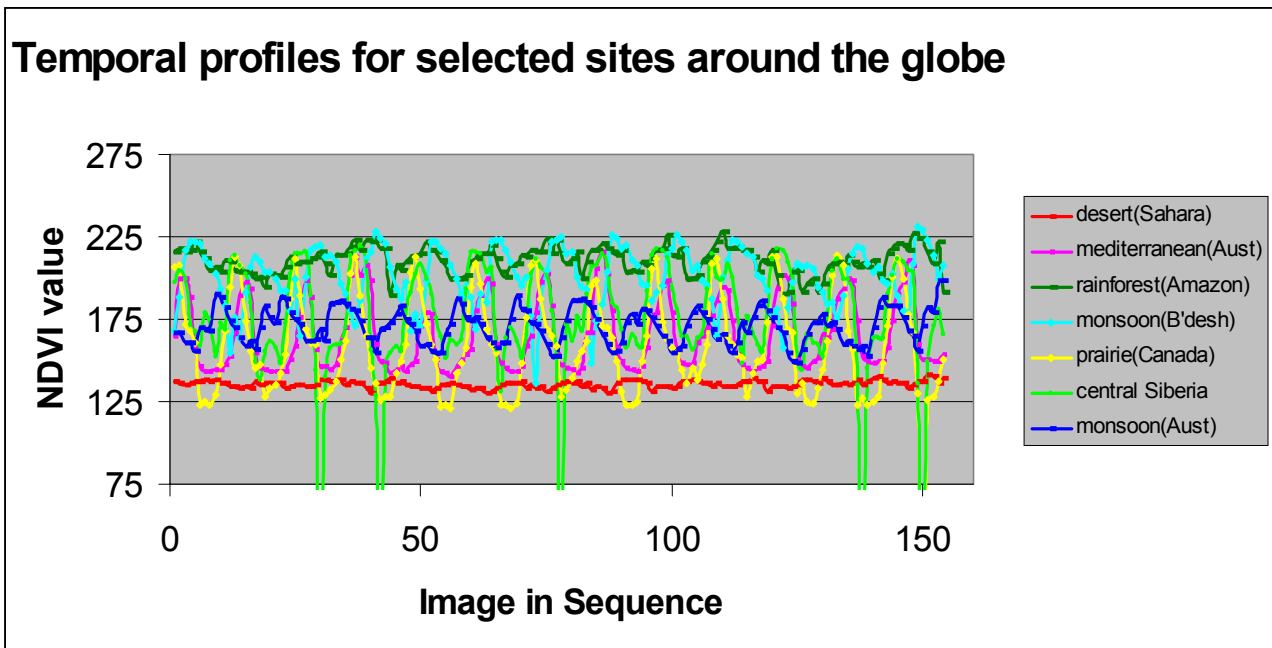


Figure 3: NDVI Profiles for typical climatic regions around the globe. Errors in the data can be seen for the central Siberian profile, with values dipping to zero on five occasions in this data set, for the site used.
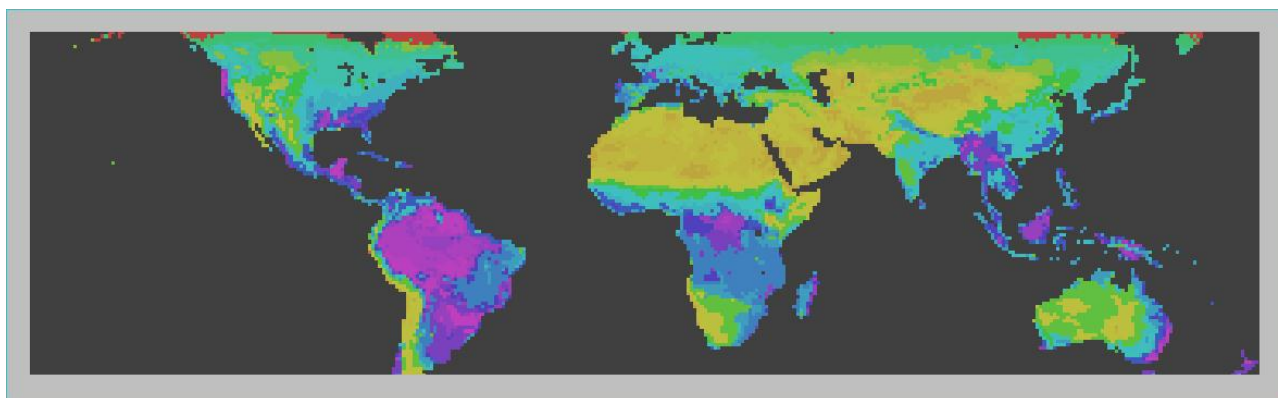
Figure 4: Classification of the NDVI image data shown in Figures 3 and 4. Areas of consistently high NDVI are shown as magenta, with areas of consistently low NDVI shown as yellow and red. Intermediate classes sare shown in cyan and green.
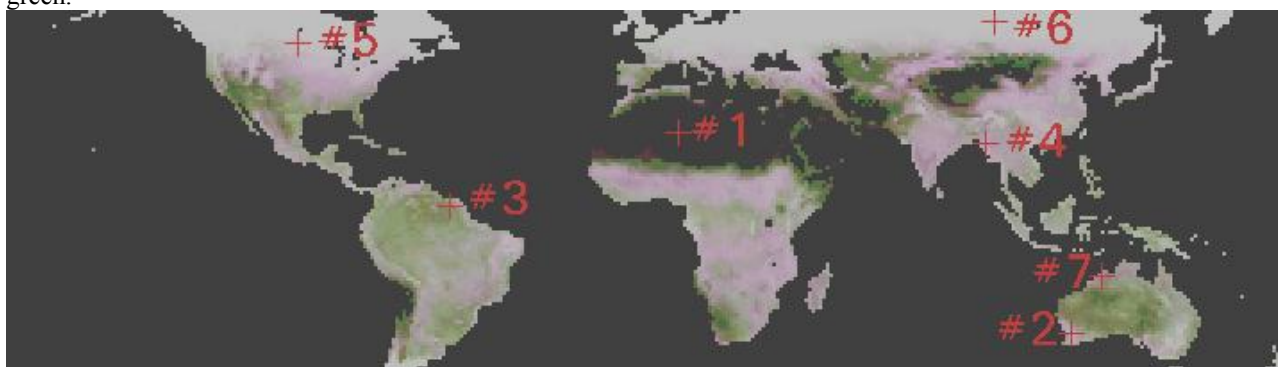


Figure 5: Temporal Semi-variograms for the Global NDVI data shown in Figure 2, with the same sites as used for profiles in the original image data. The Semi-variograms for these sites are shown in Figure 7.
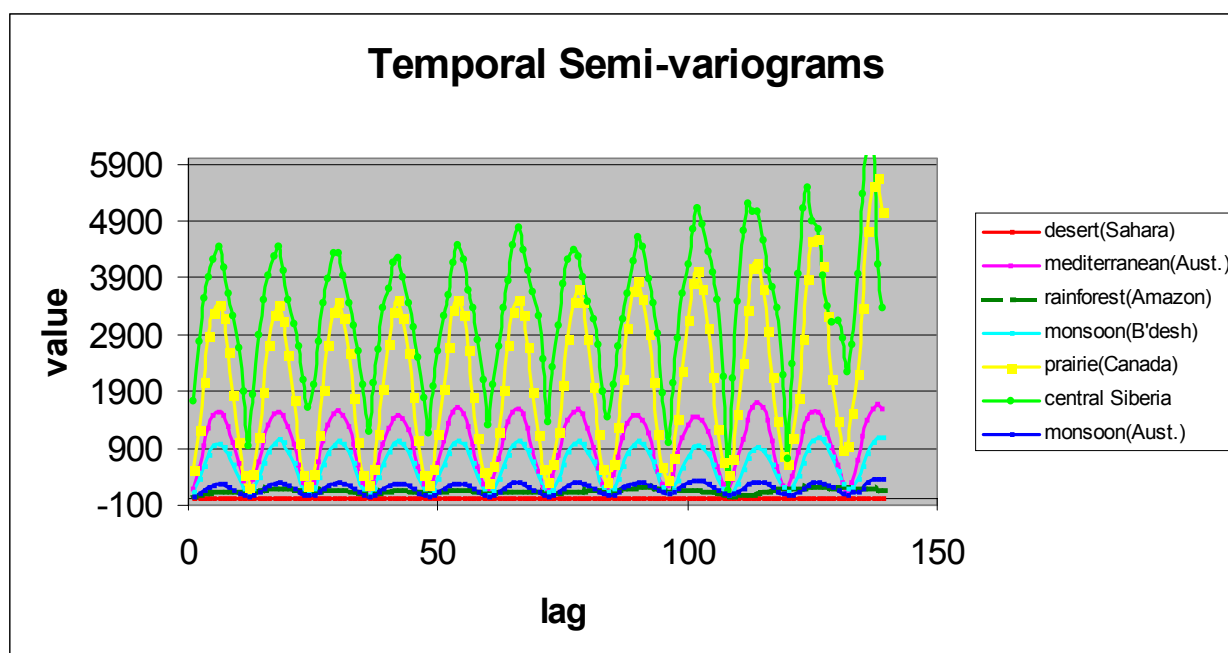


Figure 6: Semi-variograms for the seven sites shown in Figures 3 and 6. The strong 12 monthly cyclic pattern in most of the cover types is very obvious. Only the desert and rainforest sites do not exhibit cyclic patterns. There are strong differences in the amplitude of these patterns, and so one way to categorise climatic regions is by the amplitude of variation that they experience.
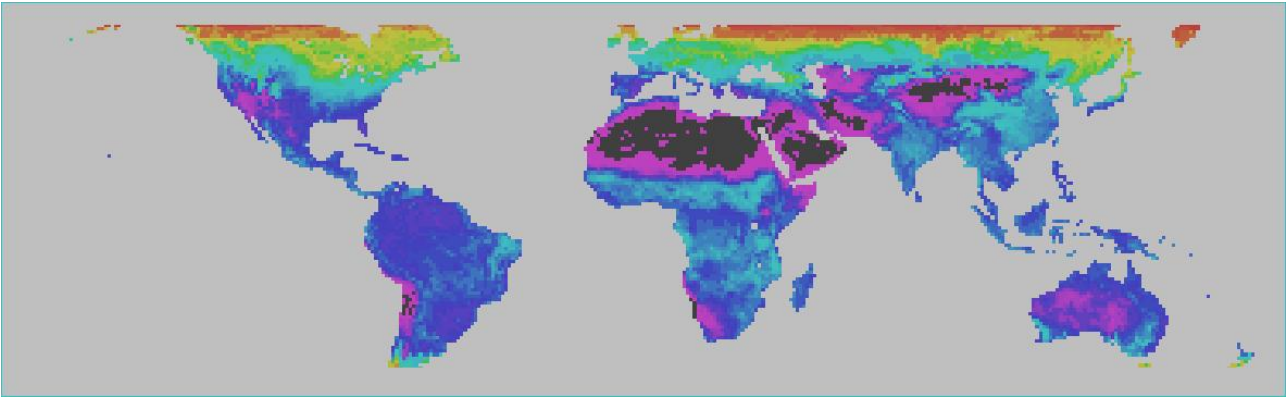
Figure 7: Classification of the Temporal Semi-variograms, depicting areas that are similar in annual variation in NDVI values. The lowest values of black and magenta occur in the Saharan desert, and other desert areas. The next lowest levels of variation are shown in the rainforest areas (blue), as well as central USA. Higher ranges of variation are found in the areas of monsoons and temperate climatic areas, whilst the maximum levels of variation are at higher latitudes.
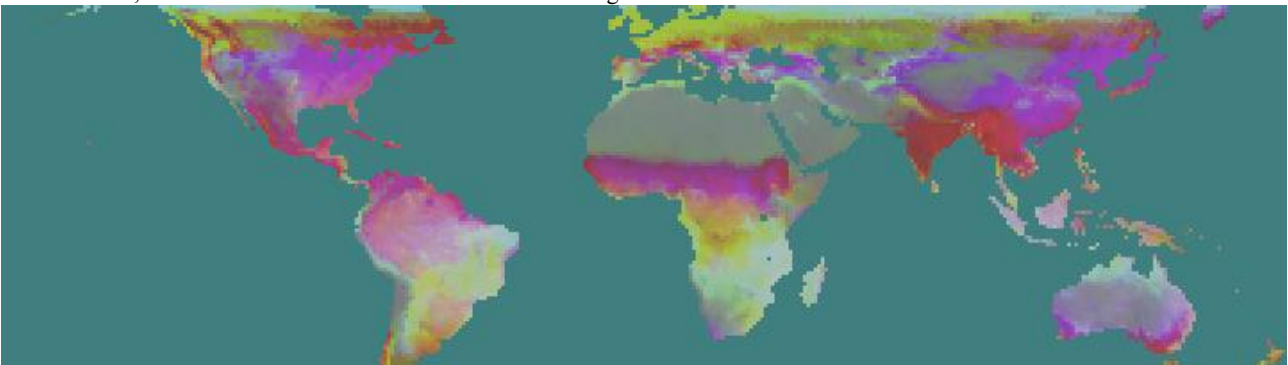


Figure 8: Principal components 1, 3 and 5 as red, green and blue respectively, as derived from the NDVI data displayed in Figure 3.
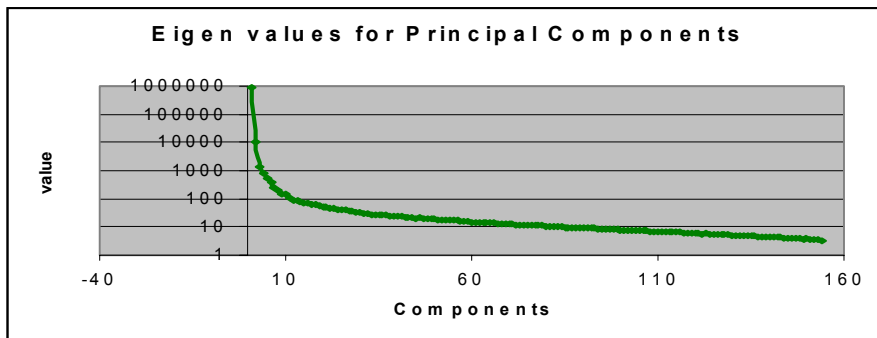


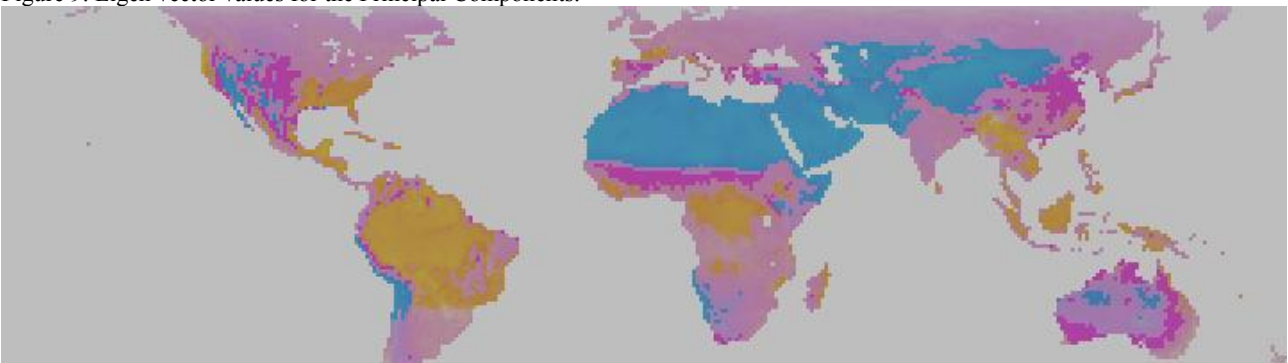Figure 9: Eigen vector values for the Principal Components.



Figure 10:Composite of three Temporal Distance images. Areas with NDVI values like desert are depicted in cyan, areas like rainforest in yellow, and areas like Mediterranean climates in magenta. Intermediate areas will have intermediate colours between these limits. The enhancement used is critical. In this image the enhancement is designed to clearly delineate "core areas", or areas with short distances to the cover type of interest.