Changing patterns of global-scale vegetation photosynthesis, 1982-1999

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Abstract. The primary objective of this research was to assess changes in global vegetation photosynthesis between 1982 and 1999. Global-scale AVHRR NDVI data from the PAL and GIMMS data sets were analysed for 96% of the non-Antarctic land area of the Earth. The results showed that over 30% of the Earth's surface increased and less than 5% decreased in annual average photosynthesis greater than 4%. Although both the PAL and GIMMS data sets produced broadly similar patterns of change, there were distinct differences between the two data sets. Changes in vegetation photosynthesis were occurring in spatial clusters across the globe and were being driven by climate change, ENSO events and human activity.

Keywords

global, vegetation, NDVI, persistence, photosynthesis, change

1. Introduction

From empirical evidence it is becoming clear that the flora and fauna on the surface of the Earth, from the Arctic to the tropics, are rapidly changing (Hughes 2000, McCarty 2001, Myneni et al. 1997, Parmesan and Yohe 2003). Change is occurring to the phenology and physiology of organisms, to the distribution and range of species and to the structure and dynamics of ecosystems (Wuethrich 2000, Walther et al. 2002, Hughes 2000, McCarty 2001). Peñuelas and Filella (2001, 793), for example, note that for Mediterranean ecosystems:

> the leaves of most deciduous plant species now unfold on average 16 days earlier and fall on average 13 days later than they did 50 years ago,

while Fitter and Fitter (2002, 1689) report that the

> average first flowering date of 385 British plant species has advanced by 4.5 days during the past decade [i.e. since 1990] compared with the previous four decades.

Much of this biological change is being driven by climate change, especially global warming: the Earth's climate has warmed by approximately 0.6 °C over the past 100 years (IPCC 2001). Additional drivers for the biological change include El Niño – Southern Oscillation (ENSO) events (Myneni et al. 1996, Anyamba et al. 2001) and human activity (Turner et al. 1990).

Now that satellite Earth observation data are available for decadal time scales, it is possible to identify major trends in vegetation cover over most of the land surface. In this paper we analyse for the majority of the Earth's land surface a near-20 year time series (1982-1999) of a vegetation indicator calculated from data provided from the Advanced Very High Resolution Radiometer (AVHRR) instrument carried on NOAA satellites (Cracknell 1997, Kidwell 1998).

In the process of studying vegetation change, we have used two different data sets derived from the AVHRR sensor, the NOAA / NASA Pathfinder AVHRR Land (PAL) data set and the Global Inventory Modeling and Mapping Studies (GIMMS) data set. In this paper we examine changes in vegetation photosynthesis at the global scale, plot the inter-annual patterns of change, discuss the main drivers bringing about this change during the last two decades of the 20th century, and compare the results from the two different AVHRR data sets. Using the Earth observation data from 1982 to 1999 we have found a substantial increase in photosynthesis over many parts of the planet.

Based on the analysis of the PAL data, more than 40 million km^2 of the land area showed an increase in annual average photosynthetic activity greater than 4 per cent while more than 2 million km^2 showed a decrease of greater than 4 per cent. When viewing persistent increases and persistent decreases in the vegetation indicator during the period, we found more than 21 million km^2 of the land area showed a persistent increase in annual average photosynthetic activity greater than 4 per cent between 1982 and 1999, while approximately 1 million km^2 showed a persistent decrease of greater than 4 per cent for the same period. Based on our analysis of the GIMMS data set, more than 55 million km^2 of the land area showed an increase in vegetation photosynthesis greater than 4 per cent while more than 15 million km^2 showed a decrease of greater than 4 per cent. When viewing persistent change, we found more than 27 million km^2 of the land area showed a persistent increase in vegetation photosynthesis greater than 4 per cent between 1982 and 1999, while more than 4 million km^2 showed a persistent decrease of greater than 4 per cent for the same period. When comparing the two data sets (PAL and GIMMS) we found that both captured many of the same patterns, but with important differences in how much change occurred and where the changes occurred: these changes are discussed in the paper

2. Data and methodology

2.1 Base data

For the research reported in this paper we used two data sets, the NOAA / NASA Pathfinder AVHRR Land (PAL) data set (Agbu and James 1994) and the Global Inventory Modeling and Mapping Studies (GIMMS) data set (Tucker et al. in press), both with a pixel size of 8 km by 8 km. The data were for the period January 1982 to December 1999 and were in a monthly Maximum Value Composite (MVC) Normalized Difference Vegetation Index (NDVI) format (see below). The base data are from the AVHRR sensor on-board NOAA's Polar Orbiting Environmental Satellite (POES) series (NOAA -7, -9, -11 and -14) (Kidwell, 1998). The AVHRR scanner records electromagnetic energy in five channels: channel 1 0.58-0.68 μm; channel 2 0.725-1.1 μm; channel 3 3.55-3.93 μm; channel 4 10.5-11.5 μm; channel 5 11.5-12.5 μm (Cracknell 1997, Hastings and Emery 1992). For global coverage the 1.1 km data are not recorded on-board, but rather are resampled on-board and stored as a daily Global Area Coverage (GAC) data set with a pixel size of approximately 4 km. For both data sets the GAC data have been re-sampled by into a coarser spatial resolution of 8 km. From the AVHRR GAC data there is now a long-term, global-scale data set that stretches back to mid-1981.

To detect vegetation we used the Normalised Difference Vegetation Index (NDVI). The NDVI is calculated as (Channel 2 – Channel 1) / (Channel 2 + Channel 1) using the AVHRR data noted above (Tucker 1979, Kidwell 1997). Plant leaves have a distinctive spectral profile because chlorophyll absorbs strongly in portions of the visible light spectrum, centred at about 0.45 μm and 0.67 μm, while the structure of the leaves' cells (particularly the mesophyll) creates a high reflectance and scatter in near-infrared light (Curran 1985, Gates et al. 1965, Tucker 1979). Reflectance measurements can therefore be used to detect the presence of growing vegetation (Sellers 1985, Steven et al. 2003). AVHRR NDVI data have been correlated with a number of vegetation indicators and characteristics, including seasonal variations of vegetation (Tucker et al. 1985, Justice et al. 1985), vegetation phenology (Lobo et al. 1997), land cover types (Townshend et al. 1991), net primary productivity (Goward et al. 1985, Goward and Dye 1987, Running and Nemani 1988), the spatial variability of vegetation activity at different scales (Justice et al. 1991), biomass burning (Malingreau et al. 1985), vegetation stress (Nicholson et al. 1990), large-scale climatic effects on vegetation (Eastman and Fulk 1993, Anyamba and Eastman 1996, Batista et al. 1997) and climatic variables in a wide range of environments and at different scales (Nicholson et al. 1990, Anyamba et al. 2001). Because NDVI is related to photosynthetic activity and so to plant respiration (Asrar et al. 1984, Tucker and Sellers 1986), relationships have been developed between annual variations in NDVI and variability in atmospheric carbon dioxide (Fung et al. 1986). Other biophysical properties that have been related to NDVI data including Leaf Area Index (LAI), evapotranspiration and vegetation biomass (Box et al. 1989, Goward and Hope 1989, Thomas et al. 1989, Nemani and Running 1989).

However, caution must also be exercised when using NDVI as a variable for the study of vegetation change as it is not only sensitive to vegetation characteristics but also to atmospheric variables, particularly the amount and variability of water vapour in the atmosphere and the presence of aerosols. NDVI data are also affected by sensor degradation, orbital drift, cloud cover, the anisotropic and transmissive radiation properties of plant canopies, soil moisture and soil colour (Bannari et al. 1995, Mennis 2001). For some arid and semi-arid regions, where bare soil reflectance accounts for a large percentage of the reflectance of a pixel (Harris 2003), soil colour and conditions may cause large NDVI variations spatially (Huete and Tucker 1991). However, for most vegetation types across a variety of environments the use of AVHRR NDVI data for the study of inter-annual variability of vegetation has become a well-established technique, especially when trends in vegetation change are analysed (Tateishi and Ebata 2004, Lim and Kafatos 2002, Myneni et al. 1998, 1997, Burgan and Hartford 1993). This paper uses changes in NDVI over time as an indicator of changes in vegetation photosynthesis. We do not quantify biomass production, but qualitatively review which parts of the Earth are increasing in vegetation photosynthesis, or productivity, and which parts are decreasing as revealed by changes in annual average NDVI.

2.2 Data quality

With more studies using AVHRR-derived global data sets, it has become apparent that there are some spatial, temporal and radiometric problems in the data (Goward et al. 1993, Kidwell 1997, 1998, Young and Anyamba 1999). To correct these known problems, the PAL data have been reformatted from the original GAC data with new algorithms (Agbu and James 1994). Gutman and Ignatov (1995) analyzed the PAL data set and found that the new calibrations (Rao 1993, Rao and Chen 1994) have removed both the drift in the NOAA-9 data and the discontinuity with the introduction of the NOAA-11 data. A small trend of increasing NDVI over the Sahara desert, however, was still found for most of the NOAA-11 period. Prince and Goward (1996) and Smith et al. (1997) have also confirmed that the new calibrations in the PAL data have decreased the sensor discontinuities between satellites. Young and Anyamba (1999), however, have found that there are still some radiometric miscalibrations in the PAL data and some spatial misregistration problems of data from NOAA-9 relative to data from NOAA-7 and NOAA-11, though not as severe as in NOAA's global vegetation index (GVI) data. Gutman (1999) has identified additional problems with the AVHRR derived data when undertaking long-term inter-annual studies. In particular, errors have been found in the PAL data especially from 35N to 35S, with a positive slope of the NDVI with respect to time over the 1981 to 2000 period, largely due to calibration errors and solar zenith angle effects due to sensor drift (Tucker et al., in press).

To correct these problems, the AVHRR data have been reformatted into a new data set, the Global Inventory Modeling and Mapping Studies (GIMMS) data set (Tucker et al., in press; Pinzon et al., 2004; Pinzon, 2002). The GIMMS data set has reduced variations in AVHRR NDVI, which were primarily caused by calibration issues, volcanic aerosols, and view geometry. Concerning calibration issues, for the GIMMS data the coefficients created by Vermote and Kaufman (1995) were used and invariant targets in the Sahara Desert were used to further reduce degradation errors in the data. Concerning volcanic aerosols, the GIMMS data corrects for the known changes of atmospheric aerosols due to the eruptions of El Chichon in 1982 and Mt. Pinatubo in 1991. However, a reduction of NDVI over densely vegetated tropical land covers do still appear for brief periods. The AVHRR NDVI data have been plagued with problems arising from the orbital drift of the NOAA platforms. The GIMMS data have been processed with a satellite overpass time drift correction (Empirical Mode Decomposition) that has reduced the variation of NDVI due to changes in solar zenith angle. For more detail concerning the significant changes in the processing of the AVHRR data to create the GIMMS data set please see: Tucker et al., in press; Pinzon et al., 2004; Pinzon, 2002. The processing of the AVHRR data for the GIMMS data set has reduced inter-annual variability related to the PAL data (figure

3b). Tests of the GIMMS data with measures of vegetation and climate have shown that the GIMMS data are able to capture general patterns of vegetation, inter-annual variations of vegetation, and climate signals (Poveda and Salazar, 2004; Jia et al., 2003; Lotsch et al., 2003; Nemani, et al., 2002).

There is some concern about using AVHRR-derived data for human-induced change detection research because of inter-annual climatic and atmospheric variations as well as sensor degradation (Kineman and Ohrenschall 1992, Goward et al. 1993, Gutman and Ignatov 1995). We have used a coarse spatial scale and long-term averages so that many of the minor inter-annual climatic fluctuations drop out and more long-term climate or human-induced changes can be discerned from the time series (Ehrlich and Lambin 1996). In addition, we use annual averages which reduce a variety of external factors. First, the data are in an NDVI format that reduces a number of sun angle and atmospheric problems (Kidwell 1997). Monthly maximum value composites (MVC) (the base data of the annual averages) also reduce atmospheric problems such as cloud cover (Holben 1986). The MVC is created on a pixel-by-pixel basis where each pixel's NDVI value is the highest value over the monthly period. Clouds have low NDVI values and so if there is one day without cloud cover, the NDVI from vegetation will be the resulting NDVI in the monthly value composite. Monthly MVCs are successful at removing cloud contamination effects, and large pixels (8 km) also reduce the effects of cloud cover (Mennis 2001). Cloud cover has been one of the major problems with satellite-based studies of land cover (Skole and Tucker 1993). The NDVI maximum value composite imagery is highly related to green-vegetation dynamics and is ideal for large area land cover research as the problems common to single-date remote sensing studies, such as cloud cover, atmospheric problems and view and illumination geometry, have been minimized (Holben 1986).

The data in an annual average composite captures the average vegetation status over the course of the entire year and thus reduces the problem of capturing vegetation information at different times of the phenological cycle. In addition, an annual average as opposed to a growing season average is important because some parts of the Earth have agriculture throughout the year, as well as capturing winter productivity from evergreen trees. The only exceptions were for areas poleward of 45^0 latitude where only nine months of data are used and the three months of lowest NDVI (generally the dormant part of the year for photosynthesis) are omitted for the PAL data set (section 2.3 below). However, it must be noted that all possible non-signal effects (atmospheric scatter, orbital drift, changing illumination, etc.) have not been completely removed from either of the data sets and some of the conclusions below are most likely influenced by them as well as actual changes in vegetation. Tropical areas and tropical forests in particular provide a challenge to global-scale analysis of AVHRR NDVI (Tucker et al., in press). Fires, cloudiness, and volcanic aerosols especially influence calculations from tropical areas, in addition to changes in illumination and other AVHRR related problems. We do believe though, that our use of Maximum Value Composites and Annual Averages help to reduce these effects and that our paper provides a good “first-cut” analysis of global-scale, long-term changes in photosynthetic activity.

2.3 Data preparation

The accuracy of the measurements of radiation in the AVHRR visible channels degrades rapidly when the sun is close to the horizon (high solar zenith angles), and therefore for the PAL data set all data with a solar zenith angle greater than 80 degrees are discarded (Agbu and James 1994).

In the winter hemisphere data are often discarded at higher latitudes. As the solar zenith changes along a scan, only part of the data is discarded creating a "saw tooth" pattern of missing data. This situation was extreme during the latter part of the NOAA-9 data series (1987-88) when, due to orbital drift, the late local time at satellite overpass meant that some data were collected at high solar zenith angles. To overcome the problem of missing winter data in the PAL data set, we created three annual average images with different months of the year based on latitude, and then concatenated the three images to create a global annual average image for each year. The three base images are listed below.

1. A twelve-month central Earth image from 45^0 N to 45^0 S, with 360^0 of longitude, created from images for all months January to December being added together with the resulting image divided by 12.

2. A nine-month northern image from 45^0 N to 70^0 N, with 360^0 of longitude, created from images for all months from February to October being added together with the resulting image divided by 9.

3. A nine-month southern image from 45^0 S to 60^0 S, with 360^0 of longitude, created from images for all months from August to April being added together with the resulting image divided by 9.

For each year these three images were concatenated together in order to produce an annual average NDVI image that had a minimum of noise, due to low sun angles, but a coverage of a maximum amount of the Earth's land surface. Together these three images capture 96.7 per cent of the non-Antarctic land area of the Earth. Because of the lack of data in September, October, November and December 1994 and also noise in the data for 1994, no direct data from 1994 were used in the PAL data for this study. In order to create continuity within the long-term data set, a PAL image data set for 1994 was created where the image for 1994 is an average of the images for 1993 and 1995. The GIMMS data set did not have missing winter data and so we did not exclude winter months from the data, but we did window out the data to be directly compatible with the spatial extent of the PAL data, namely 60^0 S to 70^0 N.

To determine change over the course of 18 years (1982 to 1999) a univariate differencing, or simple differencing, methodology was undertaken. Simple differencing is the difference between the values of the same pixel in two spatially registered images of the same area at different dates and has been found to be one of the more accurate change detection techniques (Woodwell et al, 1983, Jensen 1996, Singh 1986, Singh, 1989). The simple differencing technique is most appropriate where the objective is not to classify the specific land covers, which do change, but rather to assess the amount and direction of major change.

We processed both the PAL and GIMMS data sets at the beginning and end of the time series. The annual average images of 1982 and 1983 were added together and divided by two to create a 1982-83 average composite image. The images for 1998 and 1999 were also added together and divided by two to create a 1998-99 average composite image. These composites were created as the end points of the time series and to reduce any extremes or other anomalies in the data. We were interested in capturing long-term trends and so we wanted to reduce any seasonal or short-term inter-annual variations. The 1982-83 average composite image was then subtracted from the 1998-99 average composite image to create a difference image where positive values indicate increases in NDVI during the time period and negative values indicate decreases.

To determine the per cent change in NDVI between 1982-83 and 1998-99, the difference image (1998-99 minus 1982-83) was divided by the 1982-83 average image creating a per cent change image. To show the direction and magnitude of change, a simplified threshold image was created where the per cent change image was value sliced into five categories based on the percentage of change: 1) < -8 per cent change, 2) from -8 to < -4 per cent, 3) from -4 to +4 per cent, 4) from > +4 to +8 per cent and 5) > +8 per cent change.

Some of the vegetation change since 1982 has been ephemeral, but much has been persistent (Menzel and Fabian 1999, Walther et al. 2002). To determine the pixels of persistent increase and persistent decrease in NDVI throughout the period, we created an index of persistence. First we produced the simple difference NDVI image for seven time periods that increased in length: years 1982-1987, years 1982-1989, years 1982-1991, years 1982-1993, years 1982-1995, years 1982-1997 and years 1982-1999. We then created per cent difference images by dividing each of the resulting images by the 1982 image, and then we created a per cent threshold image where each pixel falls either above or below a threshold per cent of change. For the first two periods the threshold was 2 per cent, for the next three periods it was 3 per cent, and for the final two periods it was 4 per cent. For each period a score of 1 was given to the pixels increasing above the threshold and a score of –10 to the pixels decreasing below the threshold. A magnitude of difference was used so that no persistently increasing (decreasing) NDVI would have a single period of decrease (increase). The sum of these scores was used to indicate persistent pixels where a score of 5, 6 or 7 indicated persistently increasing vegetation (no periods of decrease beyond threshold) and a score of –50, -60, and -70 indicated persistently decreasing vegetation (no periods of increase beyond threshold). We also included a score of -4 (six positive increases and one negative) in the persistent increase and a score of -59 (six periods of decrease and one period of increase) as persistent decline. An image based on these scores was used to mask out non-persistent pixels in the normalised simple differencing image of 1998-99 minus 1982-83 divided by the image for 1982-83. The resulting images for the PAL data (figure 1) and the GIMMS data (figure 2) show the spatial distribution and magnitude of persistently increasing and persistently decreasing NDVI across the globe.

To analyse changes in land cover types for the PAL and GIMMS data, we used the University of Maryland Global Land Cover Facilities' land cover (8 km) image (DeFries et al. 1998). This image was derived from the PAL data (same projection and same pixel size as the PAL data used in this paper) and is classified into 13 land cover types. In Idrisi we resampled the land cover image to fit the projection and parameters of the GIMMS data. We overlaid this image on our vegetation change images to extract percentages of land cover types experiencing change.

After all of the PAL data were processed, we produced an analysis of the annual average NDVI data for the Sahara desert (5.7 million km^2) and the Taklimakan desert (0.25 million km^2) as calibration zones and found that although the NDVI varied slightly from the base year of 1982, the end values used for the simple differencing, 1982 and 1999, were only 0.1 per cent and 0.7 per cent different respectively from each other (see figure 3a). Therefore we did not recalibrate the PAL data. We also produced an analysis of the same calibration zones for the GIMMS data and found less variability throughout the time series (figure 3b).

3. Results and discussion

3.1 Overview

Between 1982 and 1999 the general trend of vegetation change throughout the world has been one of increasing photosynthesis as represented by NDVI. For the PAL data, globally more than 30 per cent of land pixels increased in annual average NDVI greater than 4 per cent (table 1) and more than 16 per cent persistently increased greater than 4 per cent (table 2). During the same period less than 2 per cent of land pixels declined in NDVI (table 1) and less than 1 per cent persistently declined (table 2). On every continent over 20 per cent of land pixels increased in annual average NDVI more than 4 per cent (table 1) and only Australia had less than 10 per cent of the pixels showing a persistent increase (table 2). Concerning the GIMMS data, even more areas were found to be persistently increasing (greater than 20%) and persistently decreasing (more than 3%) (Table 2). Changes in vegetation photosynthetic activity across the globe are clearly showing a spatial clustering (figures 1, 2). Europe and North America have the greatest percentage of pixels persistently increasing in NDVI, while Australia, South America, and Africa have the greatest percentage of pixels showing a persistent decline (table 2). In our research we were not only interested in finding areas of significant increase or decrease, but we were also interested in understanding the inter-annual patterns of change from 1982 to 1999 (figure 3). Both areas of increase and areas of decrease show the following four broad patterns of change.

1) a discrete period of change or step change (figure 3c);

2) a progressive change with minor inter-annual fluctuations(figure 3d);

3) a cyclic pattern of change with a moderate level of inter-annual fluctuations(figure 3e);

4) a pattern with severe fluctuations between 1982 and 1999, so much so that an opposite change could be recorded for several years throughout the time period (figure 3f).

For the initial simple differencing image (1998-99 minus 1982-83) for both data sets, approximately half of the pixels increasing and decreasing beyond the 4 per cent threshold level displayed a high range of inter-annual fluctuation and most were filtered out with the persistence index (described in the methodology section above).

3.2 Filtered areas

Both the PAL and the GIMMS data sets displayed similar effects from filtering. For brevity our analysis of filtering focuses on the PAL data. Most of the pixels filtered out using the index of persistence were those of moderate change (+/- 4 per cent to 8 per cent) (tables 3, 4, 7). These filtered pixels displayed wide fluctuations of change (pattern number 4 above). Decreasing NDVI was filtered out at a higher percentage than increasing NDVI (tables 4, 7). This was especially true for the GIMMS data. Two factors could be causing this to happen. First, the broad overall global trend was one of increasing NDVI, and so areas of decrease could have been pixels in a minor period of decrease during the time period, while much of the time series showed a positive increase or neutral state. Second, this could be due to the nature of the declining NDVI where many of the areas of declining NDVI are discrete declines which occur for a specific period of time, because of (say) deforestation, and if this discrete period did not start until the 1990s it would not fall into the category of persistent decline for the entire time series which began in 1982.

Looking at a regional perspective, the filtered areas are found throughout much of the world, and most of these areas are widely spread out. Concerning areas of increasing NDVI, there are a few large areas of distinct clustering, notably: southeast and western Australia; eastern Mongolia and Inner Mongolia (China); western Iraq and north-western Iran; much of Turkey; the western Georgia-Russia border region; central Romania; north-western Iberian Peninsula; parts of the African Sahel, especially in central Chad; north-eastern Kenya into south-eastern Somalia; south-central Mozambique; the Pampas region of Argentina; the coastal border region of Ecuador and Peru; north-central United States, especially in the Great Lakes region and the Dakota prairie; eastern Newfoundland (Canada); and northern Manitoba along Hudson Bay (Canada). Each of these regions has a similar temporal profile in that the change in NDVI varies widely between 1982 and 1999, although the specific variations are different for each region.

There are undoubtedly numerous causes for these fluctuations for each of the areas, but climate variation is a major reason as some of these regions have already been identified as highly susceptible to ENSO events, such as southwest Australia, southern Africa and southern South America (Myneni et al. 1996, Anyamba et al. 2001). In addition, other vegetation zones such as the savannas and grasslands of the African Sahel are known to be variable because of large-scale climatic variations (Zeng et al 1999).

We not only analysed change from a regional perspective, but we also analysed it from a land cover perspective (tables 5, 6, 7). We found the widely fluctuating pixels (pattern number 4 above, and filtered out) in all land cover types, with the greatest percent of pixels filtered out being areas of mild increase and mild decrease with a higher overall filtering in the decreasing NDVI. Here we do not present temporal profiles or explanations for all of these areas, but we do show two interesting cases, Australia and the Ecuador – Peru coastal region.

Two large regions of fluctuating NDVI values, one in western Australia (16,000 km^2) and the other in eastern Australia (17,000 km^2), show PAL data temporal profiles of fluctuations that indicate a pattern of ENSO influence (figure 4b). The pixels not filtered out in these areas, demonstrating a progressive increase, tend to be those that fall above the 8 per cent threshold and are also influenced by the ENSO events, but have some strong underlying rise throughout the period. A profile of persistent increase (13,000 km^2) shows the underlying trend (figure 4d). The coastal Peru and Ecuador border region is characterized as an arid and semi-arid region with a low level of vegetation photosynthesis. The dominant land cover here is open shrubland (Defries et al. 1998). During ENSO events these regions receive additional moisture and thetemporal PAL data NDVI profiles of this region clearly reflect the ENSO influence on vegetation. The varying pixels are picking up the signal of increased precipitation related to El Niño and a consequent increase in NDVI. In non-El Niño years there are deep decreases of NDVI. This is a region sensitive to change as figure 4a shows variations of over 200 per cent.

Concerning areas of negative values filtered out, many are widely distributed. Three areas of clustering include north-central Australia, north of the Caspian Sea, and a number of locations in South America. These regions show considerable fluctuation in their temporal profiles and interpretation of them is inconclusive.

3.3 Persistent change – PAL data

Major areas with a clearly defined persistent increase (numerous spatially coherent pixels with >8 per cent increase) in the PAL data include ten broad areas: western Australia, North China Plain, India, coastal west Africa, east Africa, Turkey - Iraq, central-northern Europe, north-eastern South America, south-eastern Canada, and north west Canada. All of these areas have a cyclic pattern, although some of the patterns are more pronounced than others. Except for western Australia and the Turkey-Iraq region, all of the other major areas of greater than 8 per cent increase also have substantial areas of 4 to 8 per cent increase (figure 1).

There are fewer major areas of vegetation decrease at the global scale: they include central Australia, southern Iraq and a scattering of places in South America. Of these three major areas, the declines in Australia show considerable inter-annual fluctuation and appear to be related to ENSO events. There appears to have been a major decline in NDVI between 1984 and 1985 (figure 4c, 5a). Many of the declining regions of South America demonstrate clear patterns of decline (figure 4f) as do smaller areas in Africa, Canada, the Middle East and Southeast Asia (figures 3c, 4e). A very clear area of decline is that which occurred in the marshes of southern Iraq as a direct result of government policy (figure 3c).

Along with analyzing geographic regions of change, we looked at different land covers to determine if there were certain biomes that experienced change greater than others. Using as a basis the land cover map created by the University of Maryland Global Land Cover Facility (see section 2.3), we analysed change in NDVI for 13 different land cover types across the globe. Although all 13 land cover types experienced change, Evergreen Needleleaf Forest, Mixed Forest, Wooded Grassland and Cropland changed the most, with all of them experiencing high levels of increase in NDVI (tables 5, 6). For these four land cover types, more than 40 per cent of the annual average NDVI increased greater than 4 per cent (table 5) and more than 20 per cent persistently increased greater than 4 per cent (table 6). As expected, the Bare Ground land cover class experienced the least change with more than 94 per cent of this land cover category not changing. Few areas showed declines in vegetation, with only one land cover type, Closed

Shrubland, having more than 3 per cent of the area declining greater than 4 per cent between 1982 and 1999. Much of this land cover type, however, had a pattern of considerable inter-annual fluctuation and so it is uncertain if there is truly a pattern of decrease for this cover type.

3.4 Persistent change – comparisons with GIMMS data

As noted earlier, the PAL data and the GIMMS data are both derived from the AVHRR GAC data, but have been processed differently in order to remove various problems in the AVHRR data. The GIMMS data set is a more recent processing of AVHRR data and it appears to have reduced a number of problems found in the PAL AVHRR NDVI data. This research analyzed global vegetation change using the same methodology on both the PAL and the GIMMS data sets, with results showing patterns of change that are more similar than they are dissimilar. Of the ten broad areas of change indicated by the PAL data results, eight of these regions are also pronounced in the GIMMS data along with an additional six regions: Southeast Australia, Central Asia, southern Caspian region, areas in the African Sahel, southwestern South America, and central North America. Both data sets indicate that the majority of change on the Earth is one of increasing NDVI with only a few areas of declining NDVI. The GIMMS data set pointed to more areas both increasing and decreasing in NDVI (figure 2, table 2). The GIMMS data indicated that 24.3% of the Earth's surface was either persistently increasing or persistently decreasing in NDVI. Of that 24.3%, 85.4% was increasing and 14.6% was decreasing. For the PAL data, 17.1% of the Earth was persistently changing, with 96.4% of those pixels increasing and only 3.6% decreasing.

Comparing the data sets region by region we again found more similarity than dissimilarity. Concerning Australia, in both data sets central Australia showed broad areas of decline in vegetation photosynthesis while extensive areas in southeast and southwest showed regions of increase. The main difference is that the GIMMS data showed more pixels of increase and decrease. Many of these additional pixels found in the GIMMS data were captured by the PAL data as well, but were filtered out as not being pixels of persistent change (Table 3 Austral realm shows that almost 20% of the region had pixels of non-persistent change, both increase and decrease). This might indicate that the processing used to create the GIMMS data set has decreased the inter-annual variability of the AVHRR data (figure 5).

Concerning Southeast Asia, the two data sets show different patterns of change. The PAL data set indicates that more areas experienced change than the GIMMS data set indicates. One area of considerable difference can be found in the Philippines, where the PAL data pointed to extensive areas of mild increase (between 4 and 8%). When reviewing the Southeast Asian PAL data with temporal profiles, we found that much of the region showed considerable inter-annual variation (figure 3f, New Guinea, figure 5b, Philippines). It again appears that the GIMMS data has reduced inter-annual fluctuations, but unlike Australia this has led to a reduction in pixels indicating long-term change. One of the main concerns about the PAL data is errors found between 35^0 N and 35^0 S, where there is a positive slope over the 1981 to 2000 period, due to potential calibrations errors and orbital drift. The GIMMS data appears to have corrected aspects of this problem (figure 5b). One area, which does show up on both data sets, and in area profiling a clear progression, is that of the Mekong delta region (Figure 3d). In East Asia the two data sets illustrate different levels of change where the GIMMS data shows more areas changing than the PAL data. Similar to the situation in Australia, many of the change pixels found in the GIMMS data were filtered out as non-persistent change in the PAL data. However, one different issue is that the GIMMS data indicates more areas of negative change which did not show up on any of the East Asian PAL analyses, especially the broad area of change in east Siberia (the Yakutsk region) and the concentrated area of negative change in Inner Mongolia (the Baotou area). Both data sets do illustrate the increasing NDVI of the North China Plain (figure 3d). South Asia is indicated on both data sets as an area of extensive and intensive increases in NDVI. At the global scale this region stands out as a major area of increasing NDVI. The GIMMS data indicates that the change was at a greater level (more pixels greater than 8%) and there was a broader area of decline in west India (Rajasthan). Like East Asia and Australia, Central Asia is shown to have much more change in the GIMMS data than in the PAL data, where many PAL pixels were filtered out as non-persistent change. Southwest Asia shows many similar patterns in the two data sets except that once again the GIMMS data set shows more areas of increasing and decreasing NDVI. Like East Asia, the GIMMS data shows regions of decline that none of the PAL analyses indicated. Both data sets did show the decline of NDVI in the southern marsh region of Iraq and the greening up of the Tigris-Euphrates region as well as the greening up of agricultural regions in Saudi Arabia. One major difference is the increasing NDVI found in the GIMMS data at the southeastern portion of the Arabian Peninsula (figures 2, 5c). The PAL data filtered out the change as non-persistent.

In Europe, although both the PAL and GIMMS data sets show similar broad patterns of change, there are three large areas of distinct differences. On the PAL data, southern Sweden is indicated as an area of extensive increasing NDVI, while it is not on the GIMMS data and some parts are even indicated as areas of mild decline (figure 5d). The northern portions of the Scandinavian peninsula and parts of neighbouring Finland and Russia are indicated as areas of intensive increasing NDVI on the GIMMS data and not as extensive or intensive on the PAL data. Finally, southeast Finland is shown to be an area of declining NDVI on the GIMMS data, while neither declining nor increasing on the PAL data. In Africa, the two data sets displayed many similar patterns. As in many other parts of the world, the GIMMS data showed more areas of change and many of these areas were filtered out from the PAL data. There were, however, two main differences between the two data sets. First, like in other parts of the world, the GIMMS data showed more areas of decline than the PAL data, and areas where filtering was not the issue. In Africa, more than anywhere else in the world the data sets differ concerning areas of decline (Table 2). The GIMMS data shows numerous areas throughout Africa indicating declining NDVI which none of the PAL data analyses found. The other major difference is that the PAL data indicates coastal West Africa as a broad coherent area of increasing NDVI, while the GIMMS data do not. The GIMMS data shows parts of this area increasing, such as the Niger Delta, but not the region as a whole like the PAL data does (figure 5e, 5f). The GIMMS data also shows more of the West African Sahel region and northern Africa greening up than the PAL data, but as in other parts of the world many PAL pixels in these regions were filtered out.

In South America many of the broad patterns of change were similar, especially when considering the pixels filtered out from the PAL data. Again like other part of the world, the GIMMS data indicates that there are more areas declining in NDVI, though the two data sets do show many similar areas of decline (figures 1, 2; Table 2). Another difference is that the southwestern portion of the continent shows a much greater increase in NDVI in the GIMMS data than in the PAL data. Central America and the Caribbean show greater change in the results from the PAL data than from the GIMMS data, though not as extensively as in Southeast Asia.

The one exception is the island of Cuba which shows more change in the GIMMS data, though like elsewhere the PAL data where filtered out for much of Cuba. Another difference is that there are more pixels of decline in the GIMMS data. For North America, like much of the world, the GIMMS data show more areas increasing and decreasing in NDVI. Like other areas as well, areas of increase on the GIMMS data, but not on the PAL data are areas where the PAL pixels were filtered out. There is, however, a major pattern of increasing NDVI (>8%) on the GIMMS data which stretches west from the central western shores of Hudson's Bay which does not show up as extensive on the PAL data and have not been filtered out. Another major area of distinction similar to coastal West Africa and Southeast Asia is that the southeastern portion of the United States is shown to be broadly increasing in NDVI on the PAL data, but not on the GIMMS data.

Overall both data sets displayed more similarity than dissimilarity, and both data sets indicated that much more of the Earth has been increasing in NDVI than decreasing. The GIMMS data shows more areas increasing and decreasing in NDVI than the PAL data. The GIMMS data also shows that the increases and decreases are of a greater intensity (a higher percent of pixels greater than 8% change). For many parts of the world the larger areas of increase in the GIMMS data includes pixels which were filtered out of the PAL data. Most of the additional areas of decline found on the GIMMS data, however, were never captured by the PAL data. The GIMMS data set is a reprocessing of AVHRR data due to concerns found in the PAL data, especially for areas between 35^0 N and 35^0 S. Most of the differences found between the two data sets do fall within this latitudinal range. Based on the comparisons of temporal profiles between the two data sets (figure 5), the GIMMS data appears to have reduced inter-annual variations.

3.5 Reasons for change

Climate change, and in particular global warming, has been postulated to be a major driver in changing the flora and fauna throughout the world (Walther et al. 2002, Hughes 2000, Peñuelas and Filella 2001). In addition to temperature change, associated precipitation change and increases in atmospheric carbon dioxide have had an influence on vegetation change (Myneni et al. 1997, Ichii et al. 2002). The change in climate, which affects vegetation broadly, appears to be most influential at higher latitudes (Hansen et al. 1999, IPCC 2001, Slayback et al., 2003, Zhou et al. 2001) with much of the increase in photosynthesis across northern Europe and North America being driven by an increase in winter temperatures along with an earlier arrival of spring and a later onset of cooling in the autumn. Several remote sensing based studies have shown that areas in the northern high latitudes are increasing in photosynthesis and postulate that it is due to global warming (Myneni, et al. 1997, Ichii et al. 2002). Sturm et al (2001, 546) for example have noted that:

> The warming of the Alaskan Arctic during the past 150 years has accelerated over the last three decades and is expected to increase vegetation productivity in tundra if shrubs become more abundant; indeed, this transition may already be under way.

We found that the NDVI inter-annual profiles for the higher latitude areas showed a cyclic pattern, which increases over time, and is consistent with a fluctuating, climate-influenced change. Studies in Europe and North America have revealed phenological trends that reflect responses to recent warming trends in higher latitudes (Peñuelas and Filella 2001, Hughes 2000).

The El Niño/Southern Oscillation is also a primary driver of inter-annual variability in global climate (Myneni et al. 1996, Anyamba et al. 2001). Some areas showing a potential influence in vegetation photosynthesis from ENSO events based on their temporal NDVI profiles include northeast Brazil, southern Africa, south western Australia and south eastern Australia. Many of the pixels in the unfiltered change image in these areas showed an increase in NDVI over the period, although their temporal profiles showed considerable variation that makes long-term trends uncertain.

Human activity also affects global-scale vegetation change at the decadal time scale and is responsible for both increases and decreases in vegetation photosynthesis. Human influence on vegetation change can be divided into three major factors: extraction of biological resources, improved land management and development, and altering water resources. We have found a number of examples of each factor influencing changes in vegetation photosynthesis. Many of the areas of decreasing NDVI are the result of human activity. These areas are characterised by having little inter-annual fluctuation in NDVI, but often a discrete pattern of change (figure 3c) which may result from the extraction of biological resources. For example, the Santa Cruz region of Bolivia is an area which has been experiencing intensive deforestation (Steininger et al. 2001) and shows up as an area of declining NDVI (figure 4f) as do a number of other areas in South America experiencing deforestation (Skole and Tucker 1993). Another example of the extraction of biological resources is urbanization where vegetation cover is removed by the expansion of cities. Urban areas showing evidence of decreasing photosynthesis include Shanghai, Bangkok and Yangoon, although the greatest decline around an urban area is from Guangzhou in Southern China, an area experiencing rapid urbanization (Seto et al. 2000) (figure 4e).

Development activity by humans may also be responsible for considerable increase in vegetation photosynthesis across the globe. Photosynthesis in cropland has increased dramatically throughout the world (table 5, 6). For example, cropland had the greatest area increasing above 8 per cent (over 760,000 km^2) in the persistent PAL data and the second highest increases above 4% in the persistent GIMMS data (3.5 million km^2). Concerning land cover types showing persistently increasing NDVI above the 4 per cent level, after Evergreen Needleleaf (28.1 per cent) Cropland had the second greatest per cent of pixels (25.5 per cent), but had the largest area (3.6 million km^2, see table 6). Areas such as the North China Plain, much of India, and the Mekong Delta show up as striking examples of increasing photosynthesis (figures 1, 2, 3d). Reflecting this development are the increases in agricultural production statistics for India, Egypt, China and Vietnam (FAO 2000). Numerous other agricultural regions show up with increasing photosynthesis. The changing use of water resources has influenced both increases and decreases of photosynthesis. A well-documented case of decreasing photosynthesis due to the diversion of water has occurred in southern Iraq, where the government denied water access to the inhabitants of the marshlands of southern Iraq (UNEP 2001). This region clearly shows up as an area of vegetation decrease (figure 1), with a clear temporal profile of declining photosynthesis after the 1991 Gulf War, until the region reaches annual average NDVI values for bare land in the late 1990s (figure 3c). On the positive side, water extraction has assisted many areas in increased vegetation productivity, such as Saudi Arabia (figures 1, 2, 3d). There are questions, however, about the sustainability of such water extraction and the resultant agriculture in these arid areas.

4. Conclusions

Satellite Earth observation data are now available for sufficiently long time periods to allow analysis of environmental change over the whole planet. With suitable processing, the Normalised Difference Vegetation Index has been found by many scientists to be a robust indicator of vegetation photosynthesis, especially for large areas and yearly time periods. The evidence presented here for the broad-scale increases in photosynthesis across the Earth is consistent with published work on recent environmental change (Walther et al 2002, Parmesan and Yohe 2003) and can be ascribed to two main causes. First, climate change (primarily global warming and ENSO events) and ecological adaptation (Wuethrich 2000, Walther et al. 2002, Hughes 2000, McCarty 2001, Peñuelas and Filella 2001). Second, human activity, specifically the extraction of biological resources, the improved management of land and the development and alteration of water resources. This research demonstrates that while the PAL and GIMMS data sets show similar patterns of change, there are distinct areas of difference that need to be explored further. It is also apparent that the reformatting of the AVHRR data in the GIMMS data has reduced inter-annual fluctuations in the data.

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