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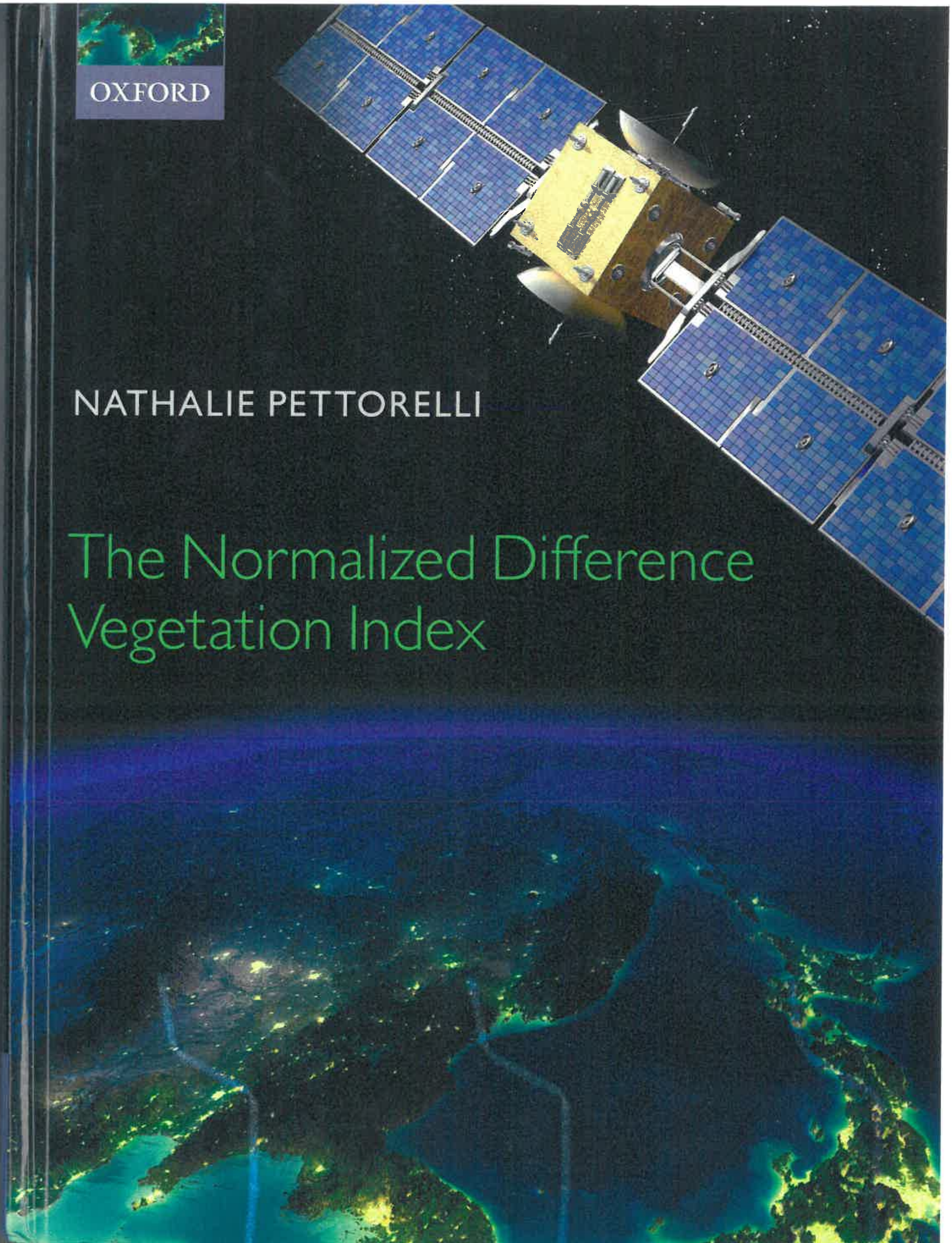
NATHALIE PETTORELLI

The Normalized Difference Vegetation Index



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Inc., GeoEye-1, is currently the world's highest resolution commercial Earth-imaging satellite, with images collected at 41 cm (panchromatic mode) and 1.65 m (multispectral imagery) resolutions. Satellites such as QuickBird, IKONOS or GeoEye-1 can be perfect for gathering high resolution, spatially precise information, and may help to map the distribution of human infrastructures such as road or rail networks, or city delimitation. In very rare cases, these satellites can also help ecologists to detect and count wildlife: Fretwell et al. (2012) demonstrated how images from the QuickBird, WorldView-2, and IKONOS satellites could be used to detect emperor penguin *Aptenodytes fosteri* colonies and estimate colony size, at the scale of the whole continental coastline of Antarctica. In Australia, very high resolution SPOT 5 and Quickbird imagery helped in mapping the distribution of an invasive plant species, *Lantana camara* (Taylor et al. 2011). Because of the costs of very high resolution images (all of these satellites are commercial), and because of the number of images required to cover a typical study area, such satellites are rarely used in ecology and conservation.

1.2.3.2 Monitoring at lower resolution: the example of Landsat

The Landsat Program is a series of Earth-observing satellite missions jointly managed by the National Aeronautics and Space Administration (NASA) and the US Geological Survey (USGS). The Landsat system consists of spacecraft-borne sensors that observe the Earth and transmit information by microwave signals to ground stations that receive and process the data for dissemination. The Earth Resources Technology Satellite, also known as the first Landsat satellite, was launched in 1972, and the most recent, Landsat 8, was launched in May 2013. Landsat sensors have a moderate spatial resolution (Landsat 8 spatial resolution ranges from 15 to 100 m). Landsat provides access to an important spatial resolution that is coarse enough for global coverage, yet detailed enough to characterize human-scale processes such as urban growth. Landsat satellite data are the only record of global land surface conditions at a spatial scale of tens of metres spanning the last thirty years (Tucker et al. 2004).

The particularity of Landsat satellites is that they collect several images at once (all of the images are obtained at the same time, and at exactly the same location), with each image showing a specific section of the electromagnetic spectrum. Landsat TM, for example, collects information in seven bands, with each band maximizing the ability to differentiate particular objects or structures. Band 1 helps coastal water mapping, soil/vegetation discrimination, forest classification, and man-made feature identification. Band 2 helps vegetation discrimination and health monitoring, as well as man-made feature identification. Band 3 helps plant species identification and man-made feature identification, while Band 4 is useful when monitoring soil moisture and vegetation, as well as for water body discrimination. Band 5 is generally used for vegetation moisture content monitoring and Band 6 for monitoring surface temperature, vegetation stress, and soil moisture. Band 6 can also help with cloud differentiation and volcanic monitoring. Band 7 helps with mineral and rock discrimination, as well as with vegetation moisture content monitoring (see Table 1.2). It is the combination of the information collected in each band that allows the mapping of specific habitats.

Landsat data are probably among the most widely used satellite imagery in ecology and conservation. Examples of applications include coral reef (Ahmad and Neil 1994; Palandro et al. 2008), mangrove (Giri et al. 2011), and seagrass meadow (Wabnitz et al. 2008) detection and mapping; emperor penguin colony detection and mapping (Fretwell and Trathan 2009); or the mapping of Giant panda *Ailuropoda melanoleuca* habitat for the whole of China (De Wulf et al. 1988), as well as the monitoring of vegetation changes in the species' habitat (Jian et al. 2011). The success of Landsat in ecological and environmental monitoring may be attributed to the fact that access to Landsat imagery has been free for several years: this was recently discussed by Wulder et al. (2012a) who reported that, while the Earth Resources Observation and Science Centre provided about 25,000 Landsat images at a price of US$600 per scene in 2001, this number increased to about 2.5 million images distributed free in 2010.

1.2.3.3 RAdio Detection And Ranging (RADAR) and Light Detection And Ranging (LiDAR)

RADAR and LiDAR are active sensors (see Box 1.3 for a definition of these). The principle of RADAR

1.2.4 Why is remote sensing useful?

Data collected on the ground are generally difficult to use for mapping and predicting regional or global changes in climatic conditions, land cover distribution or vegetation dynamics, because such data are traditionally collected at small spatial scales and vary in their type and reliability. Furthermore, such data often come from a single time period during the year, which is usually not synchronized spatially, making it difficult to gather information on temporal changes and phenology. Collecting data on the ground, especially over large areas or at multiple times over a year, can be extremely costly. Imagine the human and financial effort required to map the extent of the forest in the Congo basin on a regular basis!

Remote sensing, on the other hand, offers a relatively inexpensive and verifiable means of deriving complete spatial coverage of environmental information for large areas in a consistent manner that may be updated regularly (Muldavin et al. 2001; Duro et al. 2007). It has considerable potential as a source of information on biodiversity at landscape, regional, ecosystem, continental, and global spatial scales (Roughgarden et al. 1991; Gillespie et al. 2008). It can help to monitor the occurrence of extreme events such as droughts, fires or storms (Horning et al. 2010), changes in ecosystem functioning (Kerr and Ostrovsky 2003; Alcaraz-Segura et al. 2009), changes in the distribution of natural habitats (Aplin 2005; DeFries et al. 2007), and land use change or land degradation (Goetz et al. 2009; Prince et al. 2009) across the world. Thus remote sensing makes it possible to collect data from dangerous or inaccessible areas. War zones, the middle of the Amazon basin, or the Antarctic can all be monitored, providing information on deforestation rates, desertification, ocean depth, or changes in the extent of the ice sheet cover.

Satellite imagery can be applied retrospectively across wide regions, with some data having been collected relatively frequently over a long time period. For example, the Landsat Program, which is still running, gives ecologists access to nearly forty years of information on ecosystem distribution. This is an excellent opportunity to reanalyse old data and make use of previously unavailable information. Remote sensing can be applied to ecological research directly related to individuals, species or communities of interest (Turner et al. 2003; Aplin 2005; Pettorelli et al. 2005b). As detailed in the following chapters, remote sensing can enable study on the nature of the environmental conditions that shape individuals' reproductive outputs, species' distribution, or communities' complexity. Remote sensing can also help to quickly identify areas of concern on a global scale, supporting managers in their effort to design and apply adaptive management strategies. It can provide a cost-effective way to target monitoring effort, by identifying areas with rapid changes in the functional attributes of ecosystems where more intense monitoring might be required. Two advantages of remote sensing particular to vegetation studies are that it is non-invasive and non-destructive (Jones and Vaughan 2010).

Altogether, remote sensing technologies can help to support a dynamic approach to environmental and wildlife management (see Chapters 5–7), where the relevance and efficiency of management actions can be regularly evaluated. Useful monitoring tools require long-term commitment: programs such as Landsat have demonstrated that satellite-based monitoring can be sustainable. Satellite-based data enable projects, organizations, and nations to report standardized and transparent information (discussed in more detail in Chapter 10); free access to some of these data enables the reported information to be verified using ground-based methodologies. Moreover, developments in satellite and sensor technology are continuous, meaning that our ability to gather relevant environmental information will further improve, and new opportunities will arise (Gillespie et al. 2008).

1.3 Getting started: the remote sensing user toolkit

What are the tools and information required to start using remote sensing technologies for ecological research purposes? In this section, I deal briefly with some of the main issues that need to be considered when using remote sensing data. The first step is to define clearly the objectives of the study, in order to best match data requirements with data availability. A second important consideration is the realization

CHAPTER 3

NDVI from A to Z

Nothing tends so much to the advancement of knowledge as the application of a new instrument.
Sir Humphry Davy

The NDVI has been associated with more applications, especially in ecology, than any other vegetation index. In all, 693 articles with the topic 'NDVI' and subject area 'ecology' have been published since 1990 and cited more than 12 500 times (ISI Web of Science search, 13 March 2013; Figure 3.1).

The NDVI's popularity can be attributed partially to the fact that it is easy to calculate, requiring only the information collected by the red and near-infrared bands (which are common to almost all passive space-borne sensors; Gillespie et al. 2008). The NDVI has been readily available from as early as the 1970s (through Landsat) at various spatial and temporal resolutions. However, there may be less easy access to pre-existing, processed data for other vegetation indices (Pettorelli et al. 2011). The popularity of the NDVI may also be linked to the wide array of disciplines in which it has been used successfully, ranging from environmental monitoring and agronomy, to macroecology, community ecology, animal behaviour or paleoecology. Examples of successful applications are detailed in Chapters 5 to 8. The breadth of possible applications has allowed the audience of potential users to increase steadily over the past decades, and to establish the NDVI as a reliable addition to the traditional set of environmental variables available to scientists.

This chapter gives an in-depth presentation of the NDVI, from detailing the rationale behind the NDVI's formulation, to reviewing the current set of available NDVI datasets and illustrating the diversity of measures that can be derived from these data. The main caveats and limitations associated with the NDVI in ecology are discussed, and the benefits of complementing NDVI datasets with ancillary information are highlighted.

3.1 How does it work?

3.1.1 Rationale behind the formulation of the NDVI

The absorption, reflection, and transmission of a given vegetation canopy are primarily controlled by the physiology and pigment chemistry of its leaves. Green leaves absorb incoming solar radiation in the photosynthetically active radiation spectral region, drawing from this the energy needed to power photosynthesis (see Chapter 2; Jensen 2007). Leaves from live green plants have also evolved to scatter solar radiation in the near-infrared spectral region, as the energy level per photon in that domain (wavelengths longer than about 700 nm) is not sufficient to synthesize organic molecules. A strong absorption at these wavelengths would only result in overheating the plant and denaturing its proteins (Jensen 2007). Because leaves have high visible light absorption and high near-infrared reflectance (Figure 3.2), green vegetation appears relatively dark in the photosynthetically active radiation spectral region and relatively bright in the near-infrared. By comparison, clouds and snow tend to be rather bright in the visible red band (as well as other visible wavelengths) and quite dark in the near-infrared. The rationale behind the NDVI is based on these characteristic patterns of vegetation absorption and reflectance in the red

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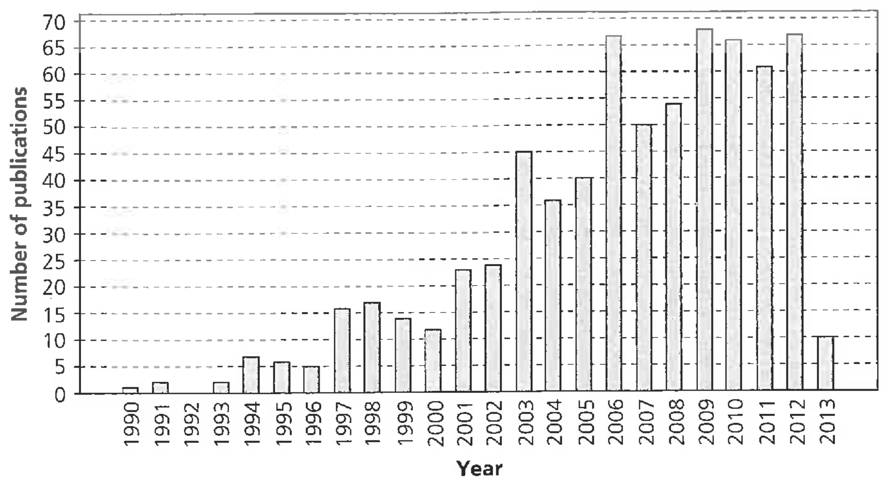

Figure 3.1 Number of ecological publications per year, from 1990 to 2013, with the topic 'NDVI'. The numbers presented have been sourced from an ISI Web of Science search, performed on 13 March 2013.

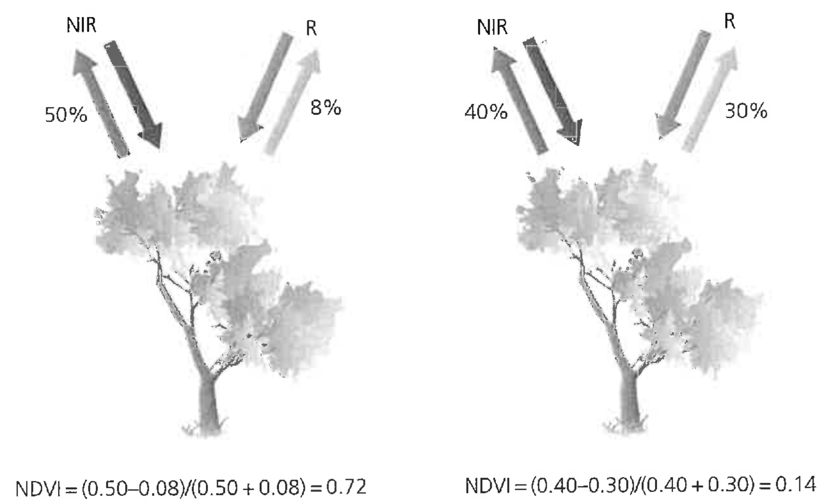

Figure 3.2 NDVI calculation for healthy (left) and senescent vegetation (right). Healthy vegetation absorbs incoming red light, while reflecting infrared radiation. Senescent vegetation reflects more visible light and less near-infrared light, leading to a reduced NDVI value (see also <http://earthobservatory.nasa.gov/Features/MeasuringVegetation/measuring_vegetation_2.php>). See also Plate 2.

and near-infrared, being computed as (NIR – R)/(NIR + R) (see Chapter 2 for more information on the principles guiding the construction of vegetation indices such as the NDVI). The NDVI can be seen as an index of 'greenness,' supplying information about the level of photosynthetically active material available in a given spatial unit.

The NIR and R spectral reflectance are both expressed as ratios of the reflected over the incoming radiation in each spectral band individually: therefore, NIR and R only take on values between 0 and 1. Thus, the NDVI itself can only vary between –1.0 and +1.0. Negative NDVI values correspond to an absence of vegetation (Justice et al.

Table 3.1 Examples of typical ranges of NDVI values for a selection of ecosystems.

Ecosystem	Typical NDVI values	Location	References
Boreal forest	0.6–0.8	Alaska	Parent and Verbyla 2010
Temperate forest	0.3–0.7	France	Pettorelli et al. 2006
Coastal rainforest	0.88–0.92	Solomon Islands	Garonna et al. 2009
Alpine pastures	0–0.35	Italy	Pettorelli et al. 2007
Annual grassland	0.15–0.45	California	Gamon et al. 1995
Desert	0.06–0.12	Sinai, Egypt	Dall'Olmo and Karnieli 2002

1985). Very low values of NDVI (≤0.1) correspond to barren areas of rock, sand, or snow. Free-standing water (such as oceans, seas, lakes, and rivers) generally has a rather low reflectance in both R and NIR spectral bands, and thus NDVI values associated with free-standing water tend to be in the very low positive to negative values. Soils generally exhibit NIR reflectance somewhat larger than the R reflectance, and thus tend to generate rather small positive NDVI values (roughly 0.1–0.2). Sparse vegetation such as shrubs and grasslands or senescing crops may result in moderate NDVI values (~0.2–0.5). High NDVI values (~0.6–0.9) correspond to dense vegetation such as that found in temperate and tropical forests or crops at their peak growth stage (Jensen 2007; Neigh et al. 2008). Other examples of typical NDVI ranges for corresponding ecosystems can be found in Table 3.1.

3.1.2 NDVI as a proxy for greenness

The NDVI has been linked to various parameters of vegetation dynamics. Asrar et al. (1984) and Sellers (1985) both demonstrated a near-linear relationship between the NDVI and the intercepted fraction of photosynthetically active radiation, the driving energy for photosynthesis. Later the NDVI was shown to be highly correlated with photosynthetic capacity, net primary production, LAI (see Box 2.1 for definition), carbon assimilation, and evapotranspiration (Myneni et al. 1995; Buermann et al. 2002; Hicke et al. 2002; Wang, Q. et al. 2005; see Box 3.1 for definition of evapotranspiration (ET) and photosynthetic capacity).

In short, the NDVI thus provides a measure of 'greenness' (one value per temporal and spatial unit) for the whole world. NDVI data can be manipulated and aggregated in a number of ways: NDVI values for one time-step may be averaged across years to establish 'normal' growing conditions in a region. Figure 3.3 represents the average NDVI curves for two natural reserves in France, namely Trois Fontaines and Chizé (Pettorelli et al. 2006). For each year considered (1982–2003) and

Box 3.1 Some definitions

Evapotranspiration (ET): The sum of evaporation and plant transpiration from the Earth's land surface to the atmosphere. Apart from precipitation, evapotranspiration is one of the most significant components of the water cycle. Actual evapotranspiration (AE or AET) is the quantity of water removed from a surface due to the processes of evaporation and transpiration. Potential evapotranspiration (PET) is a measure of the ability of the atmosphere to remove water from the surface through the processes of evaporation and transpiration assuming no limitation on water supply. PET is thus considered the maximum ET rate possible with a given set of meteorological and physical parameters.

Photosynthetic capacity: A measure of the maximum rate at which leaves are able to fix carbon during photosynthesis.

Bidirectional Reflectance Distribution Function (BRDF): This refers to a four-dimensional function that defines how light is reflected at an opaque surface. The function enables access to the reflectance of a target as a function of illumination geometry and viewing geometry. The BRDF is needed in remote sensing for the correction of view and illumination angle effects (for example, in image standardization and mosaicking), for deriving albedo, for land cover classification, for cloud detection, for atmospheric correction and other applications. The BRDF describes what we all observe every day: that objects look differently when viewed from different angles, and when illuminated from different directions.

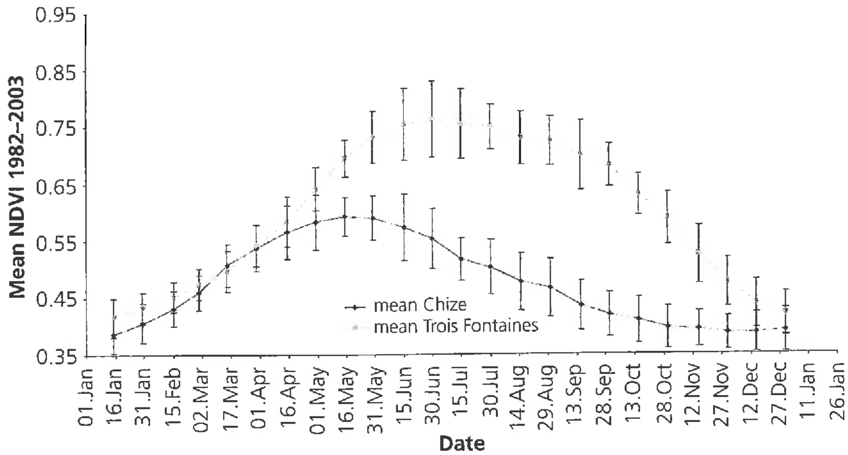

Figure 3.3 Average NDVI values over the period 1982–2003, with associated standard errors, in relation to date at Chizé and Trois Fontaines reserves, France. (Reproduced from Pettorelli et al. 2006 with permission from John Wiley & Sons.)

each pixel located in the two French reserves, the corresponding NDVI values were extracted. The NDVI data originated from the Global Inventory Modelling and Mapping Studies (GIMMS) dataset (see Table 3.2) with a spatial resolution of 8 km and a temporal resolution of 15 days (i.e. two NDVI values per month). Due to the size of the two study areas, only one pixel fell in each reserve. For each date, the NDVI values over the whole period were averaged. This led to the production of one average NDVI value per date for all years, with an associated standard error (yielding information on the level of inter-annual variability in NDVI values for each date).

Properties of NDVI time-series can also be summarized in a variety of related indices. These include measures of overall productivity and biomass, such as the Integrated NDVI (INDVI) or the annual maximum NDVI value; measures of variability in productivity (such as the relative annual range of the NDVI); and a variety of phenological measures (Reed et al. 1994; see also Figure 3.4). Examples of phenological measures include: the rate of increase and decrease of the NDVI; the dates of the beginning, end, and peak(s) of the growing season; the length of the growing season; and the timing of the annual maximum NDVI (Table 3.3). Changes in NDVI-based indices over time can be used for

Table 3.2 Frequently used NDVI datasets in ecology.

Name	Satellite	Instrument	Period covered	Spatial resolution	Temporal resolution
PAL/PAL II	NOAA	AVHRR	1981–2001	~8 km	10 day
GVI	NOAA	AVHRR	1982–present	~16 km	Weekly, monthly, seasonal
GIMMS	NOAA	AVHRR	1981–present	~8 km	Bi-monthly
LTDR	NOAA	AVHRR	1981–1999	~0.05°	Daily
FASIR	NOAA	AVHRR	1982–2000	0.25–1°	10 day/monthly
MOD13	TERRA	MODIS	2000–present	250 m to 1 km	Bi-monthly
	TM/ETM	Landsat	1984–present	15–60 m	Up to 16 days
	VGT	SPOT	1998–present	~1 km	10 day

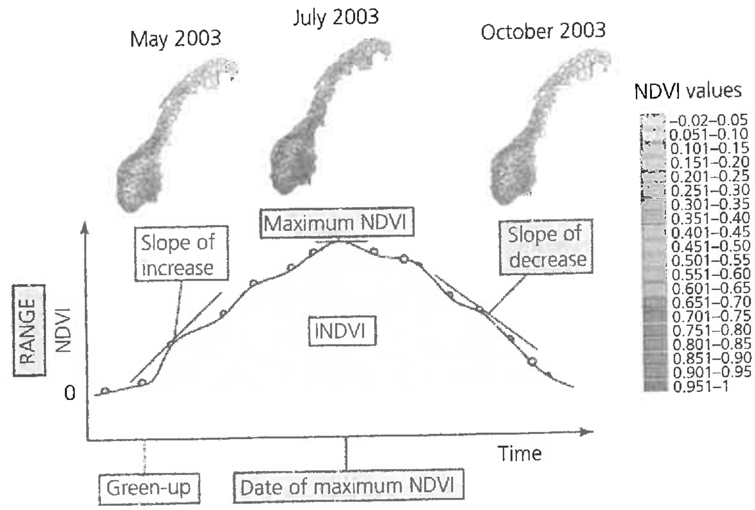

Figure 3.4 Presentation of the different indices (the slopes of increase (spring) and decrease (autumn), the maximum NDVI value, the Integrated NDVI (INDVI, i.e. the sum of NDVI values over a given period), the date when the maximum NDVI value occurs, the range of annual NDVI values, and the date of green-up (i.e. the beginning of the growing season) that may be derived from NDVI time-series over a year. Maps presenting NDVI values (ranging from 0 to 1) for Norway in May, July, and October 2003 are also shown. See also Plate 3. (Reproduced from Pettorelli et al. 2005b with permission from Elsevier.)

Table 3.3 Examples of phenological measures that can be derived from NDVI time-series.

Measure	Biological meaning	Reference
Annual maximum NDVI	Maximum photosynthetic capacity of the system under consideration	Alcaraz-Segura et al. 2009
Annual minimum NDVI	Minimum photosynthetic capacity of the system under consideration	Alcaraz-Segura et al. 2009
Integrated NDVI (INDVI)	Primary productivity proxy for the period when the NDVI values are integrated	Pettorelli et al. 2005c
Annual relative range (RREL)	Descriptor of the intra-annual variation of light interception in the system under consideration (this can be interpreted as a measure of seasonality)	Alcaraz-Segura et al. 2009
Maximum slope between any two successive bimonthly NDVI values during this period	This can supply information on the speed of the green-up phase	Pettorelli et al. 2007
Dates of the beginning (or end) of the growing season	This can yield information on the timing of the green-up	Mysterud et al. 2008
Length of growing season	Proportion of the year with significant green biomass production	Herfindal et al. 2006

many purposes, including the assessment of ecological and ecosystem responses to global warming (Pettorelli et al. 2005b; Alcaraz-Segura et al. 2009), phenological change (White et al. 2009), crop status (Tottrup and Rasmussen 2004), land cover change (Hüttich et al. 2007), or desertification (Symeonakis and Drake 2004). Several of these potential applications are discussed in Chapters 5 to 8.

How are these metrics useful for understanding the functioning of the area under consideration. Looking at the differences in NDVI dynamics between the two reserves in France (Figure 3.3), it becomes evident that (i) annual net primary production is higher in Trois Fontaines than in Chizé; (ii) seasonality in primary production is more marked in Trois Fontaines than in Chizé; (iii) the period of maximum photosynthetic capacity occurs earlier in Chizé than in Trois Fontaines; (iv) vegetation senescence also starts earlier in Chizé than in Trois Fontaines. Such conclusions are supported by independent data on climatic conditions and wood production: Trois Fontaines is known to experience a continental climate with relatively severe winters, whereas Chizé has an oceanic climate with mild winters and hot dry summers. Spring is therefore known to start earlier in Chizé, and hot dry summers known to limit primary productivity in summer in this area. Trois Fontaines is, on the other hand, recognized as being a highly productive forest lying on rich soils: wood production in Trois Fontaines reaches a long-term average of 5.92 m^3 of wood produced per hectare per year; in Chizé, wood production reaches only 3.77 m^3 per hectare per year (Pettorelli et al. 2006).

Table 3.3 and Figure 3.4 detail classical measures generally extracted from NDVI curves. However, recent studies have demonstrated that non-classical indices derived from NDVI time-series can be useful according to the situation and the issue considered. For example, determining annual variation in the INDVI over the vegetation onset period can yield the same type of information as estimating annual variation in the date of the beginning of the growing season: such a conclusion was reached by Pettorelli et al. (2005c) as they were trying to link vegetation onset in Norway to red deer *Cervus elaphus* body mass and climatic conditions in winter and spring. In Norway, vegetation dynamics are highly seasonal and highly predictable (Loe et al. 2005), which leads to a high correlation between the INDVI over the vegetation onset period (which was roughly occurring in May for the area considered) and the estimated date of the beginning of the growing season.

Another example where non-classical phenological measures derived from NDVI curves can supply ecologically relevant information comes from mountainous areas (Pettorelli et al. 2007), where the timing of snowmelt and the timing of vegetation onset are expected to affect the life histories of alpine wildlife (Rutberg 1987). Because plant phenology is the major factor affecting forage quality, it is frequently described as the driving force in habitat use by herbivorous vertebrates (Albon and Langvatn 1992). Higher forage quality is indeed associated with early phenological stages (Crawley 1983), while feeding patch choice and forage selection by ungulates are positively associated with plant quality (White 1983). A shorter period when high-quality forage is available should thus lower herbivore performance (Albon and Langvatn 1992). Because forage quality peaks during early phenological stages, slow vegetation growth should prolong access to high-quality forage. Moreover, spatial heterogeneity in snowmelt may lead to spatial heterogeneity in the timing of vegetation green-up onset, which may lengthen the period when high-quality forage is accessible to herbivores (Mysterud et al. 2001). Rapid temporal changes in plant productivity might thus correlate both with fast vegetation growth and reduced spatial heterogeneity in the timing of vegetation onset in alpine areas. Interestingly, the continuous nature of NDVI time-series actually allows partitioning of the effect of an early start of vegetation growth from that of a rapid rate of changes in vegetation phenology—a technique that was applied by Pettorelli et al. in 2007. The rate of change in plant productivity during green-up can be defined as the rate of increase between two fixed dates: the dates considered are generally the estimated date when vegetation starts growing and the estimated date when vegetation biomass reaches a plateau. For all sites considered, these correspond to early May and early July (Pettorelli et al. 2007). Considering the slope between early May and early July as an index of the rate of vegetation changes during green-up, however, is associated with a major constraint: such an index would not capture any deviation from a linear increase in the NDVI between those two dates and would average the rate of change during green-up. For example, a linear and a logarithmic increase between the two dates would yield the same slope. The authors therefore indexed the rate of vegetation change during green-up as the maximum slope between any two consecutive bimonthly NDVI values (maximum temporal resolution given the dataset considered) from early May to early July. Higher maximum increases indicated faster changes in vegetation growth and higher deviations from a linear increase in NDVI during green-up (Pettorelli et al. 2007).

Information on habitat structure can also be derived from NDVI images by compiling texture measures, which are defined as the variability of pixel values in a given area. NDVI texture analyses aim to capture heterogeneity in the amount of vegetation (Hepinstall and Sader 1997). High texture can be induced by high horizontal variability among plant growth forms: habitats that are heterogeneous either in terms of plant species composition, or in terms of the spatial distribution of plants, can be expected to display high texture; sometimes, these habitats can also be expected to be associated with an increased number of ecological niches that species can exploit. In other words, high texture can be expected to correlate with high species richness. Such an expectation was supported by Hepinstall and Sader (1997), who showed that image texture calculated from the variance in NDVI values can help to explain the occurrence of seven bird species in Maine, US. Three years later, Gould reported similar results, with the texture of NDVI accounting for up to 65% of the variability in plant species richness in the Canadian Arctic (Gould 2000). More recently, texture of the NDVI was reported to account for up to 82.3% of the variability in bird species richness in the northern Chihuahuan Desert of New Mexico (St-Louis et al. 2009).

3.2 Available datasets

Many sensors carried on board satellites measure red and near-infrared light waves reflected by land surfaces (Table 3.4). Yet reliable NDVI time-series are not readily available to ecologists for all optical sensors, and several NDVI datasets can originate from the same raw data. There are several explanations for this. First, raw data can be altered by several sources of bias and noise, and not all optical sensors capture the information required to make the required corrections. Second, correcting raw information to produce reliable NDVI datasets is costly and not necessarily part of the agenda for the agencies behind the collection of these data. Third, not everybody agrees as to how raw data should be corrected to produce reliable NDVI values, explaining the diversity of datasets than may be associated with the same raw data.

The NDVI datasets most often used in ecology are generally those that have been made freely available to the end-users. These can be distinguished according to the time-periods they cover as well as their spatial and temporal resolutions (Tables 3.2 and 3.4).

Without a doubt, the most frequently used NDVI datasets originate from the AVHRR sensor on board the NOAA satellites (Gutman 1999; Tucker et al. 2005; Pettorelli et al. 2005b, 2011). The first NOAA satellite was launched in 1979. Several others have been launched since, with lifetimes of up to seven years. The spatial resolution of the NDVI data originating from the NOAA satellites is 1.1 km nominal, the highest temporal resolution available is daily, and the spectrum spans from visible red to thermal

Table 3.4 Non-exhaustive list of relevant optical satellite sensors that can be used to derive NDVI datasets.

Sensor	Launch year	Spatial resolution	Repeat frequency	Coverage
MSS on board Landsat	1972, 1975, 1978, 1982, 1984	56–82 m	16–18 days	185*185 km
AVHRR on board NOAA	1979	1.1 km	1 day	3000 km sw
TM and ETM+ on board Landsat	1982 (TM 4) 1984 (TM 5) 1999 (ETM+)	15–60 m	16 days	185*170 km
SeaWIFS on board OrbView-2	1997	1.1 km	1 day	1500*2800 km
HRVIR on board SPOT 4	1998	10–20 m	2–3 days	60*60 km
IKONOS-2	1999	1–4 m	1–3 days	11.3 km sw
ASTER on board Terra	2000	15–90 m	16 days	60*60 km
MODIS on board Terra	2000	250 m to 1 km	~1 day	2330 km sw
QuickBird	2001	61 cm to 2.44 m	1–3 days	16.5 km sw
HRG on board SPOT 5	2002	2.5–20 m	2–3 days	60*60 km
MERIS on board ENVISAT-1	2002	~300 m	3 days	1150 sw
GeoEye-1	2008	41 cm to 1.65 m	2–8 days	15.2 km sw

sw, swath width.
Source: Horning et al. (2010).

infrared. AVHRR data represent an invaluable and irreplaceable archive of historical land surface information: those data have literally revolutionized vegetation studies. It is interesting to note that the original primary aim and design of NOAA satellites was not to collect data on vegetation; yet, to date, this is the only freely available dataset that supplies daily information for an extensive time period (1981–present). There are several NDVI datasets that originate from the raw data collected by the AVHRR sensors: examples include the Pathfinder AVHRR Land product (PAL; James and Kalluri 1994); the Global Vegetation Index (GVI; Gutman et al. 1995; Kogan and Zhu 2001); the Fourier-Adjusted, Sensor and Solar zenith angle corrected, Interpolated, Reconstructed (FASIR) adjusted NDVI dataset (Los et al. 2000); the Land Long Term Data Record (LTDR) dataset (Pedelty et al. 2007); and the GIMMS NDVI product (Tucker et al. 2005). The differences among these datasets are linked to differences in the spatial and temporal resolutions available, to differences in the type of corrections applied, and to differences in the temporal periods covered (Table 3.2).

Other NDVI products commonly found in the literature are based on data collected by the moderate-resolution satellite sensors with the proper instrumentation for studying vegetation greenness. These sensors are MODIS carried aboard NASA's Terra and Aqua satellites, SeaWIFS on board GeoEye's OrbView-2, and the high-resolution visible and infrared (HRVIR) instrument on board the SPOT satellites. Data produced by the GIMMS group have shown good correlation with data from these higher quality sensors (Tucker et al. 2005; see also Box 3.2). NDVI data originating from MODIS are frequently used in ecological research and applications due to their ease of access.

Readily available, free-of-charge data gathered by Landsat Thematic Mappers' sensors can also be used to generate NDVI data (see, e.g., <http://glovis.usgs.gov>). The ≥30 years' record of data acquired by the Landsat satellites constitutes the longest continuous record of the Earth's continental surfaces. With a resolution of <100 m, TM/ETM+ data can be transformed into NDVI images that have greater spatial detail than those derived from AVHRR (Table 3.2). Importantly, Landsat's orbit repeats every 16 days, compared with AVHRR's daily coverage: because of this difference in temporal resolution, creating cloud-free NDVI products from Landsat data can be more difficult (van Leeuwen et al. 2006)

Box 3.2 Are GIMMS data reliable?

At present, the only updated global coverage NDVI dataset, covering the full period from 1981 to present, is the GIMMS 8 km resolution 15-day composite dataset (Tucker et al. 2005). This NDVI product is also currently the most frequently used for evaluating vegetation patterns and trends around the world. Yet several authors have been discussing its reliability for some regions of the world (e.g. Baldi et al. 2008; Parent and Verbyla 2010; Alcaraz-Segura et al. 2010a and 2010b). These authors pointed out that, although for some regions, the NDVI trends were consistent across the different datasets and sensors (e.g. humid Sahel or the Chilean arid zones), in other regions the use of different datasets could lead to conflicting findings. This view has been opposed by others, who reported good consistency between the GIMMS products and NDVI products from the Sea-viewing Wide Field-of-view Sensor (SeaWiFS), MODIS, and SPOT (Tucker et al. 2005; Brown et al. 2006; Fensholt et al. 2006a, 2009; Song et al. 2010). As a general rule, the comparative use of different NDVI products in situations where such a choice is feasible and meaningful is probably worth considering. It might also be useful to track the future performance of the LTDR dataset: the production of the LTDR data is associated with the NASA-funded project REASoN, which aims to produce a consistent long-term dataset from AVHRR, MODIS, and the Visible/Infrared Imager/Radiometer Suite sensors. This project aims to reprocess the entire original AVHRR data from 1981 to present by applying the pre-processing improvements identified by the Pathfinder AVHRR Land II project, and the atmospheric and Bidirectional Reflectance Distribution Function (BRDF; see Box 3.1) corrections used in MODIS pre-processing steps.

3.3 Known caveats and limitations

Like any tool, the NDVI is associated with caveats and limitations which can sometimes reduce its reliability and/or usefulness. This section reviews the factors that may influence NDVI measurements and discusses situations where the NDVI has been shown to yield less reliable information on photosynthetic capacity, net primary production, and leaf area index.

3.3.1 Caveats

Atmospheric conditions such as the presence of clouds, water vapour or atmospheric contaminants have a strong, negative influence on NDVI values (i.e. clouds, atmospheric contaminants, smoke, and water vapour lower NDVI values; Forster 1984; Holben 1986; Gutman 1991). Detecting such a source of bias can be difficult: optically thick clouds may be quite noticeable in satellite imagery, yet thin clouds (such as the ubiquitous cirrus), or small clouds with typical linear dimensions smaller than the diameter of the area actually sampled by the sensors, can be harder to notice, leading to NDVI values becoming inexact representations of the vegetation status on the ground (Tanré et al. 1992; Achard and Estreguil 1995). Similarly, cloud shadows can affect NDVI values and lead to misinterpretations. In tropical ecosystems, smoke and cloud cover can lead to paradoxes: Saleska et al. (2007), for example, reported that reduced rainfall resulted in higher satellite-based primary productivity estimates in a South American wet tropical region. This result was also observed by Garonna et al. (2009), who reported lower NDVI values in Makira, Solomon Islands, during the wet season. In both cases, the results can be linked to the effect of clouds on NDVI values: with clouds being more likely to bias NDVI estimates in wet months than in dry months, and with more light reaching the canopy during the dry season, NDVI values appeared higher during the dry season.

Orbital degradation and the deterioration of sensors (Kogan and Zhu 2001), sensor calibration error, sensor radiometric resolution, sensor drift (i.e. sensitivity of sensors that changes with time), mistakes associated with signal digitization (i.e. transformation of the signal into digital numbers; Curran and Hay 1986), and transmission errors, such as line drop-out causing localized NDVI increases (leading to the appearance of abnormally high NDVI values in the dataset; Viovy et al. 1992), are other examples of abiotic factors that can affect NDVI measurements (James and Kalluri 1994). As briefly discussed in Chapter 2, soil may also influence NDVI values: soils tend to darken when wet, with their reflectance being a direct function of water content. If the spectral response to moistening is not exactly the same in the two spectral bands, the NDVI of an area can appear to change as a result of soil moisture changes (precipitation or evaporation) and not because of vegetation changes. Additional issues may occur when using the NDVI in winter in areas of high latitudes (>60°), as reflectance resolution in such areas can become coarse (Goward et al. 1991) and as a greater incidence of spuriously high NDVI values has been reported (Justice et al. 1985). Topography and altitude also affect NDVI measurements (Thomas 1997), and caution should therefore be taken when comparing NDVI measurements in topographically variable areas.

To eliminate much of these sources of noise in the data, processing algorithms are generally applied to the raw data (Markon and Peterson 2002; Tucker et al. 2005). Bias can be minimized by forming composite images from daily or near-daily images. In some cases, post-processing noise reduction procedures may be required to further reduce noise (Reed et al. 1994); for example, when the period chosen for the temporal aggregation was mainly cloudy or when transmission errors occur (Sellers et al. 1994), causing false NDVI increases (Viovy et al. 1992). To account for those problems and to 'correct' vegetation profile, various smoothing techniques have been proposed (Table 3.5 and Figure 3.5).

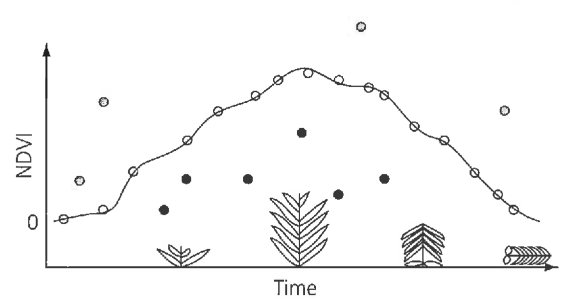

Figure 3.5 The three types of NDVI data: data collected during a cloudy day (dark circles), a clear day (open circles), and 'false high' NDVI values (grey circles) owing to transmission errors. Because of this diversity in the quality of information contained in NDVI values, time-series need to be smoothed. A typical smoother (black line) rebuilds the NDVI profile based mainly on clear-day estimates. (Reproduced from Pettorelli et al. 2005b with permission from Elsevier.)

Table 3.5 Non-exhaustive list of NDVI smoothing procedures.

Procedure	What it does	Advantages	Disadvantages	References
The Maximum Value Compositing (MVC)	NDVI values are temporally or spatially aggregated. The highest NDVI value for the considered period and area is retained.	Easy; often works well because most errors are negative	Temporal aggregates might still be contaminated by cloud cover. The procedure will be confused by a single false high.	Holben 1986; Box 3.3
Curve-fitting	Polynomial or Fourier functions are fitted to NDVI time-series	Easy; the trajectory can be predicted and the time-series can be summarized by several indices linked to the function	Medium-order polynomials can be too inflexible to recreate an entire seasonal NDVI pattern, and can smooth the data too much. Fourier analysis fails to characterize each annual NDVI trajectory separately; it can generate spurious oscillations in the NDVI time-series. Neither approach accommodates the skewed error structure, and is therefore heavily affected by false lows or highs.	Van Dijk et al. 1987; Verhoef et al. 1996; Olsson and Eklundh 1994
Stepwise logistic regression	A series of piecewise logistic functions are used to represent intra-annual vegetation dynamics. Four key transition dates are estimated: green-up, maturity (the date at which plant green leaf area is maximal), senescence and dormancy	Because the method treats each pixel individually without setting thresholds or empirical constants, it is globally applicable; it enables vegetation types to exhibit multiple modes of growth and senescence within a single annual cycle	The method does not accommodate the skewed error structure, and will therefore be heavily affected by false lows or highs.	Zhang et al. 2003
Best Index Slope Extraction method (BISE)	NDVI observations are judged as trustworthy or not depending on whether the rate-of-change in the NDVI is plausible	The algorithm is robust to false highs that cause implausibly rapid increases in the NDVI	The delicate purpose of this method is to estimate correctly to what extent a rate of change in the NDVI is plausible, according to the temporal resolution under consideration	Viovy et al. 1992
Weighted least-squares linear regression	A sliding-window combination of piecewise linear approximations to the NDVI time-series, placing more weight on 'local peaks' (NDVI values higher than the preceding and following observations). Tuning parameters are the weights affected to the local peaks and window widths	Works well when successive false lows are rare, so that local valleys occur separately, such as in the biweekly MVCs	When several false lows occur in sequence, they cause false local peaks, which bias the estimated value downwards. Thus, this approach might not be suitable for daily data, and its applicability will depend on the frequency of cloud contamination and the strength of seasonality	Swets et al. 1999; Chen et al. 2004

Smoothing techniques do not always necessitate complex modelling approaches to remove contamination; sometimes – depending on the aims of the study and the level of contamination – targeted, intuitive approaches can work well. For instance, Pettorelli et al. (2012) smoothed NDVI time-series from Africa by identifying rapid changes in NDVI values (of ≥0.25 from one composite to the next) for each pixel, which were immediately followed by a return to the original values or higher. Once these contaminated values were identified, they were replaced by the average of the previous and following values, so as to 'smooth' the annual NDVI curve for that pixel. If two consecutive 'drop'

Box 3.3 A quick highlight on the Maximum Value Composite method (MVC)

Atmospheric contaminations, lowering NDVI values, have early been identified as a major source of error when using remote sensing data (Curran and Hay 1986). Yet atmospheric contaminations are extremely common: clouds, for example, cover about 60% of the land surface at any given time (Rossow and Schiffer 1999). One first attempt to correct for the systematic negative biases associated with atmospheric contaminations was proposed by Holben (1986) in the form of the MVC. The principle is as follows: if all contaminations depress NDVI values, then it makes sense to retain only the highest value for each pixel over a given period, as this means that one will be extracting the information from the most cloud-free day. This is the principle adopted by the MVC: the procedure creates a composite NDVI image where each pixel takes the highest NDVI value from the sequence of NDVI values available over the period considered. One problem with this method is the temporal resolution, which does not allow precise estimates of plant phenology. For example, when a green wave is advancing, NDVI values will tend to be chosen from the end of the time period, whereas at the end of a growing season, with the advance of a brown wave, NDVI values will tend to be chosen from the beginning of the time period. Moreover, sudden water stress, causing a reduction in plant biomass can occur during the growing season: depending on the original and achieved temporal resolutions, these will not be captured by a method such as the MVC (Townshend and Justice 1986; Taddei 1997).

values were present, the average of the closest higher NDVI values was calculated.

In some situations, the choice of method might not be critical. Loe et al. (2005) used the NDVI to characterize predictability of spring phenology, and used locally weighted regressions to smooth the NDVI time series, which placed low weight (in this case, 0.005) on local valley points (i.e. when NDVI values are lower than the previous measure) since they most likely occur due to cloud cover at the time of sensing rather than reversed plant phenology. The results obtained using non-weighted least-squares smoothing and cumulative maximum gave qualitatively the same results.

It is important to understand that eliminating the noise means inevitably removing information from the raw data – information which might be of particular interest in the detection of environmental change. Alcaraz-Segura et al. (2010b) recently compared different processing schemes of the same raw data (from the AVHRR sensor), showing that spatial and temporal inconsistencies exist between processing schemes. More research into the effect of different image processing on detection of environmental change is needed to optimize removal of noise from the data while retaining valuable variation stemming from actual environmental variability in the image.

3.3.2 Limitations

One major limitation to the use of the NDVI for environmental monitoring purposes is linked to the fact that the relationship between the NDVI and Aboveground Net Primary Production (ANPP) is not constant over the entire range of ANPP (Asrar et al. 1984; Sellers 1985; Paruelo et al. 1997). Studies on various vegetation types, such as agro-ecosystems (Cohen et al. 2003), grasslands (Friedl et al. 1994), shrublands (Law and Waring 1994), conifer forests (Chen and Cihlar 1996; Cohen et al. 2003), and broadleaf forests (Fassnacht et al. 1997) have indeed led to the general conclusion that vegetation indices such as the NDVI show considerable sensitivities to the LAI (Turner et al. 1999; Asner et al. 2003). In sparsely vegetated areas with LAI <3, the NDVI is strongly influenced by soil reflectance (Huete 1988), whereas for LAI >6 (in densely vegetated areas), the relationship between the NDVI and the near-infrared reflectance saturates (Asrar et al. 1984; Birky 2001). This change in the relationship between the LAI and the NDVI was also reported by Tucker et al. (1986), who demonstrated that the NDVI had an obvious tendency to reach a plateau at high LAI levels. More recent work further highlighted the existence of seasonal and annual variation in the relationship between the NDVI and the LAI (Wang, Q. et al. 2005). Results showed that the NDVI–LAI relationship varies in tune with variation in the phenological development of deciduous trees, as well as responding to temporal variation in environmental conditions. Strong linear relationships were obtained during the leaf production and leaf senescence periods for all years, but the relationship between the NDVI and the LAI in the French beech forest under study became poor during periods of maximum LAI. Altogether, these results suggest that the NDVI can underestimate the green biomass of stands with high production of green biomass and strong foliage density. Wang, Q. et al. (2005) also reported that the NDVI–LAI relationship was relatively weak when all data were pooled across the years, apparently due to different leaf area development patterns in the different years. This suggests that attention must be paid to the temporal scale when applying NDVI–LAI relationships.

A second limitation emanates from the fact that the NDVI integrates the composition of species within the plant community, vegetation form, vigour, and structure, the vegetation density in vertical and horizontal directions, reflection, absorption, and transmission within and on the surface of the vegetation or ground (Markon et al. 1995; Markon and Peterson 2002), which means that variation in NDVI values can stem from multiple sources. For example, Pinter et al. (1985) showed that reflectance of all wavebands is usually higher for planophile than for erectophile canopies of spring wheat, and that reflectance from erectophile canopies varies more with changing Sun zenith and azimuth. Heterogeneous habitats, such as those with interspersed woody and herbaceous vegetation or sparse vegetation and abundant bare ground, are therefore more likely to exhibit a weakened link between the NDVI and primary production (Elvidge and Lyon 1985; Huete et al. 1985; Huete and Tucker 1991). Likewise, dead material can also affect NDVI estimates (Tucker 1979). These factors (presence of dead material, canopy orientation, level of habitat heterogeneity) can therefore influence the ability of the NDVI to reliably index spatial variation in photosynthetic capacity, making it difficult to track subtle change in greenness across relatively small study areas. Because of such potential limitations, independent field measurements are generally recommended to validate the biological significance of NDVI measures (Hamel et al. 2009; Santin-Janin et al. 2009).

3.4 Complementing NDVI with other datasets

One way to reduce the likelihood of deriving incorrect information about the patterns in primary production from the NDVI time-series is to complement NDVI datasets with ancillary information. This section explores those ancillary data that can yield relevant information, which, if used together with NDVI data, may help to increase users' confidence in the interpretation of NDVI patterns.

3.4.1 With geographic information

Misregistration refers to situations when NDVI values are wrongly assigned to a point on the globe as a result of errors in back-calculating the position of the satellite at the time the images were taken. Because misregistration can occur, the accuracy of the downloaded data should always be checked by superimposing NDVI data on known maps using a geographic information system (Pettorelli et al. 2005b). The rise of GIS promoted the development of a variety of spatially explicit databases that have granted free access to information such as the distribution of biomes and ecoregions, climatic conditions, land-cover and vegetation types, or human population and footprint, among many others (see Table 3.6). Information on topography and elevation (derived from DEMs, such as the ones associated with the Shuttle Radar Topography Mission (SRTM)) and coastline can be particularly useful to help address misregistration issues (see Table 3.6).

3.4.2 With information on atmospheric conditions

Clouds may influence NDVI values (section 3.4.1) and methods have been developed to reduce the remnant noise in NDVI data that can be attributed to variation in cloud cover. When available, information on cloud cover can be used to better inform noise reduction approaches (Jönsson and Eklundh 2002). The Clouds from the AVHRR Extended

Table 3.6 Freely available geo-referenced datasets available on the World Wide Web.

Dataset	Description	url
VMAP0	VMAP is a vector-based collection of GIS data about Earth at various levels of detail	<http://geoengine.nima.mil/ftpdir/archive/vpf_data/v0noa.tar.gz>
GSHHG	Global Self-consistent, Hierarchical, High-resolution Geography Database	<http://www.ngdc.noaa.gov/mgg/shorelines/gshhs.html>
GADM	Spatial database of the location of the world's administrative areas	<http://www.gadm.org/>
Natural Earth Data	Supplies a variety of spatial, cultural and physical datasets (e.g. administrative boundaries, roads)	<http://www.naturalearthdata.com/>
SRTM 90 m Digital Elevation data	Elevation data at the global scale	<http://srtm.csi.cgiar.org/>
ASTER DEM	DEM based on ASTER, offering a spatial resolution of 30 m with a global coverage	<http://asterweb.jpl.nasa.gov/gdem.asp>
Global Land Cover Facility	Portal supplying access to land cover data for local to global systems	<http://landcover.org>
GlobCover	Global 300 m landcover classification approach based on MERIS onboard ENVISAT for 2004–2006 and 2009	<http://dup.esrin.esa.int/globcover/>
GLC2000	Global landcover dataset is available on a 1 km spatial resolution and for the year 2000 based on VEGETATION onboard SPOT 4	<http://bioval.jrc.ec.europa.eu/products/glc2000/products.php>
GLWD-2	The database for global lakes and wetlands supplies spatial datasets for inland waters which are >1 km^2	<http://geonode.twap.iwlearn.org/data/geonode:glwd_2>
Geodata	Portal with links to a wide variety of environmental databases	<http://geodata.grid.unep.ch/>
WorldClim	Portal with access to global climate data	<http://www.worldclim.org/>
TRMM	Tropical Rainfall Measuring Mission by NASA supplies daily precipitation information about each location. However, data is only available for locations between 35°N and 35°S.	<http://trmm.gsfc.nasa.gov/>
Last of the Wild	Dataset aiming to capture human influence on terrestrial ecosystems	<http://sedac.ciesin.columbia.edu/>

(CLAVR-x; Stowe et al. 1991, 1999) processing system is NOAA's operational cloud processing system for the AVHRR on the NOAA-POES and EUMETSAT-METOP series of polar orbiting satellites. CLAVR is derived from an algorithm that uses reflected and thermal AVHRR wavelength bands to classify pixels into clear, mixed, and cloudy categories (Stowe et al. 1991; Gutman and Ignatov 1996). Another means of gathering information about cloud cover comes from the geostationary Meteosat satellite and its sister satellites. In tropical regions it can be assumed that areas with temperatures lower than a certain threshold are covered with rain clouds. Based on this assumption, the cumulated number of hours in a dekad (a period of 10 days) with this low temperature can be calculated and stored in a dataset called 'Cold Cloud Duration' (CCD; Dugdale et al. 1991).

3.4.3 With field data

As Pinzon et al. (2004) wrote, 'users . . . are strongly encouraged to validate their results using independent data' (p. 18). Remote sensing and fieldwork are not irreconcilable alternatives, they are complementary. Field data can help to ensure the accuracy of NDVI interpretation, or to validate results based on satellite-derived information. For example, geo-referenced vegetation data collected on the ground using a Global Positioning System (GPS) device can enable assessment of the biological significance of NDVI-derived phenological measures; these data can also help to determine whether the biological signal of large-scale NDVI time-series is representative of the variation observed at smaller scales. Whenever possible, NDVI data should thus be complemented with relevant geo-referenced field data.

3.5 Conclusions

The NDVI is among the most intensely studied and frequently used vegetation indices in ecology. Not only is the NDVI the vegetation index associated with the highest number of applications in ecological research, but various other data products also use the NDVI as primary input, e.g. global land-cover maps (DeFries et al. 1995, 1999), net primary production datasets (Prince and Goward 1995), burned area product (Barbosa et al. 1999), fraction of absorbed photosynthetically active radiation, leaf area index (Myneni et al. 1997), land surface temperature (Otterman and Tucker 1982; Jin 2004), and air temperature (Prihodko and Goward 1997). Despite the many limitations of the NDVI in capturing the spatio-temporal variability in primary productivity, remote sensing-based indices remain the only means of obtaining direct, quantified measures of this parameter at such spatial and temporal extents, as well as at such spatial and temporal scales. The NDVI is best applied through understanding what the index can and cannot do.

CHAPTER 8

NDVI for informing conservation biology

> For a century, environmentalism has divided itself into warring camps: conservationists versus preservationists. . . . The struggle pits those who would meddle with nature against those who would leave it be. . . . The only sensible way forward lies in a melding of the two philosophies. We must manage nature in order to leave it alone.
>
> **David Barron**

'What is conservation biology?' asked Michael Soulé in 1985, and this is a question worth answering before discussing the potential of any tool to inform this discipline. The term conservation biology was introduced as the title of a conference held at the University of California, San Diego, in La Jolla, California in 1978. According to one of the conference organizers, conservation biology can be defined as the application of science to conservation problems, addressing the biology of species, communities, and ecosystems that are perturbed, either directly or indirectly, by human activities or other agents (Soulé 1985). There are many definitions of conservation biology (e.g. Hunter 1996; Meffe and Groom 2006; van Dyke 2008), but Soulé's has the advantage of highlighting three important aspects of the discipline, namely that conservation biology: (i) is often a crisis discipline; (ii) has a strong applied nature; (iii) is a component of environmental and wildlife management.

We now turn to how the NDVI can be useful to conservation biology. Chapters 5–7 reviewed study cases in which the NDVI was successfully linked to the distribution and functioning of ecosystems, as well as to plant and animal ecology; we saw not only that the NDVI could inform theoretical and applied ecology, but that it could also yield insights into conservation biology. For instance, the NDVI could be applied to monitor ecosystem functioning and map habitat degradation (Chapter 5), or could be used to assess the relative impact of the direct and indirect effects of climate on animals (Chapter 7).

This chapter begins by discussing how the vegetation index can be used to inform the expansion and management of the current protected area network (Section 8.1), and then demonstrates how the NDVI can support the implementation of reintroduction programmes (Section 8.2). Landscape-scale connectivity among preserved patches is of paramount importance to buffer biodiversity against environmental change, highlighting the importance of taking pertinent, informed land-use management decisions. In this respect, the NDVI can be a useful tool in detecting and mapping wildlife corridors (Section 8.3). The NDVI offers great potential to better predict and mitigate the consequences of climate change on biodiversity, and Section 8.4 discusses recent examples of how the index may furnish realistic scenarios about climatic changes impacting on wildlife. The final section focuses on the NDVI in relation to invasion biology, that is, the detection, mapping, and monitoring of invasive species.

The Normalized Difference Vegetation Index. First Edition. Nathalie Pettorelli.

8.1 Supporting the management and expansion of protected areas

8.1.1 Protected areas as the cornerstone of global conservation efforts

Since the late nineteenth century the backbone of the conservation of biodiversity throughout the world has been the establishment of protected areas (Pressey 1996), which are defined by the World Conservation Union as 'an area of land and/or sea especially dedicated to the protection and maintenance of biological diversity, and of natural and associated cultural resources, and managed through legal or other effective means' (International Union for the Conservation of Nature (IUCN) 1994). These areas are renowned for their ability to act as refuges for species and ecological processes that cannot persist in intensely managed landscapes and seascapes, as well as for their capacity to enable natural evolution and future ecological restoration (Chape et al. 2008; Gaston et al. 2008; Dudley et al. 2010). Famous examples of protected areas include the Serengeti National Park in Tanzania, the Yosemite National Park in the USA, or the recently established Chagos marine reserve in the Indian Ocean, which contains the world's largest coral atoll. Aside from conserving biodiversity, protected areas can perform many other functions, such as protecting cultural heritage; maintaining vital ecosystem services; providing a range of socio-economic benefits; helping maintain microclimatic or climatic stability; or shielding human communities from natural disasters (Fiske 1992; IPCC 2007; Chape et al. 2008; Ezebilo and Mattsson 2010). Altogether, protected areas therefore constitute an important stock of natural, cultural, and social capital, yielding flows of economically valuable goods and services that benefit society, secure livelihoods, and contribute to the achievement of the Millennium Development Goals (Millennium Ecosystem Assessment Board 2005).

Protected areas can take many forms depending on their use and level of protection, ranging from conservation areas, national parks, game reserves, or forest reserves. The IUCN has classified protected areas into six categories. These are:

Ia: Strict Nature Reserves—managed mainly for science.
Ib: Wilderness Area—managed for wilderness protection.
II: National Park—managed mainly for ecosystem protection and recreation.
III: Natural Monument—managed mainly for conservation of specific features.
IV: Habitat/Species Management Area—managed mainly for conservation through specific intervention.
V: Protected Landscape/Seascape—managed mainly for landscape/seascape protection and recreation.
VI: Managed Resource Protected Area—managed mainly for sustainable use of natural ecosystem (IUCN 1994).

It is important to acknowledge that, although the IUCN has developed guidelines for the management of protected areas, individual countries have their own systems of protected area classification and management (IUCN 1994).

8.1.2 Identifying new protected areas

The creation of new protected areas is a key instrument in the battle to reduce biodiversity loss worldwide, and the Convention on Biological Diversity Programme of Work on Protected Areas is the accepted framework for creating comprehensive, effectively managed and sustainably funded national and regional protected area systems worldwide. Creating new protected areas ranks high in the 2010–2020 environmental agenda for many countries, with the parties of the CBD recently agreeing on specific goals in terms of protected area coverage. The Aichi Target 11 indeed states that 'By 2020, at least 17 per cent of terrestrial and inland water areas, and 10 per cent of coastal and marine areas, especially areas of particular importance for biodiversity and ecosystem services, are conserved through effectively and equitably managed, ecologically representative and well-connected systems of protected areas and other effective area-based conservation measures, and integrated into the wider landscapes and seascapes' (see also Chapter 10).

How do stakeholders decide where and how to set new protected areas? There are many factors that can be expected to influence the decision to establish a new protected area, such as the envisaged location, size, and shape; the level of biodiversity or endemism; the presence of threatened species; the establishment and management costs as well as the likely impact of climate change on some of these parameters (Brooks et al. 2006; McCarthy et al. 2006; Hannah et al. 2007; Gaston et al. 2008). Accessing reliable and comprehensive information about the distribution of biodiversity and the functioning of ecological systems at the scale required to inform the process of setting new protected areas can be extremely challenging, highlighting the importance of identifying practical, cost-effective tools to guide decision-making.

In some situations, the NDVI can be used to derive relevant information for the setting of new protected areas. Krishnaswamy et al. (2009) introduced a new multi-date NDVI-based Mahalanobis distance measure to index tree biodiversity and ecosystem services for the Western Ghats. This measure successfully quantified habitat and forest variability, with low values corresponding to moister, denser, more evergreen forest habitats with high evapotranspiration, and high carbon storage; higher values, on the other hand, corresponded to more open, dry deciduous, and scrub habitats with low evapotranspiration and lower carbon storage. This approach thus enabled the description of forest type and ecosystem services over large landscapes to be captured by a single continuous numerical scale. Such a tool could help stakeholders prioritize areas of high conservation value, thereby supporting the development of new protected areas in this region, and possibly elsewhere.

Another example is that of Singh and Milner-Gulland (2011), who discussed how to best develop a set of protected areas in Kazakhstan for the benefit of a threatened migratory species, namely the Saiga antelope *Saiga tatarica*. This species is found in central Asia, and has experienced a 95% reduction in population size over the last two decades (Milner-Gulland et al. 2001). The authors investigated the factors influencing the species' migration patterns in the considered area, and concluded that Saiga distribution in spring was determined by an intermediate range of temperature and intermediate primary productivity (as indexed by the NDVI), by the availability of areas at intermediate distance from water and away from human settlements. This enabled them to derive a habitat suitability map for the country and explore the current match between suitable habitats for Saiga and protected area distribution. They then explored the potential effect of climate change on temperature and primary productivity in the region, using recent predictions for the area (IPCC 2007; de Beurs et al. 2009; Zhao and Running 2010). From these predictions they derived spatially explicit information about how climate changes might affect the distribution of suitable habitats for the species. Thus they were able to assess the fit of the existing protected area network for Saiga antelope in the light of the predicted impact of climate change on the distribution of their suitable habitats, and to make recommendations for adapting the development of the network accordingly. The framework presented by Singh and Milner-Gulland illustrates well the capacity for the NDVI to support the identification of new protected areas, and is a step forward in terms of designing protected area networks that are robust to future changes in distributions and densities of key target species.

8.1.3 Monitoring protected area effectiveness

Over the last few decades, the number of protected areas worldwide has increased rapidly (Coad et al. 2009), yet this has not been followed by a reduction in the rate of biodiversity loss (Millennium Ecosystem Assessment Board 2005; Secretariat of the Convention on Biological Diversity 2010). Such an absence of correlation illustrates the point made by Chape et al. (2005), that is, that the number and extent of protected areas do not supply information on a key determinant for meeting global biodiversity targets, namely the 'effectiveness' of protected areas. Since protected areas are associated with one of the most significant resource allocations on the planet (Balmford et al. 2003b), the monitoring of their effectiveness (Box 8.1) is of key importance for making relevant management decisions in the face of future environmental change (Gaston et al. 2008).

Assessing protected area effectiveness relies on the evaluation of a series of criteria represented by carefully selected indicators (quantitative and qualitative) against agreed objectives or standards (Box 8.1). But what are, and what should be,

Box 8.1 Monitoring protected area effectiveness

Protected area monitoring is defined as 'collecting information on indicators repeatedly over time to discover trends in the status of the protected area and the activities and processes of management' (Hockings et al. 2006). The evaluation of effectiveness is generally achieved by the assessment of a series of criteria represented by carefully selected indicators (quantitative and qualitative) against agreed objectives or standards. Accordingly, Salzer and Salafsky (2003) distinguished between 'status assessment' and 'effectiveness measurement,' whereby status assessment indicates the existing condition of biodiversity at a particular point in time or over various points in time, whereas effectiveness measurement indicates whether conservation interventions are having their intended effect, i.e. links goals and objectives with activities, management processes and indicators used to measure progress toward achieving conservation goals and objectives (Stem et al. 2005).

The evaluation of protected area management effectiveness is generally undertaken for reasons such as: (i) promoting better protected area management; (ii) guiding project planning, resource allocation, and priority setting; (iii) maintaining accountability and transparency; and (iv) increasing community awareness, involvement and support (Chape et al. 2008). It can include evaluation of protected area design, adequacy of management systems and processes, and delivery of protected area objectives (Hockings et al. 2004, 2006). Unsurprisingly, effectiveness at addressing priorities in protected areas has been shown to be linked with availability of monitoring data (Timko and Innes 2009), while good monitoring was shown to correlate with overall effectiveness (Dudley et al. 2004).

these agreed objectives and standards? Although protected areas have often been established with many goals in mind, most conservationists are likely to argue that the primary objective of existing protected areas should be to maintain ecological integrity (Table 8.1; Ervin 2003a,b; Dudley 2008). Ecological integrity assessment can involve quantifying changes in ecological processes and functioning (Parks Canada Agency 2005), as well as the evaluation of the threats and pressures faced by protected areas (Parrish et al. 2003; Parks Canada Agency 2005; Stem et al. 2005).

Table 8.1 Chronological presentation of the definitions proposed to characterize the concept of ecological integrity.

Definitions	References
The sum of physical, chemical and biological integrity	Karr and Dudley (1981)
The capacity to support and maintain a balanced, integrated, adaptive biological system having the full range of elements and processes expected in the natural habitat of a region	Karr and Chu (1995)
A condition that is determined to be characteristic of its natural region and likely to persist, including abiotic components and the composition and abundance of native species and biological communities, rates of change and supporting processes	Parks Canada Agency (2000)
The ability of an ecological system to support and maintain a community of organisms that has species composition, diversity, and functional organization comparable to those of natural habitats within a region	Parrish et al. (2003)
Measures of representation and maintenance of key biodiversity features	Gaston et al. (2006, 2008)
A measure of the composition, structure, and function of an ecosystem in relation to the system's natural or historical range of variation, as well as perturbations caused by natural or anthropogenic agents of change	Tierney et al. (2009)

The idea that remote sensing information can represent a great addition to the monitoring toolkit for protected areas is not new, with various authors having recommended the use of satellite data for protected area monitoring and effectiveness assessment (e.g. Gillespie et al. 2008; Alcaraz-Segura et al. 2009; Nemani et al. 2009; Wiens et al. 2009; Kinyanjui 2011; Nagendra et al. 2013). We saw in Chapter 5 how the NDVI could be used to track the impact of global environmental change on vegetation dynamics in the African and Spanish protected area network. Making use of the NDVI time series to detect significant anomalies in vegetation dynamics and quantify changes in ecological processes and functioning was an approach also undertaken by the European Union, which funded the Assessment of African Protected Areas project <http://bioval.jrc.ec.eu/PA/> (Hartley et al. 2007).