Terrestrial ecosystems from space: a review of earth observation products for macroecology applications

Marion Pfeifer¹*, Mathias Disney²†, Tristan Quaife³† and Rob Marchant¹

¹York Institute for Tropical Ecosystem Dynamics, Environment Department, University of York, Heslington, York YO10 5DD, UK. ²Department of Geography, University College London, London WC1E 6BT, UK. ³School of Geography, University of Exeter, Cornwall Campus, Penryn, Cornwall TR10 9EZ, UK

ABSTRACT

Aim Earth observation (EO) products are a valuable alternative to spectral vegetation indices. We discuss the availability of EO products for analysing patterns in macroecology, particularly related to vegetation, on a range of spatial and temporal scales.

Location Global.

Methods We discuss four groups of EO products: land cover/cover change, vegetation structure and ecosystem productivity, fire detection, and digital elevation models. We address important practical issues arising from their use, such as assumptions underlying product generation, product accuracy and product transferability between spatial scales. We investigate the potential of EO products for analysing terrestrial ecosystems.

Results Land cover, productivity and fire products are generated from long-term data using standardized algorithms to improve reliability in detecting change of land surfaces. Their global coverage renders them useful for macroecology. Their spatial resolution (e.g. GLOBCOVER vegetation, 300 m; MODIS vegetation and fire, ≥ 500 m; ASTER digital elevation, 30 m) can be a limiting factor. Canopy structure and productivity products are based on physical approaches and thus are independent of biome-specific calibrations. Active fire locations are provided in near-real time, while burnt area products show actual area burnt by fire. EO products can be assimilated into ecosystem models, and their validation information can be employed to calculate uncertainties during subsequent modelling.

Main conclusions Owing to their global coverage and long-term continuity, EO end products can significantly advance the field of macroecology. EO products allow analyses of spatial biodiversity, seasonal dynamics of biomass and productivity, and consequences of disturbances on regional to global scales. Remaining drawbacks include inter-operability between products from different sensors and accuracy issues due to differences between assumptions and models underlying the generation of different EO products. Our review explains the nature of EO products and how they relate to particular ecological variables across scales to encourage their wider use in ecological applications.

Keywords Biogeography, earth observation, fire patterns, fire rhythms, global patterns, LAI, land cover, productivity, remote sensing.

INTRODUCTION

The dynamics and structure of ecological systems are highly complex. Understanding statistical patterns in the relationships between organisms and their environment that are consistent across large spatial and temporal scales is the central focus of macroecology (Maurer, 2000) and of particular importance for assessing the ecological effects of rapidly changing environments. Land-cover change may override the importance of climate for species distributions (Sala et al., 2000; IPCC, 2007) and...
ultimately lead to changes in spatial patterns of biomass and ecosystem productivity. Habitat fragmentation reduces habitat quantity and connectedness affecting species–area relationships and species extinction dynamics (Fischer & Lindenmayer, 2007; Fisher et al., 2010). Changes in vegetation structure may alter heat and energy fluxes at the terrestrial surface, affecting regional climates (Feddema et al., 2005), offsetting the impacts of climate change (Pielke et al., 2002) or altering surface conditions leading to new states of climate and ecosystems (Moorcroft, 2003). Land use is able to control fire activity in many areas impacting on global biogeochemical cycles and vegetation pattern formation (Bond et al., 2005; Bowman et al., 2009).

Changes in vegetation structure may in turn alter the dynamics of underlying drivers of these changes. However, the exact nature of vegetation–climate feedbacks and the spatial scales on which they act remain poorly understood (Webb et al., 2006). Terrain topography contributes to these ecological and biogeo-

Assessing general patterns in macroecology and how they are affected by human and environmental forcing (Fisher et al., 2010) requires a substantial number of data. Field assessments of ecological and surface properties, however, are inconsistent over large spatial scales and patchy over temporal scales. Bottom-down estimates of land surface properties derived using earth observation (EO) across regional and global scales provide data on large spatial scales (DeFries & Townshend, 1999; Kerr & Ostrovsky, 2003; Gillespie et al., 2008). They cover areas difficult to access due to remoteness or political instability and avoid errors introduced by subjective sampling design and judgment sampling (Yoccoz et al., 2001).

Since the review of DeFries & Townshend (1999) on EO applications in detection of land surface change, a range of new satellite sensors have been launched with improved spectral, spatial and (crucially) temporal sampling. Studies using either raw reflectance data or derived spectral vegetation indices (VIs) to assess ecological traits have increasingly been employed (Turner et al., 2003; Pettorelli et al., 2005, 2011). The use of VIs (indicating vegetation ‘greenness’ as compound effects of vegetation composition, structure and function) has limitations due to technical caveats, and EO products provide a valuable alternative or supplement to VI. However, an ISI literature search on topics such as ‘land cover change’, ‘ecosystem response and global change’ or ‘ecosystem productivity’ in combination with EO terms shows that VIs are often preferred over EO products (see Table S1 in Supporting Information), although studies using fire products have increased in the last years (Chuvieco et al., 2008; Krawchuk et al., 2009; Archibald et al., 2010). Reasons for bias in EO information use may be found in lack of user confidence regarding the spatial accuracy of EO products, preference for alternative data sources (e.g. VI for productivity studies; Sjöström et al., 2011), but also a low awareness of product availability.

In this paper, we discuss EO products developed during the past decade and their potential to address key topics in macroecology. We assess four groups of EO end-user products; land cover and land-cover change products, products related to vegetation biogeochemical structure and productivity, active fire and burnt area products, and digital elevation models (DEMs). These products represent the global earth’s surface as single year or multi-year coverage, some at near-real time, at spatial resolutions suitable for analysing patterns in ecology at regional to global scales. We describe the generation of products either from measurements by single remote sensors or multiple sensors, discuss their accuracy and briefly address issues of transferability between spatial scales. We hope that by increasing the understanding for assumptions and algorithms used for EO product generation, we can stimulate their wider use in ecological and vegetation sciences facilitating effective and accountable exploitation of EO-derived information.

EARTH OBSERVATION FROM SPACE

Depending on the type of sensor used (see Table S2), EO imagery is available at a wide range of scales: from high/low (< 10 m) to medium/moderate (10–250 m) and low/coarse (250 m–5 km) resolutions, where resolution refers to the pixel size in linear dimensions (Warner et al., 2009). Spatial resolution is traded off against temporal resolution, with high spatial resolution typically meaning low temporal resolution. Compared to early products derived from Advanced Very High Resolution Radiometer (AVHRR) data, enhanced spectral resolution and spectral coverage of MODIS (Moderate Resolution Imaging Spectroradiometer), VEGETATION and MERIS (MEdium-spectral Resolution Imaging Spectrometer) have significantly improved EO capabilities for ecosystem research (Carrão et al., 2008). (Pseudo)-multi-angle observations by POLDER (Polarization and Directionality of the Earth’s Reflectances instrument) and MISR (Multi-Angle Imaging Spectro-Radiometer) allow detailed information on atmosphere (aerosol behaviour, cloud height), canopy structure and surface roughness (Widlowski et al., 2004).

Work on operational products has focused on coarse-resolution global products, which offer a range of advantages over raw reflectance data or VIs available at higher spatial resolution (Table 1). Off-the-shelf products using TM/ETM+ (Thematic Mapper and Enhanced Thematic Mapper Plus) are almost non-existent (partly because of the small or inconsistent coverage) and mature products are not yet available from fine-resolution sensors (e.g. IKONOS, Korea Multi-Purpose SAFellite KOMPSAT) despite them providing mapping accuracies comparable to ground-truth vegetation mapping (Mehner et al., 2004).

Over the past decade, much effort has been directed towards providing EO data in inter-operable formats (e.g. HDF, GeoTIFF) as well as in developing tools for data handling. Commercial software applications now routinely provide capabilities for reading different data formats, e.g. Matlab (MathWorks), Mathematica (Wolfram Research), and IDL (ITT VIS). This is in addition to commercial software tools developed specifically for processing remotely sensed data such as ENVI (ITT VIS) and Imagine (Leica Geosystems). Freely available software tools and
libraries are available either for converting between formats and map projections or for more fundamental analyses, e.g. the MODIS reprojection tool (Land Processes Distributed Active Archive Center), the geographical information system GRASS, the Freeware Multispectral Image Data Analysis System (MultiSpec), and application programming interfaces for programming languages such as C/C++, Java and Python. The Oak Ridge National Laboratory has developed a web interface that allows the user to access MODIS data products in two different geographical projections.

### Land cover/land cover change products

Land-cover products (Table 2) are generated on the principle that different land-cover types within a remotely sensed image will tend to exhibit different spectral reflectance behaviour (Townshend, 1994), and can be separated using classification techniques (e.g. maximum likelihood analysis, decision-tree classifier, neural networks). Post-classification techniques based on multi-temporal image comparison are used for detection of land-cover change, while fuzzy sets and semantic analyses are used to handle pixel classification vagueness and sub-pixel heterogeneity (Ahlqvist, 2008).

The accuracy of satellite-derived land-cover information is primarily limited by the sensor’s ability to separate the required land-cover classes in the spectral data. High spectral resolution can improve separation capabilities for vegetation types (Carrão et al., 2008), but only if the additional spectral resolution permits the extraction of uncorrelated additional information on vegetation properties. Also, subsequent classifications may lead to overfitting, requiring specific analyses such as feature extraction algorithms to define precise classes (Landgrebe, 2005).

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**Table 1** Vegetation indices (VIs) versus global earth observation (EO) products for assessing ecological traits. Typical VI examples are the normalized difference vegetation index (NDVI) and the soil-adjusted enhanced vegetation index (EVI). Major global EO products are listed in Tables 2–5.

<table>
<thead>
<tr>
<th>Raw reflectances (RR) or spectral vegetation indices (VI)</th>
<th>Validated EO end products</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processing requirements</td>
<td>Direct implementation into spatial analyses software</td>
</tr>
<tr>
<td>Trade-off: spatial versus temporal resolution</td>
<td>High spatial resolution ( \geq 10 \text{ m} ) (SPOT) and ( \geq 30 \text{ m} ) (Landsat) but long re-visit times for specific study region</td>
</tr>
<tr>
<td>Spatial extent</td>
<td>High computational effort to cover large areas; links to ecological traits region- or biome specific; inter-comparisons limited because of processing effects; data gaps; nonlinear VI-GPP/NPP/LAI relationships in densely vegetated areas and deserts</td>
</tr>
<tr>
<td>Change detection</td>
<td>Complicated by view and sun angle impacts on RR; VI products (NDVI, EVI: 250 m spatial resolution) easy to use but require accounting for cloud and aerosol contamination</td>
</tr>
<tr>
<td>Assimilation into models</td>
<td>Limited by lack of applicability over large spatial scales; uncertainty information easily missed</td>
</tr>
</tbody>
</table>

GPP, gross primary production; NPP, net primary production; LAI, leaf area index.

**Table 2** Main land-cover products derived from remote sensing data. BIOME (not validated), GLOBCOVER and GLC-2000 are single maps produced at a certain time in the past, while MCD12Q1 is a multi-annual product, which can be used for change detection.

<table>
<thead>
<tr>
<th>Product</th>
<th>Sensor</th>
<th>Satellite</th>
<th>SR/SC</th>
<th>TR</th>
<th>Format</th>
<th>PR</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLC 2000(^1)</td>
<td>VGT</td>
<td>SPOT</td>
<td>1 km/global + regional</td>
<td>Annual, 2000</td>
<td>BIL</td>
<td>Lat/Long, WGS 84</td>
</tr>
<tr>
<td>GLOBCOVER 2005 and 2009(^2)</td>
<td>MERIS</td>
<td>ENVISAT</td>
<td>300 m, global + regional</td>
<td>Annual, 2004–06 and 2009</td>
<td>Geo-TIFF</td>
<td>Lat/Long, WGS 84</td>
</tr>
<tr>
<td>MCD12Q1 v5(^3)</td>
<td>MODIS</td>
<td>Aqua, Terra</td>
<td>500 m, global</td>
<td>Annual, 2001–07</td>
<td>HDF-EOS</td>
<td>Sinusoidal, EA</td>
</tr>
</tbody>
</table>

EA, equal area; PR, projection; SC, spatial coverage; SR, spatial resolution; TR, temporal resolution; VGT, VEGETATION.

Recent land-cover products are generated from long-term EO data overcoming earlier problems of inconsistency between land-cover datasets in terms of sensors and classification (Herold et al., 2008). Some products are available as areal proportions of each land-cover type per pixel, e.g., the MODIS vegetation continuous fields product (Hansen et al., 2003), thus picturing heterogeneous vegetation more realistically and improving the detection of changes in complex landscapes. However, generally, data are disseminated as discrete classes assigned to each pixel. This can be problematic in heterogeneous landscape mosaics affecting class accuracy and contributing to spatial disagreement between land-cover datasets (Fig. 1) (McCallum et al., 2006; Fritz & See, 2008). The spatial resolution of global land-cover products may be a limiting factor for some analyses, yet their temporal coverage enables timely estimates of land cover and cover change (Hansen et al., 2008).

**Single-year products**

Mainly aimed at ecosystem assessments, the Global Land Cover map 2000 (GLC2000, 27 classes, Bartholomé & Belward, 2005) employs the United Nations Environment Programme (UNEP)-Food and Agriculture Organization (FAO) land-cover classification system. Total accuracy of GLC2000 was 68.8% assessed using Landsat and 1265 samples distributed throughout Asia, Africa and Europe (Mayaux et al., 2006). Accuracy varied between regions and was considerably lower for heterogeneous landscapes compared with homogeneous sites.

**Multiple-year products**

Like GLC2000, GLOBCOVER (22 classes in the global product; up to 51 classes in regional maps) is compatible with the UNEP-FAO land-cover classification and available in regionally optimized or globally harmonized versions (Bicheron et al., 2008). Overall accuracy is estimated as 73.1% in the 2005 product based on 3167 globally distributed sampling points and 67.5% (weighted by class area) in the 2009 product using 2190 points. The MODIS MCD12Q1 product, a package of five land-cover classifications, is derived through supervised decision-tree classifications (Cohen et al., 2006). The International Geosphere Biosphere Programme (IGBP) scheme (Type 1: 17 classes) and University of Maryland (UMD) scheme (Type 2: 14 classes) exist to provide consistency with earlier land-cover maps (Hansen & Reed, 2000). Global accuracy of the IGBP scheme (1370 training sites) is 75%, varying between 70% and 85% for continental regions, while user accuracy is low for savanna and deciduous forests (< 45%) (Hodgens, 2002). Consistent processing and updating means that changes in land-cover classes should be accurate even if absolute land-cover classes are not. The leaf area index (LAI)/fraction of absorbed photosynthetically active radiation (fAPAR) scheme (Type 3: 11 classes; Myeneni et al., 1997) is an aggregation of land classes into structurally similar biomes, used for the generation of LAI and fAPAR (400–700 nm) maps. The Biome-BGC scheme (Type 4: 9 classes) is designed for use with the Biome-BGC model to generate the MODIS net primary productivity (NPP) product (Running et al., 2004) and for providing vegetation feedback with climate models.

**Vegetation biogeophysical structure and productivity**

Vegetation structure (height, LAI, leaf area density, and leaf inclination distribution) is a key parameter when assessing ecosystem productivity and carbon fluxes (Garrigues et al., 2008) (Table 3). LAI, in ecology broadly defined as the total canopy area per unit ground area (m² m⁻²) (Asner et al., 2003) ranges from 0 (bare ground) to over 10 (dense forest). LAI determines the interception of solar energy (and thus partly the fAPAR) for photosynthesis (Sellers, 1997). To consider radiation interception, LAI in remote sensing is usually defined as one-sided leaf area per unit ground area (0.5 × total) (Chen & Black, 1992). Gross primary production (GPP; in units of g m⁻² day⁻¹) can be estimated from fAPAR, which is inferred from satellite data, based on the Monteith equation for production efficiency (Kumar & Monteith, 1981):

\[ \text{GPP} = \varepsilon \times \text{fAPAR} \times \text{PAR}. \]  

(1)

Photosynthetically active radiation (PAR) data tend to be acquired from re-analysis of climate observations. The efficiency term \( \varepsilon \) (in units of mass of carbon per unit of irradiance) is defined as maximum light-use efficiency of the vegetation limited by environmental factors, such as temperature and water availability (Zhao & Running, 2010). The term is multiplicative (von Liebig, 1843), however, and likely to be biased when it is cold and dry at the same time. Weakness in the estimation of the efficiency term seems to be the primary source of errors in the MODIS GPP product (Sims et al., 2006). NPP represents carbon available to plants for allocation to biomass after accounting for autotrophic respiration \( R_a \) (g m⁻² day⁻¹), which is estimated by a process model describing above- and below-ground carbon allocation (Running et al., 2000), or simply by assuming \( R_a \) as constant fraction of GPP (Veroustraete et al., 2002):

\[ \text{NPP} = \text{GPP} - R_a. \]  

(2)

**Vegetation structure – spectral VIs**

Vegetation traits are often estimated using spectral VIs sensitive to the contrast between red and near-infrared reflectances of vegetation, such as the normalized difference vegetation index (NDVI; Pettorelli et al., 2005). For example, ECOCLIMAP LAI estimates one LAI value for each homogeneous ecosystem and two for mixed ecosystems from NDVI data (Masson et al., 2003; Champeaux et al., 2005) using global (IGBP, UMD) and regional land-cover maps. In situ measurements accounting for vegetation clumping at plant and canopy scales assign LAI ranges for each surface class. Comparisons with reference maps show that ECOCLIMAP overestimates LAI, probably due to algorithm uncertainties, poor description of surface spatial variability and underperformance of the NDVI time series.
Figure 1  Land cover in north Tanzania (Mount Kilimanjaro is in the upper left corner) represented using three global land-cover products. Spatial resolution increases from 1000 m (GLC2000; 27 cover classes for Africa) to 500 m (MCD12Q1 type1 in 2006; 17 International Geosphere Biosphere cover classes) and 300 m (GLOBCOVER; 22 classes including water bodies, snow/ice and bare areas). Note the differences in forest areas (purple) and woody vegetation (green). Significant discrepancies between products regarding certain land-cover types (McCallum et al., 2006; Fritz & See, 2008) require the user to make use of more than one dataset to assess impacts on their analyses.
Figure 1  Continued.
Figure 1 Continued.
Table 3 Operational biogeophysical products derived from remote sensing data.

<table>
<thead>
<tr>
<th>Product</th>
<th>Sensor</th>
<th>Format</th>
<th>Spatial Coverage</th>
<th>Temporal Resolution</th>
<th>Spatial Resolution</th>
<th>Temporal Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>LAI and fAPAR products</td>
<td>VGT</td>
<td>HDEF-EOS</td>
<td>1km, global</td>
<td>10 daily, Jan. 1999 to Dec. 2007</td>
<td>1km, global</td>
<td>10 daily, Jan. 1999 to Dec. 2007</td>
</tr>
<tr>
<td>CYCLOPES LAI/fAPAR1</td>
<td>VGT</td>
<td>ENVI Image</td>
<td>6km, global</td>
<td>10 daily, since March 2000</td>
<td>6km, global</td>
<td>10 daily, since March 2000</td>
</tr>
<tr>
<td>ECOCLIMAP LAI2</td>
<td>VHRR, VGT, NOAA, SPOT</td>
<td>HDEF-EOS</td>
<td>1km, global</td>
<td>Monthly, April 1992 to March 1993</td>
<td>1km, global</td>
<td>Monthly, April 1992 to March 1993</td>
</tr>
<tr>
<td>GLOBCARBON LAI/fAPAR3</td>
<td>ATSR-2, AATSR, MERIS, VGT</td>
<td>ENVI Image</td>
<td>1km to 0.5°, global</td>
<td>10 daily, Jan. 1998 to Dec. 2007</td>
<td>1km to 0.5°, global</td>
<td>10 daily, Jan. 1998 to Dec. 2007</td>
</tr>
<tr>
<td>MCD15 LAI/fAPAR4*</td>
<td>MODIS Terra + Aqua</td>
<td>HDEF-EOS</td>
<td>1km, global</td>
<td>10 daily, April 1998 to March 2008</td>
<td>1km, global</td>
<td>10 daily, April 1998 to March 2008</td>
</tr>
<tr>
<td>POLDER fAPAR1</td>
<td>ADEOS-1, ADEOS-2</td>
<td>SEVIRI</td>
<td>6km, global</td>
<td>Daily, since Nov. 1996 to March 2003</td>
<td>6km, global</td>
<td>Daily, since Nov. 1996 to March 2003</td>
</tr>
<tr>
<td>SEVIRI LAI/fAPAR6</td>
<td>SEVIRI MSG</td>
<td>HDEF-EOS</td>
<td>3km, regional</td>
<td>Daily, since Nov. 1996 to March 2003</td>
<td>3km, regional</td>
<td>Daily, since Nov. 1996 to March 2003</td>
</tr>
</tbody>
</table>

LAI, leaf area index; fAPAR, fraction of absorbed photosynthetically active radiation; NPP, net primary production; GPP, gross primary production; EA, equal area; MSG, Meteosat Second Generation; PR, projection; SC, spatial coverage; SR, spatial resolution; TR, temporal resolution; VGT, VEGETATION.*MOD15A2 when derived from Aqua data only.†Data source code provided, but requires compiler.

Vegetation traits – radiative transfer models

Biogeophysical traits can be estimated from the inversion of physically based radiative transfer models (RTMs), using iterative optimization approaches (Liang, 2004), artificial neural networks (Fang et al., 2003) or look-up-tables (Deng et al., 2006), comparing observed and modelled reflectance for a suite of canopy structure and environmental traits. Radiative transfer models can make various assumptions regarding vegetation structure and radiometric properties (Garrigues et al., 2008). In the simplest case, the canopy is specified as a one-dimensional (1D) homogeneous layer with light attenuated through absorption (see Fig. S1). Three-dimensional (3D) canopy models account for more ‘realistic’ canopies, where leaves are preferentially orientated, vegetation is clumped across a range of scales (Fig. 2) and light is attenuated through absorption as well as single and multiple scattering (Myneni et al., 1997). Model assumptions are important when comparing EO-derived LAI with field measurements or when integrating them with ecosystem models. Model-data fusion may require the development of transfer algorithms to avoid bias in estimates of water and gas exchanges as well as radiation interception (Pinty et al., 2006).

MODIS LAI (range 0–10) and fAPAR (range 0–1) products (MCD15A2) are derived via look-up-table inversion of the 3D RTM (Knyazikhin et al., 1998). MODIS biome information is used for clumping and woody element corrections to compute true LAI from effective LAI, which assumes randomly located foliage elements within the canopy (Yang et al., 2006). Fixed empirical relationships between LAI and NDVI are triggered should the main algorithm fail, e.g. due to lack of observations. An artificial neural network inverts the 1D RTM of Kuusk (1995) to estimate POLDER LAI (range 0–6; Lacaze, 2006) accounting for single and multiple scattering in the canopy, leaf optical properties and soil spectral properties. SEVIRI LAI (range 0–7) is derived assuming the vegetation canopy to be a horizontally homogeneous layer, while SEVIRI fAPAR is estimated from the inversion of the 1D turbid medium SAIL RTM (Garrigues et al., 2008). ECOCLIMAP-2, developed as a more precise parameter database, uses GLC2000 and VEGETATION NDVI profiles to define homogeneous ecosystems and to account for inter-annual variability of LAI (Champeaux et al., 2005).

Generally, Glenn et al. (2008) argue against the use of VIs as surrogates for canopy architecture features. VIs rely on biomespecific calibration (Chen et al., 2002), depend on view and sun angles, and are sensitive to background brightness, snow and atmospheric contamination (Nagai et al., 2010). Variations in VIs can be functions of complex, compensating biophysical processes (Brando et al., 2010). Their sensitivity to changes in canopy structure reduces asymptotically with increasing LAI, saturating at values of 4–5. Recent developments such as the generation of enhanced vegetation indices (e.g. EVI and EVI2; Huete et al., 2002), angular model fitting (requiring multiple observations) and minimizing variations in view and sun angle when comparing across dates aim to overcome some of these limitations.
GLOBCARBON effective LAI (range 0–10) is generated via look-up table inversion of a physically based model with multiple scattering (Deng et al., 2006). The iteration method starts from a precursor effective LAI, which is derived via land-cover-dependent LAI–VI relationships (Plummer et al., 2006). Similar to SEVIRI LAI, the clumping index of Chen et al. (2005) is implemented based on GLC2000 to compute true LAI. GLOBCARBON fAPAR is calculated as difference of the top-of-canopy PAR (amount of incoming photosynthetically active solar radiation; derived from RED surface reflectance) absorbance minus the PAR absorbance of soil (derived from a look-up table based on soil maps). CYCLOPES maps of LAI (range 0–6) and fAPAR have been generated using a neural network to invert the SAIL RTM corrected for 3D structure (Kuusk, 1995). The CYCLOPES algorithm accounts for clumping at the landscape level (Baret et al., 2007) and can be applied to any surface type in contrast to biome-tuned algorithms for MODIS or GLOBCARBON.

Comparisons of POLDER LAI with MODIS LAI show good agreement and similar trends over croplands and boreal forests (albeit at different magnitudes), but POLDER LAI shows unrealistic seasonal cycles over tropical forests (Lacaze, 2006). Mean product errors of SEVIRI products vary with geographical region, being low for northern Africa and western Europe (< 0.1 for fAPAR, < 0.6 for LAI) but very high for regions with large zenith view angles (e.g. northern Europe and South America), high snow cover or persistent cloud cover (Land SAF, 2008). Weiss et al. (2007) found good agreement between CYCLOPES and MODIS LAI regarding seasonality and phasing (Fig. 3), although LAI magnitude differed significantly between both products. Overall, product accuracy varies with vegetation class (GLOBCARBON LAI especially underestimates LAI over grassland and cropland), and mixed vegetation sites are generally not well described by global LAI products (Garrigues et al., 2008).

Carbon flux products: NPP and GPP

For the MODIS GPP/NPP product (MOD17), efficiency values are assigned a theoretical maximum as a function of land cover (thus accuracy depends on the MODIS land-cover product) (Zhao et al., 2006). Two MODIS NPP products are derived from the GPP estimate; a short-time-scale NPP that only accounts for maintenance respiration from leaves and roots, and an annual integrated NPP that also accounts for respiration from woody material and plant growth. The GEOSUCCESS NPP product is modelled by the C-Fix model (equation 1; Verostrate et al., 2002) computing productivity as a function of temperature and CO₂ fertilization and using fAPAR estimates from NDVI.

MODIS validation shows that global annual estimates of GPP and NPP are within 10.4% and 9% of averaged published results (MODIS Land Team, status 2008, collection 4). The accuracy of GPP and NPP products depends largely on the algorithm’s ability to describe the light-use efficiency of a given plant species and on the accuracy of the driving climatological data (Zhao et al., 2006). Garbulsky et al. (2008) showed how using specific photochemical reflectance index–radiation use efficiency relationships could significantly improve the accuracy of MODIS GPP estimates. Comparisons of VI and MODIS GPP with tower flux estimates of productivity suggest that EVI may be as good as or better than MODIS GPP to predict vegetation productivity in North America (Sims et al., 2006) or Africa (Sjöström et al., 2011). Yet, relationships were highly stand-specific and relationship accuracy varied among sites depending on the deciduousness of species. While MODIS products have a built in...
Figure 3  Maps of leaf area index (LAI) (each reclassified into 12 classes for display: increasing LAI with increasingly darker blue tones) derived from remote sensing imagery for north Tanzania in early January 2006 (Mount Kilimanjaro is in the upper left corner). Spatial resolution of the three different earth observation (EO) products is 1000 m (CYCLOPES, GLOBCARBON and MODIS). Areas with no LAI values (most likely because cloud cover did not allow for radiance measurements) are shown in white.
Figure 3  Continued.
Figure 3  Continued.
dependency on water, GEOSUCCESS NPP is not limited by water, leading to large differences between products in areas where soil water is limiting (Coops et al., 2009). Quaife et al. (2008) demonstrated how different land-cover products could produce significantly different productivity estimates. Also, the crude assumptions underlying the production efficiency models may not be applicable to short time-scales (Maselli et al., 2006).

**FIRE PRODUCTS**

Fire-related EO products include spatio-temporal maps of active fires and burnt area/burn scar maps (Table 4; see Fig. S2), as well as estimates of fire severity and combustion. The actual area burnt per fire count can vary greatly (Cardoso et al., 2005), and thus the derived amount of combusted biomass. Therefore, burnt area maps are more relevant for modelling impacts of fire on carbon fluxes and vegetation cover dynamics. Recently, focus has shifted from annual to multi-annual datasets enabling assessments of inter-relations between fire and vegetation.

**Burnt area maps**

The GLOBCAR map of burnt area (Simon et al., 2004) was derived using two global burn scar detection algorithms (K1 and E1), applied for every burnable pixel in the IGBP vegetation map (Kempeneers et al., 2002). The product allows seasonal and regional tracking of fire events and their impacts (Plummer et al., 2006). Problems at the global scale include over-detection by the K1 algorithm, severe local under-detection by the E1 algorithm, mis-registration problems and interpolation errors in the processing chain (Kempeneers et al., 2002). The Global Burned Area-2000 (GBA-2000) product uses regional change-detection algorithms adapted to land-cover types (UMD, TREES tropical forest map; Achard et al., 1998) and climatic conditions. GBA-2000 presented a major improvement over GLOBCAR, which used global algorithms, and over methods based on active fire detection, where a single algorithm only is used (Grégoire et al., 2003).

A multi-temporal multi-threshold burnt area algorithm was applied to generate the Global Burned Surface dataset (GBS 82–99; Carmona-Moreno et al., 2005). Technical limitations [e.g. increasing orbital drift with satellite lifetime, no bidirectional reflectance distribution function (BRDF) effects accounted for] make the GBS dataset unsuitable for quantitative estimations (see Fig. S3). The dataset tends to underestimate fire area, particularly at high latitudes (Carmona-Moreno et al., 2005). However, the lack of systematic trend in the sensitivity of the algorithm to calibration errors as well as the good agreement concerning fire occurrences justifies its employment to detect intra- and inter-annual trends in regional fire and to initiate or validate output from dynamic vegetation models and trace gas emission models. GLOBCARBON fire products have been generated for assimilation into carbon models. They are monthly difference products of burnt area detected within the last month with confidence ≥ 80% (Plummer et al., 2006) using two global algorithms (modified from GLOBCAR) and two regional GBA-2000 algorithms; fire location information derived from active fire databases is added (Roy & Boschetti, 2009). In the L3JRC product (Tansey et al., 2008), identification of burnt pixels is based on a globally refined version of the boreal Eurasia GBA2000 algorithm. L3JRC reports the amount of vegetation burnt using GLC2000 land cover assuming that a surface cannot be burnt more than once in the same fire season (which runs from 1 April to 31 March). The algorithm performs well for a range of vegetation types, while significantly underestimating burnt areas for low vegetation cover (Tansey et al., 2008; see also Giglio et al., 2010).

The MODIS burnt-area product MCD45A1 (Roy et al., 2005) predicts the reflectance on a subsequent day taking into account changing view and the effects of sun angle (variations in the observed BRDF). A statistical measure is used to determine whether the difference between the observed reflectance and the model-predicted reflectance in the near- and mid-infrared bands indicates a significant change of surface properties (Roy et al., 2005). The Global Fire Emissions Database (GFED3.1) provides a hybrid monthly burnt area dataset intended for use within large-scale atmospheric and biogeochemical models (van der Werf et al., 2006). Compiled from multiple sensors but primarily based on MODIS surface reflectance data (using a different algorithm from MCD45), it is the most comprehensive dataset to date available for assessing inter-annual variability and long-term trends in global burnt area and associated fire emissions over the past 13 years (Giglio et al., 2010).

Product uncertainties can result in significant discrepancies of burnt area estimates for some regions (Chang & Song, 2009; see Fig. S1). MCD45A1 appears to perform best in comparison with other fire products, partly because of the higher spatial resolution of MODIS sensors (Roy & Boschetti, 2009). Roy & Boschetti (2009) suggest that current global burnt area products may still not meet the accuracy needs of local users because of high probabilities of errors of commission and omission. Burnt areas that are small and/or spatially fragmented relative to the satellite observations may not be detected reliably (Laris, 2005), which is especially relevant in cultivated and managed areas. Fire maps contain errors because angle effects can cause a single fire event to be detected in more than one satellite pixel and fires may be hidden beneath clouds and canopies (discussed in Cardoso et al., 2005). Yet, on scales relevant for macroecology and biogeography, e.g. for testing effects of disturbance frequency on ecosystem distribution and productivity, the accuracy of geolocation (MODIS, 50 m at nadir; VEGETATION, 300 m; Roy & Boschetti, 2009), spatial extent, time and duration is likely to be sufficient.

**Active fire data**

The strong emission of mid-infrared radiation from fires (around 4 μm) is used to derive active fire products (Giglio et al., 2003) including MODIS thermal anomalies fire products (MOD14A, MYD14A) (Giglio et al., 2009) and MODIS climate modelling grids (monthly MOD14CMH, MYD14CMH, 8-day MOD14C8H, MYD14C8H). Climate modelling grids are...
Table 4. Active fire and burnt area products derived from remote sensing data. The Global Fire Emissions Database (GFED) additionally provides ASCII files of fire emissions (including CO₂, CO, CH₄, non-methane-hydrocarbons, H₂, NOₓ, and others).

<table>
<thead>
<tr>
<th>Product</th>
<th>Sensor</th>
<th>Satellite</th>
<th>SR/SC</th>
<th>TR</th>
<th>Format</th>
<th>PR</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Single year products</strong></td>
<td></td>
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<tr>
<td>GBA-2000¹</td>
<td>VGT</td>
<td>SPOT</td>
<td>1 km, global</td>
<td>Monthly, 2000</td>
<td>ASCII/*.shp</td>
<td>IGH, WGS 84</td>
</tr>
<tr>
<td>GLOBSCAR²</td>
<td>ATSR-2</td>
<td>ERS-2</td>
<td>1 km, global</td>
<td>Monthly, 2000</td>
<td>ASCII/*.shp</td>
<td>IGH, WGS 84</td>
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<td><strong>Multiple year products</strong></td>
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<tr>
<td>BAE³</td>
<td>ATSR-2, AATSR, VGT</td>
<td>ERS, SPOT 4, SPOT 5</td>
<td>1 km to 0.5°, global</td>
<td>Monthly, April 1998 to Dec. 2007</td>
<td>ENVI image</td>
<td>Lat/long, WGS 84</td>
</tr>
<tr>
<td>GBS 82–99⁴</td>
<td>AVHRR</td>
<td>NOAA</td>
<td>8 km, global</td>
<td>Weekly, Jan. 1982–Dec. 1999</td>
<td>GeoTIFF</td>
<td>Lat/long, WGS 84</td>
</tr>
<tr>
<td>L3JRC⁵</td>
<td>VGT</td>
<td>SPOT</td>
<td>1 km, global</td>
<td>Annual, April 2000–March 2007</td>
<td>GeoTIFF; ASCII</td>
<td>Lat/long, WGS 84</td>
</tr>
<tr>
<td>MCD45A15⁶</td>
<td>MODIS</td>
<td>Aqua, Terra</td>
<td>500 m</td>
<td>Monthly, since April 2000</td>
<td>HDF 4</td>
<td>Sinusoidal, EA</td>
</tr>
<tr>
<td>GFED3.1⁷</td>
<td>MODIS, VIRS, ATSR</td>
<td>Terra,</td>
<td>0.5°</td>
<td>Monthly, July 1996–Dec. 2009</td>
<td>ASCII</td>
<td>Plate carrée</td>
</tr>
<tr>
<td><strong>Active fire data</strong></td>
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<tr>
<td>C8H, CMH²</td>
<td>MODIS</td>
<td>Aqua, Terra</td>
<td>0.5°</td>
<td>8 daily, monthly, since Jan. 2001</td>
<td>FITS and HDF 4</td>
<td>Sinusoidal, EA</td>
</tr>
<tr>
<td>FRP product⁸</td>
<td>SEVIRI</td>
<td>MSG</td>
<td>3 km, global</td>
<td>15 min and hourly, since June 2008</td>
<td>HDF 5</td>
<td>Lat/long</td>
</tr>
<tr>
<td>MOD14A, MYD14A³</td>
<td>MODIS</td>
<td>Aqua, Terra</td>
<td>1 km</td>
<td>Daily and 8 daily, since May 2002</td>
<td>HDF 4</td>
<td>Sinusoidal, EA</td>
</tr>
</tbody>
</table>

*EA, equal area; FITS, flexible image transport system; IGH, interrupted Goode homolosine; MSG, Meteosat second generation; PR, projection; SC, spatial coverage; SR, spatial resolution; TR, temporal resolution; VGT, VEGETATION.

¹Minimum mapping unit 400 ha.

²Not 1994.

gridded summaries of fire pixel information intended for use in regional and global dynamic vegetation models. The NASA funded Fire Information for Resource Management System (FIRMS) and the Web Fire Mapper (http://firefly.geog.umd.edu/firemap/) provide access to a rolling 2-month archive of daily global MODIS hotspot/fire locations in near-real time as well as temporal aggregates. Care should be taken interpreting active fire locations, though, particularly at coarse spatial scales. Fires may not be detected but information regarding missing data or cloud obscuration may not be provided (Giglio, 2007). Recent work has looked at how to combine estimates of active fire products and burnt area, recognizing that active fire estimates tend to underestimate the frequency and distribution of smaller, short-lived fires which may flare up and burn out before they are detected. Burnt area products, however, may pick up fire disturbances, which tend to persist for some time after the fire.

**DIGITAL ELEVATION MODEL (DEM) PRODUCTS**

We briefly mention DEMs (Table 5) because of the importance of topography in many earth system processes and ecological applications, especially for predictive species distribution models (Platts et al., 2008). The Shuttle Radar Topographic Mission (SRTM) provides elevation data from raw radar echoes collected between 60° N and 54° S in 2000 (USGS Earth Resources Observation and Science Center). These data were filtered to produce the 30 m (horizontal) resolution NASA product SRTM90, representing 80% of the earth’s surface with a vertical accuracy of at least 16 m at 90% confidence level (Rodriguez et al., 2006). SRTM90 was further processed providing final seamless datasets for user-defined areas (CGIAR-CSI SRTM). While terrain slope and aspect affect the accuracy of CGIAR-CSI SRTM data, errors are significant only on terrain with slope values exceeding 10° (Gorokhovich & Voustanianouk, 2006). General topographic gradients are captured, although some microvalley and ridges are not, which will affect micrometeorological studies in regions with high topographic complexity (Jarvis et al., 2004). The ASTER global DEM (GDEM) product is produced fully automated without ground-control points using ephemeris and altitude data derived from positional measurements of the TERRA platform instead, reaching vertical accuracies of < 25 m in many cases (ASTER Global DEM Validation Team, 2009). Accuracy problems for high mountain conditions restrict the application for location-specific change detection. Also, the ASTER GDEM contains residual anomalies and artefacts that degrade its overall accuracy; elevation of many inland lakes is inaccurate and the existence of most water bodies is not indicated. However, the product provides topographic information on a global scale making it useful for biogeographical studies. The ASTER GDEM has a greater latitudinal extent (83° N to 83° S) than SRTM products aiding research at high geographical latitudes. A multi-temporal global land surface altimetry product (GLA14) has been generated from the Geoscience Laser Altimeter System instrument on the Ice, Cloud and Land Elevation Satellite (ICESat) designed to measure changes in ice sheet elevation (Schutz et al., 2005). The geolocation accuracy of GLA14 is below 1 m and can be a valuable supplement to other DEMs.

**POTENTIAL FOR MACROECOLOGICAL APPLICATIONS**

Global environmental changes, caused or accelerated by human activities, can have severe biotic consequences, including ecosystem degradation, species range shifts and changes in vegetation phenology and productivity (Kerr et al., 2007). Satellite reflectance analysis, in particular, has emerged as a major tool for analysing such changes and underlying drivers (see Table 1). Coverage of global spatial and continuous temporal scales of EO-derived land cover and GPP/NPP products permits investigation of trends in distribution and productivity of ecosystems over time and space, at intra-annual time-scales. Detection of temporal change of vegetation cover, structure (LAI, fAPAR) and NPP/GPP allows one to analyse seasonal patterns of vegetation traits and biological responses to climate and environmental change, such as leaf flushing and abscission in response to dry
and wet seasons to enhance photosynthetic gain (Myneni et al., 2007), dynamics of carbon capture across regions and biomes (Garbulsky et al., 2010) and drought-inductions in global ecosystem productivity (Zhao & Running, 2010).

Information on changes in landscape connectivity, area and energy allows analyses of environmental mechanisms underlying regional diversity (Turner, 2004; Honkanen et al., 2010) and invisibility of communities (Richardson & Pyšek, 2006). EO products provide information on disturbances, which may mask macroecological patterns such as species–area relationships (Higgins, 2007) and can lead to regional climate–vegetation mismatches. Fire, a major disturbance agent in many parts of the world (Bowman et al., 2009), is estimated by a range of continuously generated global EO products. Information on fire distribution combined with products on vegetation productivity and rainfall is increasingly exploited to predict wildfire distribution and changes in the susceptibility of vegetation to fire under climate changes (Bucini & Hanan, 2007; Krawchuk et al., 2009; Bradstock, 2010).

**CHALLENGES: SCALE AND UNCERTAINTY**

Spatial accuracy can be a major deterrent for ecologists attempting to use EO data. However, alternatives covering large geographical areas are rare. The current challenges faced by ecologists include issues of: (1) how ecological system properties are related to EO products at a specific aggregation level (sensu scale) and (2) accounting for uncertainties associated with specific EO products (‘validation’) for successful model–data fusion (Williams et al., 2008).

Sub-pixel surface variation is intrinsic in spatial observations of a natural surface (Cracknell, 1998) and is best described by ‘grain.’ ‘Grain’ in biodiversity modelling describes field sampling units, in landscape ecology it defines the smallest interval in the observation and in remote sensing it is equivalent to the spatial, spectral and temporal resolutions of the image (Clark & Pellikka, 2007) (see Fig. S4). Up-scaling of ecological information, often collected at scales smaller than a few metres, to the spatial grain of satellite remote sensing can introduce scaling bias if the relationship between observation and process is nonlinear (Tian et al., 2002; Stoy et al., 2009). When land cover varies at a spatial frequency that is finer than the image grain, aggregation effects lead to overestimation of areas of more common land-cover types and vice versa (Fernandes et al., 2004; Verburg et al., 2011). Clumping of vegetation at multiple scales can introduce scaling bias on LAI estimates when nonlinear LAI retrieval algorithms calibrated at the patch scale were applied on moderate-resolution scales (Tian et al., 2002). Minimizing aggregation errors to reduce spatial mismatches between data, products and models, e.g. by maintaining more information about the underlying fine-scale spectral signal (Rastetter et al., 1992) or by developing transfer functions in which relationships between LAI and spectral measurements vary as a function of scale (Williams et al., 2008), has received increasing attention (Garrigues et al., 2008).

Global validation initiatives such as VALERIE (Validation of Land European Remote sensing Instruments; Morisette et al., 2006) and BigFoot were launched to establish uncertainties in EO products, especially of those relating to the terrestrial carbon cycle (Cohen et al., 2006). These uncertainties may arise from aggregation effects, random errors and systematic errors (e.g. due to instrument capabilities and algorithms). Note that sites used for calibrating algorithms can be biased towards certain geographical regions and biomes (Baret et al., 2006), with a lack of data in tropical regions. Nevertheless, uncertainty assessments make the use of EO products for ecological modelling accountable and allow the results to be generalized.

**CONCLUSION AND PERSPECTIVES**

Many of the practical obstacles to the routine use of EO data in ecological applications that existed a decade ago, such as the lack of validated time series, tools and specialist expertise, have been overcome. Users are left with the challenge of making an informed decision about which product to choose for their...
specific question, being aware that understanding assumptions about the structural properties of the surface underlying these models is the key to effective exploitation of EO products (Grace et al., 2007). The range of EO products available provides huge opportunities for advancing our understanding of ecological processes and patterns at scales relevant for macroecology incorporating temporal dynamics as requested by Fisher et al. (2010). EO is a fast evolving field and new products are constantly generated (e.g. Space Agency Climate Change Initiative, global albedo products). Effort has increased to integrate information across sensors and scales with the potential to improve future assessments of carbon fluxes and biodiversity and to inform environmental policy on impacts of global change (Fig. 4). Large-footprint LIDAR information is fused with MODIS data to generate forest height maps (Lefsky, 2010) and the P-band of the Synthetic Aperture Radar (SAR) shows good agreement with boreal forest biomass. These developments will hopefully allow large-scale forest structure and biomass assessments. Extending field campaigns and increased information exchange between disciplines will inform future developments of products and missions will bring both research fields one step further, envisaged in an overarching distribution network.

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article:

Figure S1 Schematic representation of photon transport in vegetation canopies.

Figure S2 Maps of fire products overlaid on precipitation maps derived from WorldClim database.

Figure S3 Remote sensing essentials.

Figure S4 Effects of aggregation on canopy spatial information generated from a detailed three-dimensional model of a savanna-type canopy.

Table S1 Results of ISI Web Of Knowledge literature search using earth observation terms in combination with keywords characterizing ecological systems.

Table S2 Spatial resolution (SR) and number of spectral bands (SB) of passive satellites and sensors. Launched–time of satellite launch.

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BIOSKETCH

Marion Pfeifer is a Marie Curie IEF research fellow in the York Institute for Tropical Ecosystem Dynamics, UK. In her research, she focuses on the response of plants to environmental change across spatial scales, using demographic, genetic and modelling approaches. She is currently studying LAI–vegetation relationships for eastern Africa using KOMPSAT, SPOT and MERIS data provided by the European Space Agency (Cat-1 User Agreement).

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