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Ecosystem Services Related to Carbon Dynamics: Its Evaluation Using Remote Sensing Techniques

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CONTENTS

2.1 Introduction

Policies aimed at integrating social, economic, and environmental dimensions of sustainability have to explicitly consider evaluating the influence of human activities on the provision of ecosystem services (ESs). The decision-making process for land use planning requires ES inventory along with an estimation of the ES provision rates and the effects of related human activities. ESs are commonly evaluated on the basis of indicators that do not provide a proper representation of the whole territory and/or do not capture the temporal dynamics of the service supply (Carpenter and Folke 2006). In this sense, remote sensing techniques are particularly appropriated to map ESs in a fast and continuous way in time and space (Paruelo 2008).

One of the advantages of the ES framework is its direct relationship with ecosystem functioning and human well-being. Moreover, the Millennium Ecosystem Assessment (MA 2004) definition explicitly links the ES supply with ecosystem exchange of matter and energy (i.e., nutrient cycling of carbon gains). Díaz et al. (2007) identified a number of ESs and related ecosystem processes. These authors associated the variation in the level of ES provision with related functional changes, specifically with changes in plant functional diversity. McNaughton et al. (1989) proposed carbon (C) gains as an integrative aspect of ecosystem functioning because many other processes are tightly linked to this flux. C stocks (in live or dead biomass) are also integrative descriptors of the processes and disturbances that operate in the ecosystem. Changes in soil organic C reflect the influence of the disturbance regime and land use changes on inputs and outputs of C to/from the soil. The global C balance is a critical issue in the analysis of climate change due to its importance in determining atmospheric carbon dioxide (CO_2) and, consequently, the radiative forcing of the atmosphere (Canadell et al. 2004). Quantifying key fluxes and stocks of the C cycle would synthesize the condition of the ecosystem and, moreover, its ability to supply ESs (Cabello et al. 2012).

In this chapter, we discuss the opportunities to evaluate ESs related to the C dynamics using remotely sensed data. We present the key processes of the C cycle, the basis of its evaluation using spectral data, and the conceptual connection with the ES provision.

2.2 The Carbon Cycle: Key Processes

Carbon exchange dynamics between the biota and the atmosphere, which is tightly linked to energy flow and circulation of other materials, is an integrative aspect of ecosystem functioning. The balance between photosynthesis and respiration by plants, animals, and microorganisms is a major determinant of C dynamics. The final result of such balance—net ecosystem production (NEP) or net ecosystem exchange (NEE)—is a fundamental characteristic of terrestrial ecosystems because it is directly connected to C sequestration. The dynamics of C sequestration by vegetation and soil (assuming no lateral flows) can be described by two different equations:

$$\Delta C = \Delta AGB + \Delta BGB + \Delta L + \Delta S \qquad \text{mass balance equation} \tag{2.1}$$

$$\Delta C = GPP - RA - RH - D \qquad \text{process equation} \tag{2.2}$$

where ΔC is changes in carbon stock by vegetation and soil; ΔAGB is changes in aboveground biomass; ΔBGB is changes in belowground biomass; ΔL is changes in litter; ΔS is changes in soil carbon; GPP is gross primary production; RA is autotrophic respiration; RH is heterotrophic respiration; and D is carbon loss by disturbance. Although Equation 2.1 can be regarded as an allocation equation, where biomass is explicitly included, Equation 2.2 represents the C fluxes between the different reservoirs.

Remotely sensed data are the primary source for large-scale biomass estimations on regional to global scales (Goetz et al. 2009). However, aboveground biomass (AGB) cannot be directly measured from space by any sensor (Sun et al. 2011). Understanding terrestrial carbon processes requires integration of many types and sources of information, including ground data, ecological models, and remotely sensed data. Currently, three different remote sensing technologies are available to estimate ecosystem biomass: optical remote sensing, synthetic aperture radar (SAR), and LIDAR. These methods are highly complementary.

2.3 Conceptual Frameworks to Connect Carbon Dynamics and ESs

ESs have been defined in different ways (Fisher et al. 2009). The Millennium Ecosystem Assessment (MA 2004) definition states that ESs are the benefits that people obtain from ecosystems. The MA definition and other related definitions (Costanza et al. 1997; Daily 1997) consider subjective and cultural elements outside the ecological systems to define the benefits in the characterization of the level of ES provision. The MA classifies ESs into provisioning ESs, regulating ESs, cultural ESs, and supporting ESs (Figure 2.1). In the MA scheme, the level of ES provision, regulation, or support is not only linked to basic aspects of ecosystem functioning (e.g., ecosystem exchanges of matter and energy; Virginia and Wall 2001) but also to the societal context of values, interests, and needs.

Boyd and Banzhaf (2007) referred to ESs as the ecological components directly consumed or enjoyed to produce human well-being, without considering the subjective and cultural context. Based on this, Fisher et al. (2009) defined ESs as the aspects of ecosystems utilized (actively or passively) to produce human well-being.

2.3.1 Production Functions to Link Intermediate to Final ESs

Fisher et al. (2009) proposed an ES classification scheme where ecosystem functioning and structure are considered “intermediate” services,

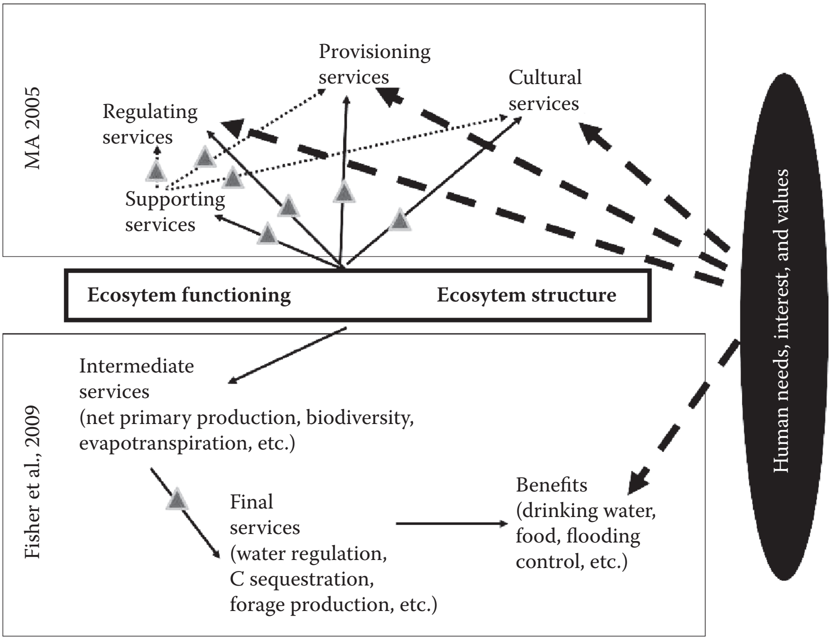

FIGURE 2.1
Main concepts related to the classification schemes of ecosystem services adopted by MA (2005) and developed by Fisher et al. (2009). Black arrows indicate the relationship between the different categories of ecosystem services (ESs) and the structure and functioning of ecosystems. Such a relationship is defined in terms of production functions (triangles). Dotted lines represent the relationship between ES categories. Broken lines represent the influence of human needs, interests, and values on the definition of ESs and on the benefits in the two classification schemes. (Redrawn from Volante, J. N., et al., *Agriculture, Ecosystems & Environment*, 154, 12–22, 2012.)

which in turn determine "final" services (Figure 2.1). Several intermediate services (e.g., primary production or species composition) may determine the level of provision of a final service (e.g., forage production or C sequestration; see Chapter 5). The link between ecosystem functioning and structure (intermediate services) and final services are defined by "production functions" (Figure 2.2a). Such production functions are well defined for final ESs with market values, such as grain production, where yields are defined by a number of biophysical (water and nutrient availability, temperature, etc.) and management factors (sowing date, cultural practices, etc.). The definition of production functions for final ESs (e.g., C sequestration) from intermediate ESs (e.g., net primary production, vegetation structure, or soil characteristics) has been identified as an important step in incorporating the ES idea into decision-making processes (Laterra et al. 2011).

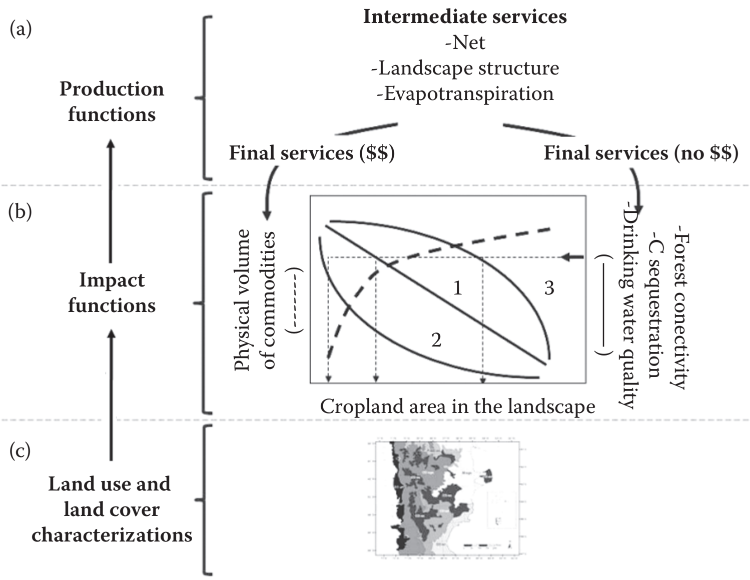

FIGURE 2.2
General scheme of the connections between (a) production functions, (b) impact functions, and (c) land use and land cover characterization. Production functions connect intermediate (ecological processes) and final services (with or without monetary value). Impact functions connect the change in the level of production of a service with the stress or disturbance factors related to human activities. The broken lines represent the change in the physical volume of commodity production, and the solid lines represent different types of change in the level of provision of other final ESs. The arrow indicates the hypothetical level of reduction in the provision of ESs that the society decides to tolerate.

2.3.2 Impact Functions to Link Disturbances or Stress Factors with ES Provision

Human activities significantly reduce the provision of some final ESs in order to increase the provision of others. Trade-offs among ESs lead to increases in the level of provision of some ESs (e.g., food production) and to reduction in others (e.g., soil protection, water regulation, C sequestration, etc.) (de Groot et al. 2010). Understanding the tradeoffs among final ESs (i.e., grain production and drinking water quality) is a critical, though difficult, task of land use planning (Viglizzo et al. 2012). Changes in the provision of final ESs are mediated by structural and functional changes, such as biodiversity losses and changes in C and water dynamics (intermediate services) (Guerschman et al. 2003; Guerschman and Paruelo 2005; Jackson et al. 2005; Nosetto et al. 2005; Fisher et al. 2009). To define the “impact functions” that account for such changes, it would be necessary to identify the main disturbance and stress factors and quantify their effects—for instance, how the level of ESs (e.g., C sequestration) changes with a particular stress or disturbance (e.g., deforested area).

Given a change in the magnitude of a stress factor or disturbance agent related to human activities (i.e., an increase in the agricultural area in a landscape or an intensification of the activity), the final ESs will change (Figure 2.2b). In general, some will increase (i.e., physical volumes of commodities, with market value) and others will decrease (i.e., water quality, biodiversity conservation, atmospheric regulation, without market value). Understanding the functional relationship between the magnitude of the stress factor and the ESs is critical to define the level of modification that the society would tolerate. The level of reduction of a given ES that society is willing to tolerate (considering society as an entity that expresses in an unified way, to simplify the analysis) is indicated by the horizontal arrow on the right axis of Figure 2.2b; the level of transformation of the landscape would differ depending on the functional relationship of ESs. If the relationship is linear (curve 1, Figure 2.2b), the amount of land converted into cropland should be different than in the case where the relationship is described by curve 2 (should be lower) or curve 3 (should be higher). Developing impact functions is a key step in incorporating the ES concept into land use planning or into other decision-making processes (Paruelo et al. 2011). Remote sensing techniques have an important role in quantifying the ecosystem processes that produce the final services (carbon gains, evapotranspiration, and albedo) (Figure 2.2a) in characterizing the magnitude of human intervention (spatial and temporal dynamics of land cover and land use changes; Figure 2.2b) and in land use and land cover characterization (Figure 2.2c).

2.4 Scale Issues in the Evaluation of Carbon-Related ESs

The definition of the spatial and temporal scale of the analysis is a critical step of an ecological study (O'Neill et al. 1986; Peterson et al. 1998). ESs have an associated spatial scale, but this scale may not be the same scale as the ecosystem processes that support these services. For example, the capacity to detoxify residues or to regulate the emissions of methane or nitrous oxide results from the activity of microorganisms. The mechanisms behind these processes involve complex metabolic pathways occurring at the subcellular level. Although the biophysical mechanisms operate at a microscopic level, the net results of the processes (in terms of regulating the concentration of atmospheric gases or detoxification) become relevant at coarser scales. In the case of the regulation of atmospheric gases, the scale is global. There also other benefits in addition to those supplied by the ecosystems that are providing the services or that are in particular configurations (e.g., downstream) (Fisher et al. 2009). Erosion control exemplifies how a spatial perspective is required in order to evaluate the ES provision: Even though the type and amount of plant cover, the slope, and the soil texture of a particular plot are key elements to characterize erosion risk, the landscape context (relative position, disturbance regime, characteristics of neighboring plots) is critical. Ecological succession, nutrient redistribution, runoff, or local extinctions are further examples of landscape context-dependent ecological processes that are directly linked to ES provision. All these examples highlight the importance of the landscape level in evaluating ESs. Although landscape dimensions may vary, often the landscapes' extension range from 10 to 10^5 ha and the limits are associated with those of a watershed. The spatial resolution of the ES observation protocol has to consider these scale issues.

2.5 Which Intermediate Services Should Be Monitored?

From an operational perspective, the ecosystem aspects to be evaluated (intermediate services) have to be reliable and simple to measure or to estimate at different scales, and should be logically connected to the final services. Some aspects of the C cycle are particularly appropriate for monitoring due to their ability to integrate the ecosystem C dynamics. Estimates of AGB and its change over time can reduce significantly any uncertainty in the mass balance equation (Le Toan et al. 2004). Nevertheless, direct estimation of carbon storage in moderate to high biomass forests remains a major challenge for remote sensing.

We highlight, in particular, two aspects for monitoring: net primary production (NPP) and the stock of biomass. These two attributes integrate several other functional and structural aspects of the ecosystems (McNaughton et al. 1989).

Breckenridge et al. (1995) enumerated several criteria to be considered in the selection of indicators:

- Generality and simplicity to be applied in different regions
- Correlation with key ecosystem processes
- Temporal and spatial variability
- Possibility to automate the record
- Relationship cost-effectiveness
- Response/sensitivity to changes
- Environmental impacts of the sampling
- Empirical and conceptual support of the protocol

These authors concluded that spectral data provided by satellite platforms are particularly well-suited to satisfy these criteria. Spectral data are able not only to characterize structural aspects of the landscapes (i.e., distribution of spatial and temporal land cover types) but also functional aspects of the ecosystems (i.e., C gain dynamics, evapotranspiration, disturbance regime) (Wessman 1992; Kerr and Ostrovsky 2003; Pettorelli et al. 2005; Paruelo 2008; Cabello et al. 2012).

In this chapter, we will review functional (NPP) and structural (biomass) ecosystem attributes that can be assimilated to intermediate services in the C cycle and that represent key terms of Equations 2.1 and 2.2. These attributes can be estimated from remotely sensed data using well-established techniques and simulation models. The existence of well-defined protocols allows the integration of these attributes into monitoring programs at the landscape level. Remote sensing techniques also allow the characterization of key aspects of the disturbance regime that modify stocks and flows of C—floods and fires (Di Bella et al. 2008). We discuss the possibilities of monitoring the release of energy (and C) through biomass combustion, particularly the evaluation of the fire radiative power (a component of the AGB change of Equation 2.1 and factor D in Equation 2.2).

2.5.1 NPP Estimations

Harvest biomass techniques are limited in the contribution they can make to the analysis of the spatial and temporal variation of NPP on large spatial scales (Singh et al. 1975; Lauenroth et al. 1986). Satellite imagery provides valuable data in order to monitor NPP in different vegetation types (Prince 1991; Running et al. 2000) with large area coverage, high temporal resolution, and moderate spatial resolution. Several optical sensors and platforms that record the reflectance in the red and near-infrared portion of the electromagnetic spectrum have been widely used (i.e., Landsat MSS, TM and ETM+, MODIS, vegetation, and AVHRR-NOAA.

Radiometric indices, particularly the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), are closely and positively correlated with the fraction of the absorbed photosynthetically active radiation (fAPAR) by green vegetation (Sellers et al. 1992; Huete et al. 2002; Di Bella et al. 2004). Absorbed photosynthetically active radiation (APAR) may, therefore, be estimated by multiplying fAPAR by the incoming photosynthetically active radiation (PAR), available from weather stations. NPP can be estimated according to Monteith's model:

$$\text{NPP} = \text{fAPAR} \cdot \text{PAR} \cdot \text{RUE} \tag{2.3}$$

where RUE is the radiation use efficiency, in grams of dry matter per megajoules (Monteith 1972). Remote sensing is beginning to provide estimates of RUE based on an index calculated from two bands centered at

530 and 570 nm, the photochemical reflectance index (PRI; Garbulsky et al. 2008) (see Chapter 3).

Monteith's model has been used to estimate NPP at multiple spatial resolutions, from 1 to 64 km^2 (Running et al. 2004). Piñeiro et al. (2006), Baeza et al. (2010), and Irisarri et al. (2012) provided estimates of aboveground net primary production (ANPP) over large areas in the grasslands of South America using Monteith´s model. Vasallo et al. (2013) used Monteith's model to compare C gains between native grasslands and the tree plantations that have replaced them.

Pettorelli et al. (2005) showed that the seasonal and interannual C gains, assessed using spectral indices, provide an integrative description of ecosystem functioning. Two attributes of the seasonal curve of EVI or NDVI are particularly descriptive: the annual integral and the seasonal variability (Paruelo and Lauenroth 1998). Volante et al. (2012) analyzed the impact of land clearing on these two C-related intermediate ESs in the Chaco region of South America. Although land clearing for agriculture and ranching had relatively small impacts on total annual ANPP, once deforested, parcels became significantly more seasonal than the natural vegetation that had been replaced. Such an increase in seasonality is associated with a reduction of photosynthetic activity during a portion of the year (fallow). Direct consequences of this reduction can be expected on several ESs such as erosion control and water regulation (due to greater exposure of bare soil) and biodiversity (due to the loss or decline in habitat quality and the decrease of green biomass availability for primary consumers during fallow). On a different scale, Paruelo et al. (2004) showed, again for the Chaco region, that total C gains (characterized by the annual NDVI integral) decreased as the proportion of croplands in the landscape increased (Figure 2.3). Similar patterns have been described for the Argentine Pampas (Guerschman et al. 2003) and the Great Plains in the United States (Paruelo et al. 2001a). For temperate grasslands and woodlands of South America, agricultural expansion may decrease NPP depending on the original cover and the mean annual precipitation of the landscape (Paruelo et al. 2001b). Areas with higher precipitation showed a marked decrease in NPP when compared to drier areas (Figure 2.4a). Many final ESs are directly linked to the total C gains, from C sequestration to water regulation.

The seasonality of C gains (the variation through the year) always increases with the cultivated proportion of the landscape. However, the reduction depends on the cropping system; double crops (wheat–soybean) have lower reductions than single crops (Figure 2.4b). Therefore, changes in intermediate ESs such as NPP seasonality would determine changes in final services such as erosion control (due to changes in plant cover across seasons) and climatic controls (due to changes in the leaf area index across seasons and then on the magnitude of latent heat, or of albedo), among others.

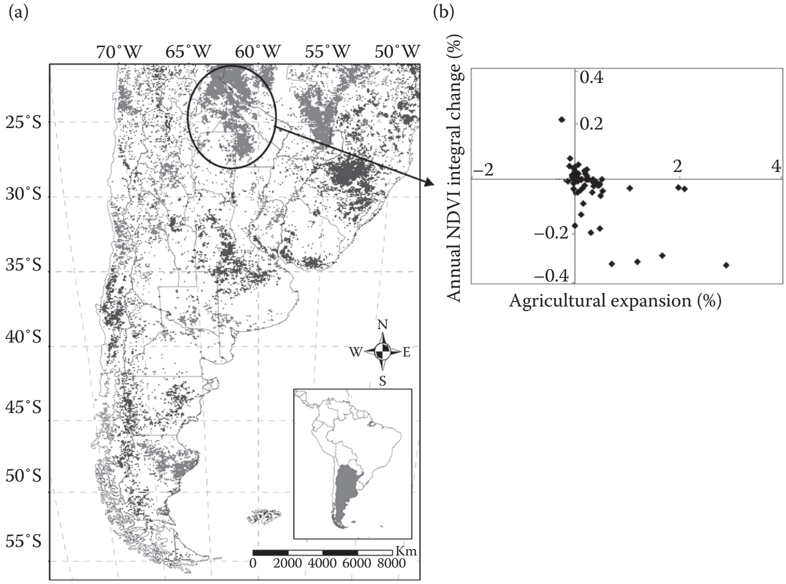

FIGURE 2.3 (See color insert.)
(a) Map of Argentina displaying the slope of the relationship between the absorbed photosynthetically active radiation (APAR) absorbed by the vegetation and time, for the 1981–2000 period. Red and blue pixels represent negative and positive slopes, respectively. APAR was calculated from the NDVI derived from PAL series of the AVHRR/NOAA satellite. (b) Relationship between the annual change in the cropped area per county and the annual change in Normalized Difference Vegetation Index (NDVI) for counties of northwestern Argentina covered by forests (Salta, Chaco, Formosa, Jujuy y Tucuman). (Modified from Paruelo, J. M., et al., *International Journal of Remote Sensing*, 25, 2793–2806, 2004).

Grazing has been identified as a major disturbance and/or stress factor in ecosystems. The effects of grazing on the structure and functioning of grasslands, shrublands, and savannas have generated controversy and debate (McNaughton 1979; Milchunas and Lauenroth 1993; Oesterheld et al. 1999; Chase et al. 2000). NPP may have a complicated response to long-term grazing pressure depending on resource availability and long-term grazing history (Milchunas and Lauenroth 1993; Oesterheld et al. 1999). Aguiar et al. (1996) proposed an impact function for NPP in the Patagonian steppes as a function of the historical grazing pressure. Moreover, this article presents a production function of a final service (domestic herbivore biomass) from the intermediate service (grass ANPP; Figure 2.4c) using a model presented by Oesterheld et al. (1992).

Protected areas and nondegraded grasslands or shrublands showed a lower sensitivity to changes in precipitation than did heavily grazed ones (Paruelo et al. 2005; Verón et al. 2011). In this case, the intermediate ES is the buffer capacity of the ecosystem, that is, the relative variability of functional attributes with respect to environmental fluctuations, in terms of C gains

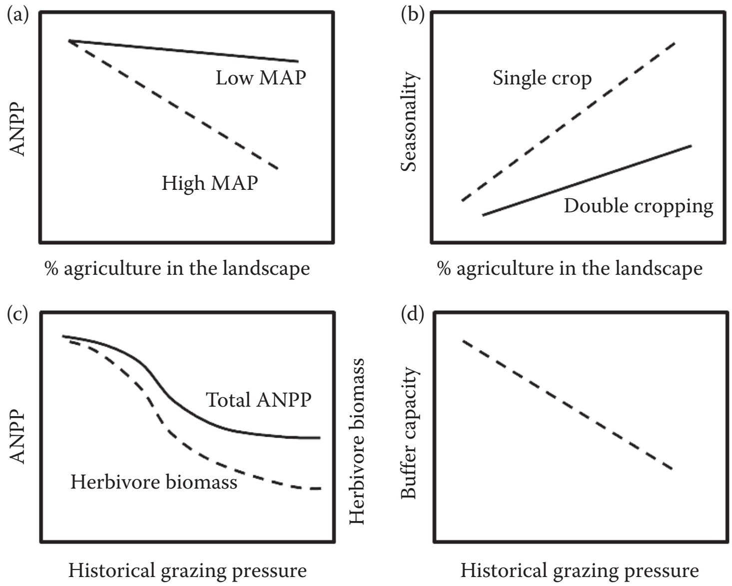

FIGURE 2.4
(a, b) Hypothetical impact functions for aboveground net primary production (ANPP) and ANPP seasonality (intermediate services) and the percent of the landscape occupied by agriculture (disturbance factor). Different lines correspond to different climatic conditions—high and low mean annual precipitation (MAP) or managements (single or double cropping). (c, d) Hypothetical impact functions for the ANPP and for the capacity of the ecosystem to buffer climatic fluctuations at the functional level (intermediate factors) as a function of the historical grazing pressure (disturbance factor) on native rangelands. (c) also shows the impact of grazing on domestic herbivore biomass (a final service). (Based on analyses presented by Aguiar, M. R., et al., *Journal of Vegetation Science*, 7, 381–390, 1996; Guerschman, J. P., et al., *International Journal of Remote Sensing*, 17, 3381–3402, 2003; Paruelo, J. M., et al., *Ecología Austral*, 21, 163–178, 2005; and Verón, S. R., et al., *Oecologia*, 165, 501–510, 2011.)

(Figure 2.4d). Land clearing also increased the magnitude of interannual differences in C gains, suggesting a lower buffer capacity against climate fluctuations of natural vegetation compared to croplands (Volante et al. 2012).

2.5.2 AGB Estimations

The difficulty in making reliable biomass estimates is well recognized, from local (Fang et al. 2006) to continental scales (Houghton et al. 2001). A lot of effort has been made to estimate biomass using field-based as well as remote sensing techniques—mainly in forests, but the development of impact functions is scarce. Estimates of biomass have been based on active sensors, meaning they generate a signal and measure the amount of energy reflected back to the sensor. The advantage of using active sensors is that they can operate day or night, and the microwaves can go across haze, smoke, and clouds. The energy transmitted can also penetrate into forest canopies and is able to measure the canopy height and vertical structure. Two main types of active sensors have been used to measure forest structure attributes and biomass at global scales: radar (SAR) and LIDAR.

SAR is an airborne or spaceborne radar system that uses its relative forward motion, between an antenna and its target region, in order to provide a high-resolution remote sensing imagery generated by recording and combining the individual signals of the sensor. Because of its penetration capability and sensitivity to water content in vegetation, SAR is sensitive to the spatial structure of forests (Le Toan et al. 2004). The backscatter is the portion of the outgoing radar signal that is redirected back to the antenna. Backscattering is influenced by surface parameters (roughness, geometric shape, and dielectric properties of the target) and radar observation parameters (frequency, polarization, and incidence angle of the electromagnetic waves emitted). SAR is known to sense the canopy volume (especially at longer wavelengths) and provide image data, with the amount of backscattered energy, which is largely dependent on the size and orientation of canopy structural elements, such as leaves, branches, and stems.

The frequency (f) of the signal defines the interaction with the forest structure and the penetration capability of the wave. The longer the wavelength, the greater the sensitivity to the vertical structure of vegetation and the greater the penetration into the forest canopy. Radar data are acquired in X, C, L, and P bands. Shorter wavelengths (X and C band, with 2.5 and 7.5 cm, respectively) are sensitive to smaller canopy elements such as leaves and small branches, and longer wavelengths (L and P band, with 23.5 and 70 cm, respectively) are sensitive to large branches and trunks. The polarization (p) is the direction of the electric field in the electromagnetic waves and is the main factor in the interaction between the signals and the reflectors. Most of the microwave sensors emit and receive signals in horizontal (H) or vertical (V) polarizations. Measuring the polarization of the transmitted and received electromagnetic waves allows for further sensitivity of AGB measurements (Goetz et al. 2009). Interferometry calculates the interference pattern caused by the differences in phase between two images acquired by a spaceborne SAR at two distinct times, and the resulting interferogram is a contour map of the change in distance between the ground and the SAR instrument (Feigl 1998). According to Kasischke et al. (1997), the best performance for biomass estimation is achieved using lower frequency (P and L band) radar systems with a cross-polarized (HV or VH) channel.

The simplest method for biomass estimation using SAR is relating the backscatter coefficient to field biomass measurement using regression analysis. This approach has been tested on different areas, and good results have been achieved in coniferous forests (Dobson et al. 1992; Le Toan 1992). Indirect methods are also used to estimate AGB, consisting of deriving forest structural estimates (e.g., tree heights or canopy heights) in order to infer forest biomass quantities through interferometry. Moreover, polarimetric and interferometric

SAR data have been used for forest biomass estimation (Dobson et al. 1992, 1995; Ranson and Sun 1994; Kasischke et al. 1995) and canopy height estimation (Treuhaft et al. 1996, 2004; Kobayashi et al. 2000; Kellndorfer et al. 2004; Walker et al. 2007). These applications require ground sampling data for training and validation purposes (Sun et al. 2011). The principal problem of using SAR to estimate biomass is the saturation level. Experimental studies with SAR over different types of forests (temperate, boreal, and tropical) indicate that saturation occurs at around 30, 50, and 150–200 tonnes ha^{-1} at C, L, and P bands, respectively (Le Toan et al. 2004). These saturation values are approximate and depend on the experimental conditions and forest characteristics. Advanced airborne SAR systems using long wavelengths or combining polarization diversity with interferometry techniques (polarimetric interferometry) have demonstrated significantly greater capabilities for estimating forest biomass (Le Toan 2002). Interferometric SAR (InSAR) is also employed to improve AGB estimations (Walker et al. 2007), where allometric equations are used to establish quantitative relations between structural patterns (e.g., tree height) and other properties of the forest (e.g., biomass).

LIDAR is a relatively new active remote sensing technology especially suitable for reproducing the three-dimensional (3D) structure of forest stands due to its ability to determine 3D measurements with high accuracy. LIDAR instrumentation uses a laser scanner that transmits pulses and records the delay time between a light pulse transmission and its reception in order to calculate elevation values. Each data point is recorded with precise horizontal position, vertical elevation, and other attribute values. The multiple returns are recorded and a classification is assigned to each point in order to identify landscape features. The intensity of the reflected energy is also captured and can be analyzed to provide additional information on terrain characteristics. LIDAR metrics are statistical measurements created from the 3D point cloud (a set of vertices in a 3D coordinate system) and are normally used when predicting forest variables from LIDAR data. Various types of LIDAR systems have been used to capture an increasingly broad range of vegetation characteristics and biomass estimations. LIDAR-based estimations of AGB can be performed by means of point cloud and rasterized data. The point collections of 3D data have to be managed and processed in a standardized binary format for storing 3D point cloud data and point attributes. The procedure of LIDAR raw point cloud-based 3D single tree modeling was first published by Wang et al. (2007). Point cloud data processing is a computationally demanding task when processing large datasets for the generation of area-wide AGB maps (Jochem et al. 2011). Using rasterized data requires the aggregation of the 3D point cloud to cells, meaning that the canopy surface is represented by a single-valued function. This procedure is accompanied by an irreversible loss of the 3D structure but makes processing less time consuming and drastically reduces the storage size. LIDAR systems are classified as either discrete return or full waveform recording and may be further divided into profiling (recording only along a narrow line directly below the sensor) or scanning systems (recording across a wide swath on either side of the sensor) (Lefsky et al. 2002; Lim et al. 2003). Within a forest, full waveform systems record the entire wave form for analysis, while discrete return systems record clouds of points representing intercepted features (Wulder et al. 2012).

LIDAR sensors have been used for extending plot-level estimates to larger spatial and ecological scales (Lefsky et al. 2002; Zhao et al. 2009). Allometric equations to estimate carbon stocks using LIDAR data are usually region-specific, involving laborious calibration methods and expensive plot inventory data (Lefsky et al. 1999; Nelson et al. 2012). Nevertheless, Asner et al. (2012) used a single universal LIDAR model to predict aboveground carbon density estimated in field inventory plots, generalizing biomass allometric equations for tropical trees. In this approach, the authors reduced the forest structural properties to mean canopy profile height (also known as MCH), which is the vertical center of the canopy volumetric profile (as opposed to a simple top-of-canopy height), and detailed a relationship with carbon density and basal area.

2.5.3 Carbon and Energy Released by Wildfires

Fires represent an important pathway of energy and C release from land ecosystems. Giglio et al. (2010) reported that, globally, between 3.3 and 4.3 million km^2 burn each year. Fires release C mainly in the form of particulate matter and greenhouse gases, including CO_2 and CH_4 (van der Werf et al. 2010) and seriously affect ESs by modifying the hydrological cycle, by triggering soil erosion, and by radiative forcing in the atmosphere (Lohmann and Feichter 1997; DeFries et al. 2002; Hoffmann et al. 2002, 2003; Mouillot and Field 2005; van der Werf et al. 2008).

The fire radiative power product (FRP) measures the radiant heat output (in megawatts) of a given fire. FRP is related to the biomass being consumed by detected fires (see also Chapter 7). It has been demonstrated (in small-scale experimental fires) that the amount of radiant heat energy liberated per unit time (FRP) is related to the rate at which fuel is being consumed (Wooster et al. 2005), and it represents a direct output of the combustion process. The integration of FRP over time provides an estimate of the fire radiative energy (FRE), which—for wildfires—should be proportional to the total biomass combusted (Verón et al. 2012).

To derive the FRP product, the process starts with the identification of fire pixels. The fire thermal anomaly (FTA) algorithm tests for elevated radiance in the mid-infrared portion of the spectrum. The algorithm includes additional tests to discriminate fires from other phenomena that may induce similar responses in this spectral band (i.e., specular reflections and cloud edges) (Roberts et al. 2005), and it works mainly on data derived from the 3.9 and 11.0 μm brightness temperatures and their differences. Thresholds for fire detection are based on contextual tests that adjust the detection from immediately neighboring nonfire background pixels. Once the fire pixel is detected, FRP is estimated from the middle-infrared (MIR, 3.9 μm) channel and the background radiance that would have been observed at the same location in the absence of fire (Giglio et al. 2003). FRP data are available from the MOD and MYD14CMG fire products (Giglio et al. 2006) generated from the MODIS (Moderate Resolution Imaging Spectro radiometer) sensor, collection 5, onboard Terra and Aqua platforms. This dataset integrates subdaily, 1 km^2 resolution data into monthly values for 0.5° x 0.5° grid cells.

On the basis of a global analysis of the energy generation and spatial distribution of fires, Verón et al. (2012) showed that between 2003 and 2010, global fires consumed approximately 8300 ± 592 PJ yr^{-1} of energy, equivalent to approximately 36%–44% of the global electricity consumption in 2008 and more than 100% of the national consumption in 57 countries. Forests/woodlands, cultivated areas, shrublands, and grasslands contributed 53%, 19%, 16%, and 3.5%, respectively, of the global energy released by fires.

2.6 Concluding Remarks

Remote sensing techniques provide the opportunity to estimate two critical aspects of the C balance: NPP and biomass. In terms of the definition of ESs determined by Fisher et al. (2009), these two variables represent intermediate services and capture many basic aspects of ecosystem structure and functioning. Moreover, they show a clear relationship with important final services, from forage and wood production to C sequestration. Both contribute, together with other intermediate services, to determining several other final services such as climate regulation, soil erosion control, or water provision.

Satellite-derived observations are a major step in determining indicators that cover large areas, based on the same observation protocols and estimated in almost real time. These characteristics represent a clear advantage in programs in order to monitor changes in the level of provision of ESs. Remote sensing techniques are able to estimate not only C related to intermediate ESs but also those processes related to the energy balance—such as latent heat fluxes and albedo.

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