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Remote Sensing of Ecosystem Services: An Opportunity for Spatially Explicit Assessment

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Abstract: Ecosystem service is an emerging concept that grows to be a hot research area in ecology. Spatially explicit ecosystem service values are important for ecosystem service management. However, it is difficult to quantify ecosystem services. Remote sensing provides images covering Earth surface, which by nature are spatially explicit. Thus, remote sensing can be useful for quantitative assessment of ecosystem services. This paper reviews spatially explicit ecosystem service studies conducted in ecology and remote sensing in order to find out how remote sensing can be used for ecosystem service assessment. Several important areas considered include land cover, biodiversity, and carbon, water and soil related ecosystem services. We found that remote sensing can be used for ecosystem service assessment in three different ways: direct monitoring, indirect monitoring, and combined use with ecosystem models. Some plant and water related ecosystem services can be directly monitored by remote sensing. Most commonly, remote sensing can provide surrogate information on plant and soil characteristics in an ecosystem. For ecosystem process related ecosystem services, remote sensing can help measure spatially explicit parameters. We conclude that acquiring good in-situ measurements and selecting appropriate remote sensor data in terms of resolution are critical for accurate assessment of ecosystem services.

Keywords: ecosystem service; remote sensing; spatially explicit assessment; surrogate information

1 Introduction

Humans rely upon nature for welfare and survival in essence. By treating nature as a stock that provides a flow of services, ecosystem service conceptually links ecosystems to human welfare, and are growing to be an important aspect of ecological research (Norgaard, 2009). The term ecosystem service was first used by Ehrlich and Ehrlich (1981). The development of ecosystem service concept is a convergence of accumulated knowledge and perspective stemming from the finite nature of natural resources and the study of ecosystems. The concept of ecosystem service was defined by Costanza *et al*. (1997), Daily (1997) and Walter *et al*. (2005). Costanza *et al*. (1997) defined ecosystem services as the representation of goods and services derived from ecosystem functions, while Daily (1997) considered ecosystem services as the conditions and processes of natural ecosystem fulfilling human life. In Walter *et al*. (2005), ecosystem services are broadly defined as benefits people obtained from ecosystems. Despite this latest definition, several scholars considered it as an evolving concept (Carpenter *et al*., 2006; Sachs and Reid, 2006).

The Millennium Ecosystem Assessment was a monumental work involving over 1 300 scientists. It introduced a new framework for analyzing ecological-social systems. And it also proposed a widely used classification of ecosystem services, i.e. supporting, regulating, provisioning and cultural services. The Millennium Ecosystem Assessment has considerably moved ecosystem service science forward. Nevertheless, ecosystem service science is still at an early stage of development. Studies after the Millennium Ecosystem Assessment are

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addressing new scientific challenges to quantify the benefits that nature provides to humans. Approaches are required to improve ecosystem service assessment for projecting and managing flows of ecosystem services (Balmford *et al*., 2008). Among several studies concentrating on ecosystem service assessment, Nelson *et al*. (2009) stressed the urgency and the importance of understanding and mapping the spatial heterogeneity of ecosystem services. The spatially explicit ecosystem service information is needed for maximizing conservation objectives (Polasky *et al*., 2008). Local management agencies also need to consider the spatial pattern of ecosystem services in landscapes to better accommodate their perceptions of values. However, spatially explicit values of ecosystem services across landscapes are still lacking (Balmford *et al*., 2002; Walter *et al*., 2005).

Remote sensing can provide a solution because it can acquire images over Earth surface. The spatially explicit nature of remotely sensed imagery allows several ecosystem service issues to be examined, especially the extent and location of ecosystem services. Nevertheless, Aplin (2005) and Newton *et al*. (2009) noted that remote sensing specialists have perhaps focused on technological issues as the major concern rather than ecological problems. On the other hand, ecologists have insufficient background in addressing ecological problems at regional, landscape, and global scales (Barrios, 2007). Spatially explicit ecosystem service studies could be marginalized by the potential division between the two research communities.

The purpose of this paper is to bridge this gap by presenting a general review of ecosystem service related research in ecology and remote sensing. Several key areas are considered such as land cover, biodiversity, carbon, water and soil related ecosystem service. By discussing how remote sensing technique can be used for ecosystem service assessment in these areas, the paper gives some recommendations.

2 Remote Sensing of Ecosystem Services

2.1 Land cover as a proxy measure of ecosystem services

Land cover was used as a proxy measure of ecosystem services because of its multiple linkages to carbon storage, watershed protection, and other types of services (Konarska *et al*., 2002). Land cover affects a range of ecosystem services through the differences among key ecological variables and processes, such as biodiversity, structure and composition of natural communities that alter the biogeochemical cycles, micro-climate and ecohydrology of ecosystems (Maes *et al*., 2009; Reyers *et al*., 2009). For each land cover type, the services provided by the ecosystem are identified and given a monetary value based on previous studies and original calculations. The estimated per hectare value of each ecosystem (the sum of all ecosystem services) is then multiplied by the area of each biome to find the total monetary value of the ecosystem. For example, Costanza *et al*. (1997) calculated the total area covered by 17 biomes, and on this basis they estimated the global ecosystem service value. Konarska *et al*. (2002) declared that the spatial scale on which the land cover is measured significantly influences both the extent of ecosystem service and its valuation. Remotely sensed imagery is becoming available at increasingly finer spatial, spectral, and temporal resolutions. At present, coarse spatial resolution data such as Advanced Very High Resolution Radiometer (AVHRR, 1 km) are used for mapping global land cover, for its broad spatial coverage of its images (Konarska *et al*., 2002). Medium resolution spatial data, such as Landsat (30 m) are widely used for mapping land covers. Based on its 30+ years of accumulated data (now being released), Landsat data are extensively being used for ecosystem service change monitoring (Zhao *et al*., 2004; Wang *et al*., 2006). In regions with small scale land use, high resolution spatial data, such as Quickbird (< 5 m), are required (Hu *et al*., 2008).

2.2 Biodiversity

A theoretical analysis conducted by Eamus *et al*. (2005) demonstrated the effect of basic ecosystem structure and biodiversity on ecosystem services. The relationship between biodiversity and the provision of ecosystem services is controversial and heated debate. However, in most studies, it is found that high species richness is required to remain a high degree of ecosystem services (Balvanera *et al*., 2006; Benayas *et al*., 2009). Maintaining biodiversity is considered as an efficient way to enhance ecosystem services.

Monitoring biodiversity is an essential component in conservation ecology. It is related to the abundance, species richness, diversity, growth, or biomass of organisms present (Walter *et al*., 2005). Remote sensing can be valuable in biodiversity monitoring because of the following three reasons. First, areas with high biodiversity are difficult for field investigations (Wiens *et al*., 2009). Second, monitoring at the regional scale is urgently needed. Third, remotely sensed spectral characteristics respond to different biodiversity conditions (Foody and Cutler, 2003; Carlson *et al*., 2007). It should be noted that the most widely used biodiversity measurement correlating with remote sensing is the number of species or species richness. While different definitions of biodiversity exist, the majority of studies are conducted at the species level. Species richness is a common measurement of biodiversity because it is easy to quantify. It is also a good surrogate for some other forms of biodiversity (e.g. genetic and ecological diversity) (Gaston and Spicer, 2004; Eamus *et al*., 2005; Isbell *et al*., 2009).

For plant species, individual species and species assemblages can be directly identified by high resolution spatial and spectral satellite sensors using land cover mapping methods (Turner *et al*., 2003; Lass *et al*., 2005). The basic method for land cover mapping is criticized because it does not directly resolve the biochemical or structural properties of vegetation, which are closely linked with taxonomic diversity. Moreover, it has been tested that increasing species richness was linked to increasing spectral diversity through increasing biochemical diversity. Based on this theory, Zarco-Tejada and Miller (1999) exploited systematic species differences at the Boreal Ecosystem-Atmosphere Study (BOREAS) forest site by focusing on the wavelength ranges that are sensitive to foliar chlorophyll content. Fuentes *et al*. (2001) used both remote sensing derived water content and the abundance of different plant pigments to produce accurate local vegetation types of the Canadian boreal forest. In a more direct way, species diversity can be assessed by examining the relationships between spectral radiance values recorded from remote sensors and species distribution patterns recorded from field observations. Carlson *et al*. (2007) predicted species richness in Hawaii using a combination of four biochemically distinct wavelength observations centered at 530, 720, 1201, and 1523 nm acquired by the National Aeronautics and Space Administration (NASA) Airborne Visible and Infrared Imaging Spectrometer (AVIRIS).

Animal assemblages monitoring relies on environmental characteristics. Habitat heterogeneity has long been recognized as a fundamental variable indicative of species diversity, in terms of both richness and abundance. Patchiness in vegetation cover, which is related to landscape heterogeneity and high species richness, can be measured as variability in the normalized difference vegetation index (NDVI) (Gould, 2000). But NDVI cannot be applied uniformly across gradients from subtropical to arid landscapes. It is particularly problematic under semiarid and arid conditions. One of the inherent problems is that the spectral signature of vegetation is often masked by the backdrops of exposed geological features and soils (Elvidge and Lyon, 1985; Huete and Jackson, 1987). A typical strategy in arid landscapes is to develop land cover maps that characterize vegetation patterns. Various vegetation cover classes are attributed with relevant biodiversity ratings because many species are restricted to discrete habitats in arid area (Fuller *et al*., 1998). Or special indexes are needed to efficiently remove the effect from the exposed soil, litter, *etc*. (Muldavin *et al*., 2001). For animal assemblages, the canopy vertical distribution information is consistently found to be the strongest predictor of species richness and functions best in areas dominated by forest, scrub, suburban and wetland species. For example, the three dimensional structure of the canopy is the essential driver of arthropod diversity in forests. The maximum tree height provides information about tall tree in a plot, which is a surrogate for habitat continuity (Ohlson *et al*., 1997). The structural diversity of the vegetation, including the density of the canopy layer and forest gaps, *etc*., is associated with the beetle assemblages (Müller and Brandl, 2009). By combining information about the known habitat requirements of species with remote sensing derived land cover maps, precise estimates of potential species ranges and patterns of species richness are possible. Light Detection and Ranging (LiDAR) is an optical remote sensing technology that can acquire the information on canopy structure. LiDAR works based on the use of laser light which is emitted from a source (normally an aircraft), and then reflected back to a sensor. Three dimensional canopy structures can be reflected by properties of reflected light back to the sensor. LiDAR can also measure the elevation of a site, which indicates the precipitation and temperature characteristics of an animal habitat. For example, Müller and Brandl (2009) had successfully used LiDAR derived variables to model both the species richness and composition of forest beetles in a mountainous region in southeastern Germany. For marine coral reefs, habitat variables including water depth, live coral and structural complexity could also be derived from LiDAR. And Knudby *et al*. (2007) provided a complete review of the potential of remote sensing in mapping these habitat variables maps.

2.3 Carbon flux related ecosystem services

Up to 90% of the carbon exchange between the terrestrial bio-geosphere and the atmosphere is mediated by plants (Ozanne *et al*., 2003). Carbon fixation by vegetation, the photosynthetic conversion of carbon dioxide to biomass, provides the basis for crop and forest yields. It creates the energetic foundation of nearly all the communities on earth and further the foundation of all other ecosystem services. Carbon fixation by vegetation can be represented as ecosystem productivity. The gross primary productivity (GPP) is the total amount carbon fixated by photosynthesis. The net ecosystem exchange (NEE) is obtained by subtracting ecosystem respiration (ER) from GPP. NEE gives the net amount of carbon untaken or released. The important issue of ecosystem productivity forms a large part of remote sensing research. It can be concluded that the development of ecosystem productivity monitoring parallels the development of remote sensing techniques, especially the optical remote sensing (wavelength coverage 0.3–18 μm, containing visible, near-, middle- and far-infrared radiation).

Remote sensing technique has been used to monitor ecosystem productivity over a long period. Monteith (1972; 1977) introduced the light use efficiency (LUE) concept, which was modified by Prince (1991). GPP was expressed as the product of the absorbed photosynthetically active radiation (PAR), defined as absorbed solar radiation between 0.4 and 0.7 μm wavelength, and the efficiency, with which the absorbed PAR can be converted into primary production as follow:

$$GPP = PAR \times f_{\mathrm{PAR}} \times \varepsilon$$

where f_{PAR} represents the fraction of PAR absorbed by the canopy. The amount of PAR absorbed by the canopy is the difference between the PAR incident upon the canopy and the amount of PAR being reflected from and transmitted through the canopy. ε is the photosynthetic efficiency term of a specific plant type. All the three parameters are spatial and temporal variables (Damm *et al*., 2010). Hilker *et al*. (2008) described the details of how remote sensing acted in LUE model. They concluded that remote sensing is developing to become a unique possibility for investigating model parameters in a spatially explicit fashion. Physical models, such as turbid models and geometric optical models, have been developed to quantitatively describe the process of radiation transfer among the canopy and its interaction. Strategies have been studied to transform the remotely sensed image to obtain the surface parameters, such as leaf area index (LAI), surface temperature and soil water content. These comprise the kernels of optical remote sensing techniques.

The launch of NASA's Terra satellite platform in 1999 with the moderate resolution imaging spectroradiometer (MODIS) instrument on-board initiated a new era in remote sensing of the Earth system, with promising implications for carbon flux research. The MODIS has the advantage of its number of spectral bands (36 in total, 7 of them primarily designed for the study of vegetation and land surface) and the daily monitoring frequency. The global MODIS 8-day average GPP product is generated based on the LUE model (Heinsch *et al*., 2002). Time series of MODIS GPP data are used to reflect the crop yield trend. It has strategic and tactical uses for agriculture and related economics. Running *et al*. (2004) declared that weekly mapping of terrestrial GPP should be as routine as the weather data that are presented today (like weather maps, maps of GPP might even be shown occasionally on the evening news when abnormal conditions are discovered).

The accuracy of LUE model estimates depends on the model parameters; however, the great number of parameters is a limitation of the model, especially regarding the need for specific sensors in some cases. Apart from that, the LUE concept can only be used for non-wetland terrestrial ecosystems (Paruelo *et al*., 2010). In regional studies, empirical GPP models have the advantage of providing possibilities for operational implementation. The NDVI, which is proved to directly relate to the land cover condition, is applied to estimating primary productivity. The possibility of predicting average primary productivity by its regression relationship with NDVI has been observed in the Arctic tundra

(Boelman *et al*., 2003) and in steppe ecosystems (Wylie *et al*., 2003). NDVI tends to be saturated when biomass increases to a high value (Myneni *et al*., 1995; Hao *et al*., 2008), this being especially obvious in evergreen forest area (Rahman *et al*., 2001). Considerable efforts have been made to improve NDVI estimation. According to Thenkabail *et al*., (2000) and Gianelle and Vescovo (2007), wavebands in the green portion of the spectrum combined with other visible and near infrared (NIR) wavebands (Green-NDVI) predict green biomass better than the broadly used NIR- and red-based NDVI. The Enhanced Vegetation Index (EVI) used in the MODIS sensor is more highly sensitive to large amounts of biomass. Olofsson *et al*. (2008) found that correlation coefficients between EVI and GPP are 0.90 for the deciduous vegetation over Scandinavian forests. In addition, the use of narrow bands has been found to improve the prediction capability. Gianelle *et al*. (2009) concluded that Hyperion and MODIS simulated NDVI and Green-NDVI can be used to estimate GPP more accurately than the ETM+ derived NDVI, when quantifying growing season GPP at a mountain grassland site in the Italian Alps. In aquatic systems, primary productivity can be computed from the upper chlorophyll-like pigment concentration or phytoplankton absorption, since they can be routinely detected by a space-borne ocean color sensor (Eppley *et al*., 1985; Antoine *et al*., 1996; Behrenfeld *et al*., 2005).

Most studies aiming at estimating NEE using remote sensing employ physiological process based models that are parameterized for a specific location using flux data together with meteorological data; the model output is then scaled up using satellite data (Cao *et al*., 2003). The NEE can hardly be calculated solely by remote sensing, because spatially explicit respiration rates can not be calculated with remote sensing data (Olofsson *et al*., 2008). Rahman *et al*. (2005) investigated the relationship between MODIS surface temperature and respiration using data from ten flux tower sites across the US. They suggest that it may be possible to estimate NEE from relatively simple pixel based models, at least for some vegetation types.

Ecosystem productivity marks the first visible step of carbon fixation and provides the basis for exploring the carbon flux related ecosystem services. Reeves *et al*. (2005) demonstrated that combining 8-day average MODIS GPP estimates with a simplified algorithm for wheat yield effectively estimated county and state level spring wheat yield in Montana, USA. The relationship between GPP and crop yield is more significant comparing with the relationship between vegetation index and crop yield (Rao *et al*., 1993; Yang, 2009). Carbon fixation is also involved in climate regulation, which reduces the atmospheric CO_2 through plant photosynthesis. Coupled climate-carbon models analyse the influence of terrestrial plant growth and the feedback mechanism between biosphere and climate. Global estimation and monitoring of primary productivity is a critical component supporting model simulation (Hilker *et al*., 2008). Carbon fixation also influences local climate dynamics by the exchange of water-heat between land and atmosphere. The carbon in the fallen leaves enters the soil, providing soil carbon nutrient. Just as Eamus *et al*. (2005) had declared, all ecosystem service grinds to a halt in the absence of carbon fixation.

2.4 Water flux related ecosystem services

For its importance to living systems, water fluxes within the continuum of soil, vegetation and atmosphere can be seen as the bloodstream of the biosphere (Ripl, 2003), driving the materials moving between different ecosystems and altering energy balances in landscapes.

Processes based hydrological models are mathematical descriptions of the water flux. Based on the awareness that water flux, erosion and nutrient movement processes within the ecosystem are strongly interacting, the development of such models tends to combine the water flux process with all other major processes within a given ecosystem (Ludwig *et al*., 2005). Numerous studies have demonstrated that such models can represent the natural processes occurring in a specific ecosystem. Thus, they are mechanism models for understanding water flux related ecosystem services. For example, the result of Soil and Water Integrated Model (SWIM) (Krysanova *et al*., 2007) showed that the water discharge and the groundwater recharge in the Elbe basin were most likely decreased under expected climate change. Williams *et al*. (2010) found that the calibrated Water Erosion Prediction Project model (WEPP) could quantify water flux and erosion process in the semiarid cropland of the Columbia Plateau. Yeh *et al*. (2006) combined the models of soil erosion, sediment transportation, runoff and the nutrient process into an integrated framework. The total annual amounts of soil erosion, sediment yield, and nutrient load between 1995 and 1999 were estimated by this integrated model for Keelung Watershed, Taiwan. Viney and Sivapalan (2001) applied a conceptual Large Scale Catchment Model (LASCAM) to the Swan-Avon catchment in Western Australia, and found that stream flow, sediment yield, and nutrient yields had all increased since European settlement in the catchment. Remote sensing techniques can benefit water flux related ecosystem service modeling in three ways (Kite and Pietroniro, 1996; Pietroniro and Prowse, 2002; Chen *et al*., 2005; Liu and Li, 2008): 1) by identifying significant areal phenomena such as snow cover, surface water (e.g. flooded areas, lake areas) or sediment plumes from original remote sensing image; 2) by developing relationships between remote sensing data and parameters of interest to provide model parameters such as soil moisture and water quality; and 3) by quantifying important surface parameters such as land cover types and the LAI from remote sensing data. Water absorbs most of the energy in the optical wavelengths. Land surface containing water or moisture appears dark in contrast to surrounding vegetation (Swain and Davis, 1978). Soil moisture quantification models based on optical wavelength data take the surface radiant temperature as a proxy (Haubrock *et al*., 2008). Microwave remote sensing (wavelength coverage 1 mm–1 000 mm) platforms are sensitive to water discrimination and are capable of almost all weather viewing, which is a distinct advantage (Alain and Robert, 2005; Song *et al*., 2007; Anguela *et al*., 2010). For water flux related ecosystem service modeling, the most important difference between optical and microwave remote sensing is the penetration depth and consequently the depth of the soil layer for which the water content can be quantified; the penetration depth for optical remote sensing is significantly less than for microwave sensing (Haubrock *et al*., 2008).

Water fluxes also can be simply divided into ′green′ and ′blue′ water (Rockström *et al*., 1999). Green water is the return water flow to the atmosphere as evapotranspiration (ET), which includes transpiration by vegetation, and evaporation from soil, lakes and water intercepted by canopy surfaces. By transporting water from the undersurface back into the atmosphere, green water alters energy balances in landscapes, regulating the regional climate. Blue water is the total runoff originating from the participation of precipitation at the land surface (surface runoff) and the participation of soil water (groundwater recharge), and drives the materials moving among different ecosystems.

Green water is represented as evapotranspiration in terms of pure remote sensing. The basic cause of evapotranspiration is thought to be the vertical temperature gradient from land surface to air (Kalma *et al*., 2008). Seguin and Itier (1983) proposed an expression relating the daily evaporation to daily net radiation by means of measuring the surface temperature and air temperature, at a given time of day: Surface energy balance (SEB) is the theoretical foundation of recent remotely sensed evapotranspiration. Based on the dispositional scheme of plants and soil in the ecosystem, SEB can be divided into one source and two source models. One source models (e.g. Surface Energy Balance Algorithm for Land, SEBAL) consider soil and vegetation as the sole source (mostly appropriate in the case of uniform vegetation coverage). Two source models (e.g. Two Source Energy Balance model, TSEB) treat soil and vegetation components of the surface energy balance separately (Minacapilli *et al*., 2009). The energy balance approach employs visible, near-infrared remote sensing data to obtain surface parameters such as albedo, vegetation index, and uses far-infrared observations to transform surface temperature and emissivity, which is simultaneously combined with the field measured wind speed, air temperature and humidity to calculate the evapotranspiration. Remote sensing interprets the surface energy aspects of evapotranspiration, which is a different view of the matter cycle from that of the ecologist.

As far as the ecosystem is concerned, plants are regulators of water flux and provide a major discharge path for water. For example, forests provide a more stable water supply than other ecosystems, thus reducing local flooding, soil erosion, sediment accumulation and nutrient input to bodies of water downstream (Eamus *et al*., 2005). The role of the plant canopy has long been recognized and applied in water flux studies. In the crop evapotranspiration estimation, using Food and Agriculture Organization (FAO) methodology, daily evapotranspiration is computed on the basis of crop coefficient and reference evapotranspiration concepts (Doorembos and Pruitt, 1977). The reference evapotranspiration from a complete green canopy of a standard crop can be predicted directly from climatic factors (Penman, 1963).

The ecologically important function of plants is represented as the crop coefficient, which is used to adjust the reference evapotranspiration. Similar to crop evapotranspiration estimation with FAO methodology, Zhang *et al*. (2001) modeled the evapotranspiration of a vegetated area as a function of precipitation, potential evapotranspiration and a plant available moisture index, which represents the relative use of water for transpiration. Zhang′s model represents the role of plant in regulating their available water resources by appropriately weighting the average of the green and blue water fluxes, adjusted for rainfall. It has been widely used to evaluate the annual water yield from forested land and its response to potential deforestation around the world (Sun *et al*., 2005; 2006; Zhang *et al*., 2008). Remote sensing provides multispectral vegetation indices (VIs) to track plant growth and estimate the basal crop coefficient and plant available moisture index in these models. González-Dugo and Mateos (2008) have declared that the determination of crop coefficients from satellite obtained vegetation indices is robust since both VI and the crop coefficient are closely related to crop growth variables such as vegetation ground cover, LAI and biomass. Theoretical relationships derived by Choudhury *et al*. (1994), indicate that the detailed connection depends on the crop structure and of the way the applied VIs are defined. Krishnaswamy *et al*. (2009) expressed the plant available moisture index as a multidata NDVI based Mahalanobis distance measure (termed ′eco-climatic distance′), and successfully mapped green water and blue water fluxes of the tropical forested landscapes in southern India.

2.5 Soil-based ecosystem services

Soil provides the basic physical substrate for human life. The majority of ecosystem processes have soil as the critical and dynamic regulatory center. The benefit of soil to the ecosystem services has been widely described. The basic conclusion is that it contributes to most of the ecosystem services defined by Millennium Ecosystem Assessment (Falkenmark and Rockstrom, 2004; Walter *et al*., 2005; Lavelle *et al*., 2006; Haygarth and Ritz, 2009). In the carbon and water related ecosystem service discussed above, soil water is released at certain rates to sustain plant growth. Nutrients in the soil are converted through plant assimilation into plant products. Soil participates in climate regulation by controlling carbon sequestration with the form of soil organic matter, and sensible heat flux between soil and atmosphere. Besides that, soil also filters toxic substances by adsorption to the clay surface, determining the quality of surface waters.

Soils systems are very complex (Ritz, 2008). Knowledge of spatially explicit soil information is a limitation to soil mapping by simply aggregating broadly similar soil groups. Haygarth and Ritz (2009) pointed out the need to map soil services in terms of identifying the land areas that are appropriate (or inappropriate) for particular uses. It gives clear direction to the purpose of, and development needs in, soil science. At present, soil organic carbon (SOC) and soil carbon sequestration are most widely mapped (Kern, 1994; Bajtes, 2000; Terra *et al*., 2004; Jones *et al*., 2005; Stoorvogel *et al*., 2009). The SOC depends on local site specific environmental conditions, including soil type, elevation, and plant condition. NDVI is commonly used to estimate the amount of photosynthesizing vegetation present, thus detecting the proportion of bare soil in a given area. In high soil moisture area, assistant moisture related indices are necessary. Kheir *et al*. (2010) used Landsat TM derived normalized difference wetness index (NDWI) and soil color index (SCI) as explanatory parameters of carbon containing soils in Denmark. NDWI and SCI were predictors of soil saturation, differentiating between high carbon soils from moist soils.

A suite of soil properties is needed to reveal the degree to which soils exert different ecosystem services (Palm *et al*., 2007). Remote sensing can be used to characterize various chemical, physical, and biological soil surface properties. For example, Demattê *et al*. (2010) evaluated soil density using spectral reflectance as evidence of compaction effects. The intensity of spectral reflectance of high soil bulk density (compacted) soils was higher than for low density (non-compacted) soils due to changes in soil structure and porosity. Lobell *et al*. (2009) found the multi-year average MODIS EVI coupled with local information captured one-third to one-half of the spatial variation of soil salinity. Rogovska and Blackmer (2009) described a significant correlation between Green-NDVI and soil acid (pH) and calcium carbonate equivalent in areas of the US Corn Belt. LiDAR can significantly contribute to soil roughness measurement (Anderson, 2009).

Soil biota plays an important role in soil based ecosystem services. They are soil engineers, determining the physical and chemical properties through biological processes (Barrios, 2007; Ritz *et al*., 2009). Increased efforts to acquire greater knowledge on the spatial distribution of soil biota would be critical to increase our predictive understanding of ecosystem service provision. For example, the positive direct impacts of microsymbiosis on crop yield due to increases in plant available nutrients, especially nitrogen through biological nitrogen fixation (BNF) by soil bacteria (e.g. Rhizobium) and phosphorus through arbuscular mycorrhizal fungi (AMF) (Marshner, 1995; Smith and Read, 1997; Giller, 2001). The ecosystem service of phosphorus supply can be found among closely related AMF species of the same genus (Barrios, 2007). Soil biota are highly diversified and widely distributed in the complex and heterogeneous soil systems. Given the difficulty of studying soil biota in landscapes, plant soil biota interactions is of particular importance in helping to understand the impacts of soil biota at larger scales (Wardle *et al*., 2004). Spatial information about the aboveground canopy obtained using remote sensing technologies could lead to inferences about the belowground component, which is expected to be a new way of assessing spatially explicit soil biota related ecosystem services in the future.

3 Evaluation of Remote Sensing for Ecosystem Services

3.1 Role of remote sensing in ecosystem service assessment

Remote sensing is in essence a technique for gathering spatial information. Based on the role of remote sensing technique, ecosystem service assessment described in Part 2 can be divided into three categories: direct monitoring, indirect monitoring and in combination with ecosystem models (Fig. 1).

Spectrum radiation directly reflects the character of plants and soils in the terrestrial ecosystem. Evapotranspiration can be calculated by interpreting the remotely sensed image based on the energy theory. Directly monitored ecosystem service includes some aspects of the plant and water related ecosystem service, including plant biodiversity, carbon fixation and green water measurement. The greatest limitation to the remote sensing technique is that the recorded information is constrained to the aboveground canopy and uppermost surface layer of the ecosystem. Radar microwaves can penetrate into the soil layer because of its relatively long wavelength. It can reflect the information for about 3 mm of the soil layer in wet conditions, and 1 m in dry conditions. Optical remote sensing images reflect only the top layer of the plant or the bare soil surface. Moreover, remote sensing is an instantaneous monitoring technique that stores the surface information at the moment of recording. It clearly can neither extend backward to historical time periods nor foreword to the future. As a result, most ecosystem service assessment can not be directly implemented from the remotely sensed image. Remote sensing promotes ecosystem service assessment by providing surrogate information. For example, the animal assemblages are inferred from the remotely sensed plant structure. FAO methodology requires the variables of a plant to reflect its regulation function in the ecosystem evapotranspiration. For ecosystem service relating to the spatial and temporal dy-

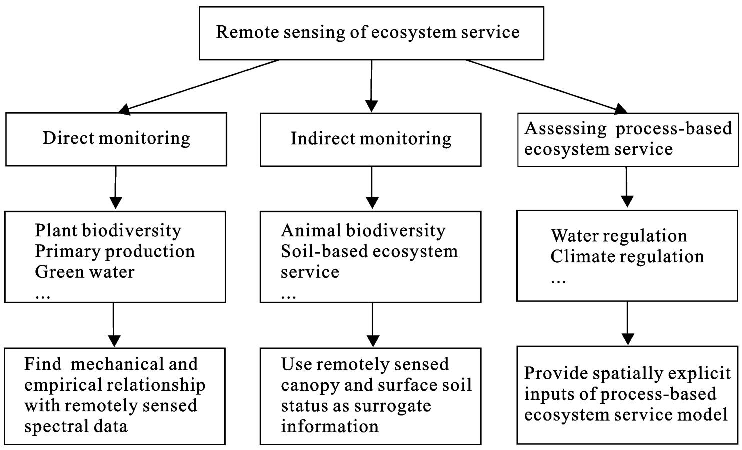

Fig. 1 Framework of ecosystem service assessment with remote sensing

namic processes, such as flood regulation, soil erosion and so on, ecosystem process models have proved to be increasingly effective. Remotely sensed spatial data provide important inputs for these models running at landscape to regional scales.

3.2 How to improve accuracy

Remote sensing has proved to be useful, but it is not a panacea for ecosystem service assessment. Accuracy remains critical among the numerous challenges inherent in remote sensing techniques. The authors emphasize two aspects of improving the accuracy of ecosystem service assessment.

3.2.1 Fieldwork is important

Remote sensing is not an alternative to field surveys. The establishment of regional empirical models needs field data. Ecosystem service measurements derived from remote sensing and spatial analyses must be validated with reference to ground truth. The importance of fieldwork simultaneously corresponding to remote sensing is emphasized (Barlow, 2009). Carlson *et al*. (2007) stated that the species richness prediction algorithm developed in one area is unique and it cannot be directly applied to other areas or different vegetation regimes. Buchanan *et al*. (2009) suggested that a remote sensing based system should involve continued collaboration between those who have biodiversity monitoring skills and remote sensing practitioners. Field observation is also an important basis for the improvement of remote sensing technique. In the paper of Yan *et al*. (2008), predicted GPP from the LUE model did not agree well with observed GPP from the eddy flux towers for estuarine wetland. Further analysis found that LUE model did not fit the specific ecosystem. Also ground based measurements of lateral carbon flow and CH_4 emission are needed to close the carbon budget of estuarine wetlands.

3.2.2 Select 'ideal' data resolution

Remotely sensed imagery with global coverage is becoming available in increasingly fine spatial and temporal resolutions. It has been found that improvement in data resolution could increases the identification of small patch in the landscape (Konarska *et al*., 2002). However, finer spatial resolution does not guarantee more accurate ecosystem service estimates. Olofsson *et al*. (2008) found the MODIS EVI at 250 m resolution was very noisy for the GPP of coniferous forests, while MODIS EVI at 1 km resolution can be used for the analysis, although the mechanism for this is unknown. Classification accuracies of forest decrease when the spatial resolution becomes finer than 60–80 m because fine resolution data may produce better results for individual trees rather than forest classes (Woodcock and Strahler, 1987). The influence of data resolution on ecosystem service monitoring is ubiquitous. All field based empirical relationships in ecosystem service monitoring depends on data resolution. It is essential that the spatial and temporal resolution of remote sensing data being matched to the sample size of field data and the relevant scales of ecosystem service being mapped. Contrary conclusion may be reached if data at different resolutions is used. Analysis to determine if pixel size does influence ecosystem service is needed before the application of a remotely sensed image in a given situation. The authors defined 'ideal' resolution as the one that could distinguish the key patterns of ecosystem service; this should jointly consider the extent of fragmented ecosystems of landscapes and the need of local management.

In addition, new tools contributing to ecosystem service assessment keep emerging. For example, passive technique has detected chlorophyll fluorescence emitted in two broad bands with peaks at about 685 nm and 740 nm. Damm *et al*. (2010) shows for the first time that including sun induced fluorescence in the LUE model improves the prediction of diurnal courses of GPP. Quantification of sun induced fluorescence yield may become a powerful tool to better understand spatio-temporal variations of carbon related ecosystem service at large scale.

Night satellite images comprise a global dataset derived as a mosaic of hundreds of orbits of the Defense Meteorological Satellite Program's Operational Linescan System (DMSP OLS). Studies of the imagery have shown that it corresponds to the extent of urban land cover, population density, energy consumption, greenhouse gas emission and other socio-economic parameters (Sutton and Costanza, 2002). These images are expected to provide spatial explicit parameters related to marketed economic activity within the ecosystem service ecological-social framework.

4 Discussion and Conclusions

Remote sensing is a technique for collecting spatial information about the Earth's ecosystems. Ecosystem service is a science with issues that can be answered in a spatially explicit way. The application of remote sensing should have the potential to address the basic issues of spatially quantifying the ecosystem services. This paper reviews the current ecosystem service related works in both fields. Two points should be mentioned: 1) remote sensing has been widely used to quantify ecosystem characterization (Cohen and Goward, 2004; Ustin *et al*., 2004; Wulder *et al*., 2004; Muraoka and Koizumi, 2009; Newton *et al*., 2009). Only those applications in relation to some specific ecosystems and the goods and benefits ecosystems provided to people are included here; and 2) ecological service is an integrated concept combining the ecological and social system—the ecologist wants to quantify specific ecosystem services, while the economist applies economic values to the changes in ecosystem services. Only ecological issues in ecosystem service are considered in this paper because remote sensing is a technique for monitoring biophysical characteristics of ecosystems. Cultural services in the Millennium Ecosystem Assessment are not included in this paper for the same reason.

Several key topics are included such as land cover, biodiversity and carbon, water and soil related ecosystem service. The traditional remote sensing researches of Earth elements (carbon, water and soil) monitoring coincides with important ecosystem service issues, for the reason that carbon, water and soil are natural gifts that ecosystems provide for mankind. Some plant and water related ecosystem services can be directly inferred by interpreting the remotely sensed image. For ecosystem service that can not be directly monitored, remote sensing facilitate the assessment by providing surrogate information for the status of plants and soils, which have important roles in ecosystem service provision. Remote sensing can also provide spatial inputs for dynamic ecosystem service model.

Accurate assessment is a never ending topic in remote sensing applications. The authors recommend a focus on collecting precise field data and selecting 'ideal' data resolution to improve the resulted accuracy. The authors also conclude that the development of remote sensing techniques should benefit the accurate ecosystem service assessment in the future.

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