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Coupled Terrestrial Carbon and Water Dynamics in Terrestrial Ecosystems: Contributions of Remote Sensing

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1. Introduction

The Earth climate is a complex, interactive system, determined by a number of complex connected physical, chemical and biological processes occurring in the atmosphere, land and ocean. The terrestrial biosphere plays many pivotal roles in the coupled Earth system providing both positive and negative feedbacks to climate change (Treut et al., 2007). Terrestrial vegetation via photosynthesis converts solar energy into carbon that would otherwise reside in the atmosphere as a greenhouse gas, thereby regulating climate. Vegetation also transfers water between belowground reservoirs and the atmosphere to maintain precipitation and surface water flows. The terrestrial carbon (C) cycle is closely linked to hydrological and nutrient controls on vegetation (Betts et al., 2000; Cox et al., 2000). Understanding the coupled terrestrial C and water cycle is required to gain a comprehensive understanding of the role that terrestrial ecosystems play in the global climate change. Much progress has been made in gaining insight of the coupling processes between C and water cycles across a range of time and spatial scales (Pielke Sr, 2001; Friedlingstein et al., 2003; Seneviratne et al., 2006; Betts et al, 2007a,b; Baldocchi, 2008). Since the early 1990s, there has been an increased interest in monitoring of the CO₂, water vapor and energy exchange between the atmosphere and terrestrial ecosystems by a variety of methods, such as the eddy-covariance techniques (EC), satellite and other airborne remote sensing, CO₂ concentration and isotope measurements. Meanwhile, there are various kinds of models have been developed to better understanding of these processes and for largescale C and water budgeting.

Remote sensing (RS) from satellite and airborne platforms, along with many other sources of land ground-based measurements (e.g., eddy covariance flux tower network, biometric plots, radar network, etc.) is playing and will continue to play a vital role in better understanding the coupled C and water cycle. Satellite RS allows the study of ecosystems from a completely new vantage point, facilitating a holistic perspective like viewing the Earth does for astronauts. Satellite-borne RS offers unique opportunities to parameterize land surface characteristics over large spatial extents at variable spatial and temporal resolutions. While there are challenges relating RS data recorded in radiance or backscatter

to variables of interest, and RS has poor temporal resolution compared to ground-based measurement devices, RS and spatial analytical techniques and distributed biogeochemical modeling embedded in Geographical Information Systems (GIS) have allowed us to better understand the coupled C and hydrological dynamics across a large range of temporal and spatial scales.

The large number of papers published since the 1980s on the terrestrial and C/water cycles have resulted in the publication of several major reviews from different perspectives. For example, Running et al. (2004) described a blueprint for more comprehensive coordination of the various flux measurement and modeling activities into a global terrestrial monitoring network by reviewing the literature published before the middle of 1990s. Baldocchi (2008) recently provided a comprehensive review of research results associated with a global network of C flux measurements systems. The topics discussed by this review include history of the network, errors and issues related with the EC method, and a synopsis of how these data are being used by ecosystem and climate modellers and the remote-sensing community (Baldocchi, 2008). Kalma et al. (2008) reviewed satellite-based algorithms for estimating evepotranspiration (ET) and land surface temperatures at local, regional and continental scales, with particular emphasis on studies published since the early 1990s; while Verstraeten et al. (2008) provided a comprehensive review of remote sensing methods for assessing ET and soil moisture content across different scales based on the literature published after 1990s. Marquis and Tans (2008) reviewed satellite-based instruments on CO₂ concentration measurements.

In this chapter, I distil and synthesise the rapidly growing literature on C and water cycles using remote sensing in direct or indirect ways across local to global spatial scales and over a range of time scales. To give the reader a perspective of the growth of this literature, a search of Web of Science produced over 1500 papers with the key words 'ecosystem carbon, water cycles and remote sensing' published since 1990 which is indicative of the large amount of research recently being undertaken on these topics. In order to filter through this large body of literature, I concentrate on papers discussing on the coupling processes between C and water and I extract information from a database of published results that I have collated during the past decade (available on request). In terms of content, the report covers the state of knowledge, monitoring and modeling of the coupled terrestrial C and water cycles. My aim is to highlight the recent advances in this field, and propose areas of future research based on perceived current gaps in the literature.

This is a synthesis of state-of-the-art research on how RS has informed the study of coupled C and hydrology cycles. The review is divided into several inter-connected sections. First, I review the scientific background of the linkage between terrestrial ecosystems and climate, and revise the state of knowledge on terrestrial C cycling, coupling of the C and water cycles. Second, I discuss the ground-based and satellite-based monitoring methods and observation networks associated with measuring C and water fluxes, CO₂ concentration and C isotopes. Third, I report on the recent advances in modeling approaches associated with the terrestrial biochemical and hydrological studies. Fourth, I discuss research gaps in C sinks/sources estimates and finally, I discuss the current research trends and the near-future directions in this field and propose an upscaling framework for landscape and regional C and water fluxes estimates.

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2. Scientific background and state of knowledge

2.1 Overview of terrestrial ecosystems and climate

The climate system is controlled by a number of complex coupled physical, chemical and biological processes (Figure 1). The terrestrial biosphere plays a crucial role in the climate system, providing both positive and negative feedbacks to climate change through biogeophysical and biogeochemical processes (Treut et al., 2007). Couplings between the climate system and biogeochemistry are mainly through tightly linked dynamics of C and water cycles. The importance of coupled C and water dynamics for the climate system has been increasingly recognized (Cox et al., 2000; Pielke Sr, 2001; Friedlingstein et al., 2003; Seneviratne et al., 2006; Betts et al, 2000, 2007a,b); however the mechanisms behind these coupled cycles are still far from well understood.



Fig. 1. Schematic view of the components of the climate system, their processes and interactions (Treut et al., 2007).

2.2 Terrestrial C cycling

One of the crucial issues in the prognosis of future climate change is the global budget of atmospheric CO_2 . The growth rate of atmospheric CO_2 is increasing rapidly. Three processes contribute to this rapid increase: fossil fuel emission, land use change (deforestation), and ocean and terrestrial uptake. As shown in Figure 2, terrestrial C budgets have large uncertainties and interannual variability.

Terrestrial ecosystems mediate a large part of CO_2 flux between the Earth's surface and the atmosphere, with ~120 Pg C yr⁻¹ taken up by photosynthesis and roughly the same amount



Fig. 2. Global CO₂ budget from 1959 to 2006. *Upper* panel: CO₂ emissions to the atmosphere (sources) as the sum of fossil fuel combustion, land-use change, and other emissions. *Lower* panel: The fate of the emitted CO₂, including the increase in atmospheric CO₂ plus the sinks of CO₂ on land and in the ocean (Canadell et al., 2007).

released back to the atmosphere by respiration annually (Treut et al., 2007; Prentice et al., 2001). Imbalances between gross ecosystem photosynthesis or gross primary productivity (GPP) and ecosystem respiration (R_e) lead to land surfaces being either CO₂ sinks or sources. The magnitudes of sinks and sources have fluctuated on annual and longer time scales due to variable climate, land use change, disturbance, and changes in the age distribution and species composition of ecosystems (Battle et al., 2000; Arain et al., 2002; Law et al., 2002; Morgenstern et al., 2004; Humphreys et al., 2005, 2006; Urbanski et al., 2007). Terrestrial ecosystems modify atmospheric C balance through many mechanisms. A detailed understanding of the interactive relationships in atmosphere-biosphere exchange is relevant to ecosystem-scale analysis and is needed to improve our knowledge of the global C cycle (Falk et al., 2008).

In recent years, scientists have learnt that terrestrial ecosystems' vegetation, soil (Melillo et al., 1989; Knapp et al., 1993) and animals (Naeem et al., 1995; Hattenschwiler and Bretscher, 2001) play key roles in mediating the terrestrial C cycle. Plants being the primary producers, it is from them that mass and energy gets transformed to other living organisms (Engel and Odum, 1999) within an ecosystem. The process of photosynthesis fixes atmospheric C into the biosphere. Atmospheric CO_2 enters the plant through stomatal opening that is controlled by a variety of environmental factors (Jarvis, 1976; Griffis et al., 2003). These factors include ambient temperature, atmospheric CO_2 concentration, nutrient availability, soil water availability and

forest age (Schimel, 1995; Prentice et al., 2001). Changes in the atmospheric CO₂ concentration and the corresponding changes in the climate have altered the magnitudes of terrestrial C cycling. For example, a climate change induced increases in vegetation growth due to earlier springs and lengthened growing seasons were detected by the phase shift of seasonal atmospheric CO₂ cycle by Keeling et al. (1996) and satellite-based vegetation index analysis by Myneni et al. (1997). Studies indicate that an increase in atmospheric CO₂ enhances photosynthesis (e.g. Woodward and Friend, 1988) and hence increases assimilation of atmospheric CO₂ by the terrestrial vegetation. Nitrogen (N) availability to plants is another factor that can affect photosynthesis. This is because N is a primary nutrient for plant growth. In the recent years, variations in plant N availability have also altered the trends in the terrestrial C cycles. Variations in plant N availability occur mainly due to natural and anthropogenic N-deposition. Based on modeling studies, e.g., researchers (Townsend et al., 1996; Asner et al., 1997; and Holland et al., 1997) have demonstrated that N deposition is responsible for about 0.1-2.3 PgC yr⁻¹ fixed by terrestrial vegetation which is almost half of the magnitude of C flux due to fossil fuel emission. Another factor that determines the nature of terrestrial C balance of an ecosystem is the age of the vegetation. Schimel et al. (1995) have demonstrated that forest re-growth can account for part of terrestrial C uptake as much as 0.5 ± 0.5 PgC yr-1, especially in northern mid and high latitudes. This is because younger vegetation actively grows and hence sequesters more atmospheric CO₂ as opposed to mature forest stands. There are many other processes that directly and indirectly affect photosynthesis and thus, the C cycle. They include land use and land cover change (Caspersen et al., 2000; Houghton and Hackler, 2006; Easter et al., 2007), reforestation (House et al., 2002; Paul et al., 2002), agricultural and grazing activities (Cerri et al., 2005), insect attack (Chapman et al., 2003; Throop et al., 2004) and invasive species (Szlavecz et al., 2006). Respiration is a process by which C is added to the atmosphere from the biosphere. There are studies that indicate that total ecosystem respiration is a major determinant of terrestrial C balances (Valentini et al., 2000). Total ecosystem respiration includes respiration by aboveground plant parts (boles, branches, twigs, and leaves) and soil respiration, which is the sum of the heterotrophic respiration, and root respiration including respiration of symbiotic microorganisms. The temporal variability of respiratory metabolism is influenced mostly by temperature and humidity conditions (Davidson and Janssens, 2006). Although ecosystem respiration has received considerable attention in recent decades, much less is known about the relative contributions of its sub- components (Jassal et al., 2007), and our understanding of how they will respond to global warming is poor. Soil respiration (root + heterotrophic respiration) is a dominant component of C exchange in terrestrial ecosystems which accounts for more than half of the total ecosystem respiration (Black et al. 2005). This is because soils of terrestrial ecosystems contain more C than the atmosphere and live biomass together (Eswaran et al., 1993). Components of respiration can have different responses to temperature and soil water content (Boone et al., 1998; Lavigne et al., 2004), thus the effects of these environmental controls needs to be understood in order to fully comprehend the soil C cycling mechanism. There are many other mechanisms that can release terrestrial C to atmosphere. This includes both natural and anthropogenic reasons. Emission of large amounts of C to the atmosphere from vegetation can occur during forest fires (Amiro et al., 2002; Soja et al., 2004; Amiro et al., 2004) or biomass burning (Fernandez et al., 1999; Tanaka et al., 2001). These C emissions are of very high magnitudes although their duration is very short. Forest fires and biomass burning also affect the nutrient status of the soil which could have positive effects on the succeeding vegetation (Prietofernandez et al., 1993; Deluca and Sala, 2006). Another form of C flux in

almost all terrestrial ecosystems is the import and export of dissolved organic carbon (DOC) (Neff and Asner 2001; Hornberger et al. 1994). DOC fluxes include C in the form of simple amino acids to large molecules that are transported through water flows. Fluxes of DOC into the ocean via runoff from terrestrial ecosystems are estimated to be 0.2 (Harrison et al., 2005) to 0.4 Pg C per year (IPCC, 2001). Since these fluxes are very small compared to the C fluxes due ecosystem is a net C sink due to the presence of soil C-pools having much longer residence times (Thompson et al., 1996; Chen et al., 2003; Canadell et al., 2007; Schulze, 2006). The strength of the terrestrial C sink was estimated to be 0.5-2.0 Pg C yr⁻¹ (Schimel et al., 1995). By sequestering atmospheric C, the terrestrial ecosystems help decrease the rate of accumulation of anthropogenic CO₂ in the atmosphere, and its associated climate change (Cihlar, 2007). Terrestrial C sinks may be responsible for taking up about one-third of all the CO₂ that is released into the atmosphere (Canadell et al., 2007). The terrestrial C sink, inferred based on our current understanding, may not be permanent (Luo et al., 2003; Cox et al., 2000 ; Friedlingstein et al., 2003). Over the last few years there have been several studies suggesting that the size of this terrestrial C sink is vulnerable to global warming (Martin et al., 1998; Nemani et al., 2002; Canadell et al., 2007). The metabolism of terrestrial ecosystems is complex and highly dynamic because ecosystems consist of coupled, non-linear processes that possess many positive and negative feedbacks (Levin, 2002; Ma et al. 2007). How the C budget of major ecosystems will respond to changes in climate is not quantitatively well understood (Baldocchi & Meyers 1998, Goulden et al., 1998; Black et al., 2000; Baldocchi et al., 2001a; Baldocchi & Wilson, 2001; Law et al., 2002; Barr et al., 2004, 2007). A detailed understanding of the interactive relationships in atmosphere-biosphere exchange is relevant to ecosystem-scale analysis and is needed to improve our knowledge of the global C cycle (Falk,M et al., 2008). The metabolism of terrestrial ecosystems is complex and highly dynamic because ecosystems consist of coupled, non-linear processes that possess many positive and negative feedbacks (Levin et al., 2002; Ma et al., 2007). Complex features of ecosystem metabolism are relatively unknown and how C budget of major ecosystems will respond to changes in climate is not quantitatively well understood (Black et al., 2000; Baldocchi et al., 2001; Baldocchi et al., 2001; Barr et al., 2004; Law et al., 2002).

2.3 Terrestrial water cycling

Most of the Earth is covered by water, amounting to more than one billion km³. The vast majority of that water, however, is in forms unavailable to land-based or freshwater ecosystems. Less than 3 percent is fresh enough to drink or to irrigate crops, and of that total, more than two-thirds is locked up in glaciers and ice caps. Freshwater lakes and rivers hold 100,000 km³ globally, less than one ten-thousandth of all water on earth (Jackson et al, 2001).

Water vapor in the atmosphere exerts an important influence on climate and on the water cycle, even though only 15,000 km³ of water is typically held in the atmosphere at any time. This tiny fraction, however, is vital for the biosphere. Water vapor is the most important of the so-called greenhouse gases (others include CO_2 , CH_4 and N_2O) that warm the Earth by trapping heat in the atmosphere. Water vapor contributes approximately two-thirds of the total warming that greenhouse gases supply. Without these gases, the mean surface temperature of the earth would be well below freezing, and liquid water would be absent over much of the planet. Equally important for life, atmospheric water turns over every ten days or so as water vapor condenses and falls as rain to the Earth and the heat of the Sun evaporates new supplies of vapor from the liquid reservoirs on earth. Solar energy typically

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evaporates about 425,000 km³ of ocean water each year. Most of this water returns back directly to the oceans as precipitation, but approximately 10% falls on land. If this were the only source of rainfall, average precipitation across the earth's land surfaces would be only 25 cm a year, a value typical for deserts or semi-arid regions. Instead, a second, larger source of water is recycled from plants and the soil through evapotranspiration. The water vapor from this source creates a direct feedback between the land surface and regional climate. This second source of recycled water contributes two-thirds of the 70 cm of precipitation that falls over land each year. Taken together, these two sources account for the 110,000 km³ of renewable freshwater available each year for terrestrial, freshwater, and estuarine ecosystems. Because the amount of rain that falls on land is greater than the amount of water that evaporates from it, the extra 40,000 km³ of water returns to the oceans, primarily via rivers and underground aquifers. A number of factors affect how much of this water is available for human use on its journey to the oceans. These factors include whether the precipitation falls as rain or snow, the timing of precipitation relative to patterns of seasonal temperature and sunlight, and the regional topography. For example, in many mountain regions, most precipitation falls as snow during winter, and spring snowmelt causes peak flows that flood major river systems. In other regions, excess precipitation percolates into the soil to recharge ground water or is stored in wetlands.

2.4 Coupling of the C and water cycles

The cycling of other materials such as C and N is strongly coupled to this water flux through the patterns of plant growth and microbial decomposition, and this coupling creates additional feedbacks between vegetation and climate. Thermodynamically, a terrestrial ecosystem is an open system. Therefore, hydrological and C cycles are closely coupled at various temporal and spatial scales (Betts, 2007; Ball et al., 1987; Levis et al., 1999; Rodriguez-Iturbe, 2000; Joos, 2001; Arain et al., 2006; Blanken and Black, 2004; Snyder 2004). C uptake for example, is closely coupled to water loss by ecosystems mainly through leaf stomatal pathway governed principally through leaf conductance (Jarvis, 1976; Harris et al., 2004; Rodriguez-Iturbe, 2001). Soil organic C decomposition is very sensitive to soil moisture content via microbial activity and other processes (Betts, 2007; Levis 1999; Snyder et al., 2004; Parton et al., 1993; D'odorico 2004). The flux of terrestrial organic C by river runoff to the ocean and wetland discharge is an important component of the global organic C cycle (Hedges, 1992; Wang et al., 2004). It is estimated that 0.25×10¹⁵ g dissolved organic carbon (DOC) is discharged to the ocean by the world rivers each year (Meybeck, 1982). The land surface hydrological processes (in particular the terrestrial river systems) play an important role in transport of dissolved and particulate organic C from terrestrial to marine ecosystems (Wang et al., 2004). However, the interactions between C and water cycles and the mechanisms how these interactions will shape future climatic and biosphere conditions are far from well understood.

3. The array of airborne and satellite sensors developed for monitoring of the coupled C and water cycles

3.1 Satellite monitoring

RS is the observation of a phenomenon from a distance, using devices that detect electromagnetic radiation. Satellite-borne remote sensing offers unique opportunities to parameterize land surface characteristics over large spatial extents at variable spatial and

temporal resolutions. There has been a substantial increase in the number of satellite sensors for Earth observations that cover a large range of the electromagnetic radiation spectrum (Tables 1 and 2) since 1960s when the earlier Landsat satellites were launched into orbit, such as the Television Infrared Observation Satellite (TIROS-1) launched in 1960. None of these sensors have been designed exclusively for C, water or vegetation applications. For example, the TIROS-1 was focused on weather analysis and forecasting (Natl. Res. Counc., 2008). However, scientists were applying these observations to vegetation studies by the next decade (Rouse et al., 1974; Tucker et al., 1979). Tuker et al. (1986) exploited the properties of chlorophyll pigments to absorb wavelengths in the red spectral region and structural properties of leaves to reflect near-infrared spectra based on the imagery data obtained by the Advanced Very High Resolution Radiometer (AVHRR) sensor onboard TIROS. This pioneer study that synoptic view of the coupled atmosphere-biosphere as C sequestration by photosynthesis from the atmosphere in the Northern Hemisphere (Tuker et al., 1986) opened possibilities for global perspectives in ecology. The first Landsat satellite launched in 1972 carried the Multispectral Scanner System (MSS) sensors which were specifically designed to map land resources with finer spatial resolution (68 m × 82 m) than the AVHRR. The program was the first civil, non-weather satellite program and Landsat provided observations for any place on Earth once every 18 days, offering a wide range of studies on terrestrial vegetation and C and water cycles. The Landsat Thematic Mapper sensors carried onboard the Landsat series of satellites, acquire images at a 30-m spatial resolution with a 16-day interval. The acquired data have been the backbone for land-cover, vegetation and C cycle studies. NASA's Earth Observing System (EOS), launched in 1999 (Tilford S. 1984), brought new capabilities for monitoring vegetation productivity and other properties with near-daily and global coverage. The multispectral sensors---Moderate Resolution Imaging Spectroradiometer (MODIS), onboard the EOS platform, have built invaluable global observation dataset for C and water cycles research since the early 2000s. MODIS provides a global coverage every 1-2 days with 36 bands. The spatial resolution of MODIS (pixel size at nadir) is 250 m for channels 1 and 2 (0.6µm - 0.9µm), 500 m for channels 3 to 7 (0.4µm - 2.1µm) and 1000 m for channels 8 to 36 (0.4µm - 14.4µm), respectively. Data from the satellite-borne MODIS are currently used in the calculation of global weekly GPP and ET at 1-km spatial resolution (Running et al., 2004).

Sensors that have potential applications in C and hydrology studies fall into two groups---optical (Table 1) and microwave (Table 2). Optical sensors cannot penetrate vegetation or clouds. In contrast, microwave sensors are able to penetrate vegetation and can collect data independently of cloud cover and solar illumination. This is important because it is difficult to acquire cloud-free imagery using optical sensors. There are two types of microwave sensors: active sensors and passive sensors. The former send and receive their own energy; while the latter detect the microwaves emitted by the Earth's surface. The microwave bands, being useful for vegetation and carbon and water cycles, are K, X, C, and L, ranked in increasing wavelengths. K- and X-bands are useful for detecting surface temperature, snow density, and rainfall rates, whereas C- and L-bands are sensitive to soil moisture (Sass and Greed, 2011).

3.2 Other airborne measurements

Besides satellite monitoring, other airborne observation techniques (*e.g.* aircraft, airplane and land surface remote sensing) have been developed rapidly since the latest decade.

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	Sensor		Bands	; (nm)		Spatial Resolution	Spatial Coverage	Temporal	Passive /Active	Operational years
		Vsible	NIR	SWIR	Thermal			Resolution		
	LiDAR		-			0.15-1m	Global	No regular repeat cycle	Active	-
	GeoEye	450–510 510–580 655–690	780–920	-	-	Pan:0.41m Multi:1.65m	Global	Less than 3 days	Passive	2008-09-06 to now
	Worldview-2	400-450 585-625 705-745	860-1040			0. 5m	Global	1.1day	Passive	2009-10 to now
	Quikbird	450-520 520-660 630-690	760-900			Pan:0.61m Multi:2.44m	Global	1-3,5days depending on latitude	Passive	2001-10-18 to now
Very high resolution	Ikonos	450-530 520-610 640-720	770-880	-	-	Pan:1m Multi:4m	Global	1.5-2.9days	Passive	1999-09-24 to now
	Orbview-3	450-900 450-520 520-600 625-695	760-900	-	-	Pan:1m Multi:4m	Global	>3days	Passive	2003-06-26 to now
	KOMPSAT-2	500-900 450-520 520-600 630-690	760-900	-	-	Pan:1m Multi:4m	Global	3 days	Passive	2006-07-28 to now
	Resurs-DK1	580-800 500-600 600-700 700-800	-	-	-	Pan:0.9-1.7m Multi:1.5-2m	Global	5 days	Passive	2006-06-15 to now
	TopSat	500-700 450-500 500-600 600-700	-	-	-	Pan:2.5m Multi:5m	Global	4 days	Passive	2005-10-27 to now
	MTI	450-520 520-600 620-680	760-860 860-900 910-970	990- 1040 1360- 1390	1550- 1750 3500- 4100 4870-		Global	5-8 min	Passive	2000-03-12 to now
					5070 8000- 8400 8400- 8850 10200- 11500 20800- 23500					
	RapidEye EOC	440-510 20-590 630-685	760-850	-	-	5m	Global	Daily	Passive	2008-8-29 to now
	Formosat-2	450–900 450-520 520-600 630-690	760-900	-	-	Pan:2m Multi:8m	Global	Daily	Passive	2004-04-21 to now

	Sensor	Bands (nm)			Spatial	Spatial	Temporal	Passive	Operational	
		Vsible	NIR	SWIR	Thermal	Resolution	Coverage	Resolution	/Active	years
	Spot4	510-730 500 - 590 610 - 680	780-890	1580- 1750	-	Pan:10m Multi:20m	Global	2-3days	Passive	1998-03 to now
	Spot5	490-690 490-610 610-680	780- 890	1580- 1750	-	Pan:2.5m,5m Multi:10m	Global	2-3days	Passive	2002-05-04 to now
	ALOS AVNIR-2	420-500 520-600 610-690	760-890	-	-	10m	Global	2days	Passive	2006-01-24 to now
	Terra ASTER	520-600 630-690	760-860	1600- 1700	-	15m 30m 90m	Global	4-16days	Passive	1999-12-18 to now
Fine	JERS-1 OPS	520-600 630-690	760-876	1600- 1710 2010- 2120 2030- 2250 2270- 2400	-	18m	Global	44days	Passive	1992-02-11 to now
	SPOT1- 3HRV	500-730 500-590 610-680	780-890	-	-	Pan:10m Multi:20m	Global	26days	Passive	1986-02 to now
	CBERS IRMSS	500-900	-	1550- 1750 2080- 2350 1040- 1250	10400- 12500	78m, 156m	Global	26days	Passive	1994-10-14 to now
	Deimos-1/ UK DMC-2	520– 600 630-690	770-900	-	-	22m	Global	3 days	Passive	2009-07-29 to now
	IRS LISS3	20-590 620-680	770-860	1550- 1700 2200- 25000	-	23m	Global	24days	Passive	2003-10-17 to now
	Landsat7 ETM	520-900 450-520 520-600 620-690	760-960	1550- 1750 2080- 3350	1040- 1250	Pan:15m Muti:30m,60m	Global	16days	Passive	1999-04 to now
	Landsat4- 5TM	450-520 520-600 630-690	760-900	1550- 1750 20800- 23500	104000- 125000	30m,120m	Global	16days	Passive	1984-03-16 to now
	Eo-1 ALI	520-900 450-520 520-600 620-690	760-960	1550- 1750 2080- 3350	1040- 1250	Pan:10m Muti:30m,60m	Global	16days	Passive	2000-11-21 to now

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	Compon		Panda	(Spatial	Spatial	Tomporal	Passing	Orestings
	Sensor	Vsible	NIR	SWIR	Thermal	Resolution	Coverage	Resolution	/Active	years
	Eo-1 Hyperion		400-2	2500		30m	Global	16days	Passive	2000-11-21 to now
	Meteor 3M-1		450nm 10500- 5700-	n-1000 12500 7100		1.4km,3km,	Global	daily	Passive	2001-12-10 to now
	Mos-1,2 MESSR	510-590 610-690	720-800 800-1100 -	-		50m	global	17days	Passive	1987-02-19 to now
	Okean MSU-SK	530-590 610-690	700-800 900-1000	-	104000- 126000n m	Visible:200m Ir:200m Thermal:600m	Global	17days	Passive	1983-7-10 to now
	landsat1-5 MSS	500-600 600-700	700-800 800-1100 -	-		80m	Global	1,2,3:18 days; 4,5:16days	Passive	1972 -07 to now
	CBERS IRMSS	500- 1100	1550- 1750 800-2350 -		104000- 125000n m	Visible, Ir:78m Thermal :56m	Global	26days	Passive	1999-10-14 to now
	SAC-C MMRS	480-500 540–560 630-690	795-835	1550 - 1700	-	175m	Global	16days	Passive	2000-06-08 to now
um	Terra MODIS		B1-B36:40 B1-B2: B3-B7: B8-B36:	0-144000 250m 500m 1000m	0		Global	1/4day	Passive	1999-12-18 to now
Medi	Fengyun-3a MERSI		410-12	25000		B1-B5:250m B6-B20:1000m	Global	1/2 day	Passive	2008-05-27 to now
	ENVISAT MERSI		410-12	25000		B1-B5:250m B6-B20:1000m	Global	35days	Passive	2002-03-1 to now
	MOS-1,2 VTIR	520-590 620-680	-		115000- 125000	Visibl:900m Thermal:2700m	Global	17days	Passive	1987-02-19 to now
	GEOS Imager	S	bortwave Vsible:5 Moisture:0 IR:10200 IR:11500	:3800-40 550-750 6500-700 0-11200 0-12500	00 0	Shortwave:4km Vsible:1km Moisture:8km IR:4km	Global	-	Active	1985-04 to now
κSE	Meteosat SEVIRI	12spect n	tral channe ear infrad	els in vis red regi	ible and on	1.25km,5km	Global	daily	Passive	2002-12-28 to now
COAR	NOAA AVHRR	550-680	725-1100 -	3550-39 10500-11	930 1150 1300 0- 1250 0	1.1km	Global	1/4 day	Passive	1978-10 to now
	GMS5	Wa	Visible: ater vapou IR:10500 IR: 1150	550-900 1r:6500-7)-11500 0-12500	7000	Visible:1.25km Water vapour:5km IR:5km	Global	daily	Passive	1995-03- 18~2003-05

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Sensor	Bands (nm)				Spatial Spati	Spatial	Spatial Temporal	Passive	Operational
	Vsible	NIR	SWIR	Thermal	Resolution	Coverage	Resolution	/Active	years
GMS1-4	Wa	Visible: ater vapou IR:1050 IR: 1150	550-900 1r:6500-7 0-11500 0-12500	000	Visible:1.25km Water vapour:5km IR:5km	Global	daily	Passive	1997-7 to now
Fengyun- 2CD	Wa	Visible:5 ater vapou IR:1050	550-1050 ar:6200-7 0-12500	600	Visible:1.25km IR:5km	Global	1 hour	Passive	C:2004-10-19 D: 2006-1208
fengYun- 2AB	Wa	Visible:5 ater vapou IR:1050	550-1050 1r:6200-7 0-12500	600	Visible:1.25km Water vapour:5km IR:5km	Global	1 hour	Passive	A:1997-06-10 B:1997-07-21
INSAT-2E	550-750	-	105 125	500 500	Visible:2km IR:8km	Global	daily	Passive	1992-04-02 to now
INSAT-2 VHRR	550-750	-	105 125	500 500	Visible:2km IR:8km	Global	daily	Passive	1995-12-06 to now
Meteosat MVIRI	Wat	Visible:4 er vapour IR: 570	150-1000 r:10500-1 0-7100	2500	Visible:1.25km Water vapour:5km IR:5km	Global	daily	Passive	Meteosat— 7:1993-11

Abbreviations: Ali, Advanced land Imager; ALOS AVNIR-2, Advanced Visible and Near Infrared Radiometer type 2; ALOS, Advanced land observing Satellite; ASTER, Japanese Earth Resources Satellite 1; AVHRR, The Advanced Very High Resolution Radiometer; CBERS, The China-Brazil Earth *Resources Satellite;* Deimos-1, Spanish Earth imaging satellite; DMC, Disaster Monitoring Constellation; Envisat, Environmental Satellite; EOS, Earth Observing System; Etm, Enhanced Thematic Mapper; Formosat-2, the first and only high-resolution satellite; GMS, Geosynchronous Meteorological Satellite; HRV, High Resolution Visible; INSAT-2E, Indian geostationary communications and weather satellite; KOMPSAT, Korea Multi-Purpose Satellite; IRMSS, Infra-Red Multispectral Scanner; IRMSS, Infrared Multispectral Scanner Camera; IRS, Indian Remote Sensing; LISS-3, Linear Imaging Self-Scanning Sensor - 3. Satellites; Lidar, Light Detection And Ranging; MTI, moving target indication radar; MOS -1, Marine Observation Satellite 1; MESSR, Multi Spectral Electronic Self Scanning Radiometer; MSS, Multispectral Scanner; Meteor 3M-1, Meteorological Satellite; 3M, Monitoring of ocean and land surfaces, Meteorological observations, and Measurement of vertical profiles of aerosol, ozone and other constituents in the atmosphere; MMRS, Multispectral Medium Resolution Scanner; MODIS, The Moderate Resolution Imaging Spectroradiometer; MERSI, Medium Resolution Spectral Imager; MVIRI, METEOSAT Visible and Infrared Imager; NOAA, National Oceanic and Atmospheric Administration; Orbview, the satellite of Orbitally company; OPS, Optical System.

Okean MSU-SK: Multispectral Scanner - Conical Scanning; RapidEyeEOC, Electro-Optical Camera; SEVIRI, Spinning Enhanced Visible Infra-Red Imager; Spot, systeme probatoire d'observation de laterre, TM, Thematic Mapper; Topsat, Tactical Operational Satellite; UK-DMC 2, British Earth imaging satellite, operated by DMC International Imaging; VHRR, Very High Resolution Radiometer; VTIR, Visible and ThermalInfrared Radiometer.

Table 1. Optical Remote Sensing Systems

Coupled Terrestrial Carbon and Water Dynamics in Terrestrial Ecosystems: Contributions of Remote Sensing

Spatial Sensor resolution		Bands	Spatial Resolution	Spatial Coverage	Temporal Resolution	Passive/ Active	Operational years
	Radarsat-2	С	3m	Global	24days	Active	2007-12-14tonow
	Radarsat-1	С	10m,25m,30m,35m,50m, 100m	Global	24days	Active	1995-11-04to now
1 resolution	COSMOS Skymed	x	1m	Global	several times a day	Passive	COSMO1:08.06.2007to now COSMO2:09.12.2007to now
Very high		56	BCI				COSMO3:25.10.2008to now COSMO4:06.11.2010to now
	ALOS PALSAR	L	7-100m	Global	2days	Active	03.01.2002to now
	ERS-1,2	С	30m,50km	Global	2days	Active	ERS-1:03.17.1991to now
							ERS-2:04.1995to now
	TerraSAR- X	Х	1m,3m,16m	Global	11days	Active	06.15.2007to now
Щ	7JERS-1	L	18mX18m	Global	44days		02.11.1992~10.12.1998
FIN	ENVISAT ASAR	Х	9mX6m;30X30m;150X15 0m;450mX450m;1800mX 1800m	Global	35days	Active	03.01.2002to now
	SIR-C	X,C,L	50m 100m	Global	-	Active	04.091994~04.12.1999; 30.091994~11.10.1999;
	SRTM	X,C	30mX30m	60°N~56°S	16days	Active	02.11.2000~02.10.2000
medium	Nimbus-7 SMMR	Ka,K,Ku, X,C	30km,60km, 97.5km,156km	Global	5~6days	Passive	26.10.1978~08.21.1987
	TRMM PR	K _u ,	4.3~5.0km	50°S~50°N 180°W~180°E	3h,1d, 3d,7d	Active	12.281997 to now
	TRMM TMI	Ka,K,C	6~50km	50°S~50°N 180°W~180°E	3h,1d, 3d,7d	Active	12.28.1997 to now
	FengYun 3a MWRI	K _a ,K,K _u , X	250m	Global	5d	Passive	05.27.2008 to now
ш	Aqua AMSR-E	K _a ,k,x	25km	Global	16day	Passive	05.04.2002 To now
DARSI	DMSP SSMI	K _a ,k		Global	4h	Passive	01.19.1965to now
S	DMSP SSMT	K _a k	174km	Global	4h	Passive	01.19.1965to mow
	MOS-1,2 MSR	K _a ,K	32km,23km	Global	17days	Passive	02.19.1987~04.19.1996
	ADEOS-1 NSCAT	K _u ,	25km	90%global sea	2days	Active	08.17.1996~06.30.1997 12.2002~10.24.2003
	SMOS MIRAS	L	50km,200km	Global	16days	Passive	02.11.2009 to now
	CRACE	K _a ,K		Global	16days	Passive	03.17.2002to now

Abbreviations: ADEOS, Advanced Earth Observing Satellite; ALOS, Advanced land observing Satellite; *AMSR-E*, The Advanced Microwave Scanning Radiometer for EOS; ASAR, An Advanced Synthetic Aperture Radar; *COSMO*, COnstellation of small Satellites for the Mediterranean basin Observation; DMSP, Defense Meteorological Satellite Program; Envisat, Environmental Satellite; ERS, European Remote-Sensing Satellites; GRACE, Gravity Recovery And Climate Experiment; JERS-1, Japanese Earth

Resources Satellite 1; MIRAS, Instrument. Synthetic. Apperture Radiometer; MSR, MicrowaveScanning Radiometer; MWR, The Microwave Radiation Imager; **NSCAT, NASA SCATterometer;** PR, Precipitation Radar; SAR, Synthetic Aperture Rada; SIR-C, Space Imaging Radar; *SRTM*, Shuttle Radar Topography Mission; *SMMR*, Scanning Multichannel Microwave Radiometer; SMOS, Soil Moisture and Ocean Salinity; SSMI, Special Sensor Microwave Imager; SSMT, Special Sensor Microwave Temperature; TRMM, Tropical Rainfall Mearsuring Mission; *TMI*, *TRMM*'s Microwave Imager.

Table 2. Microwave Remote Sensing Systems

Microwave wavelengths penetrate greater depths into plant canopies than optical sensors (Kasischke et al. 1997). The potential for using RADAR (RAdio Detection And Ranging) for studying terrestrial carbon and water cycles, particularly for assessing standing woody biomass is promising. The sensitivity of RADAR to vegetation biomass strongly depends on wavelength: the longer wavelengths, the greater vegetation volumes and biomass levels. Single-band RADAR is able to detect aboveground biomass up to approximately 100 Mg per hectare (Dobson et al. 1992, Luckman et al. 1998). In addition, multiband RADAR enables to separate biomass into component fractions (e.g., stem and canopy) (Saatchi and Moghaddam 2000). Synthetic aperture RADAR (SAR) is also sensitive to vegetation structure and to the amount of biomass, including both photosynthetic (green) and nonphotosynthetic vegetation components (Turner et al., 2004). LiDAR (Light Detection and Ranging) is a remote sensing technology that determines distances to an object or surface using laser pulses, which is a relatively new technology compared to optical sensors, and has the added capability of characterizing the distribution of foliage with height in the canopy (Lefsky et al. 2002, Treuhaft et al. 2002, 2004; Turner et al., 2004). LiDAR data have proved to be highly effective for the determination of three dimensional forest attributes. The suitability of airborne LiDAR for the determination of forest stand attributes including LAI and the probability of canopy gaps within different layers of canopy has been widely acknowledged by various studies (Coops et al., 2004; Coops et al., 2007). The interpreted LiDAR data have been further used for landscape C modeling and scaling (Hilker et al. 2008; Chen et al., 2009). The number and types of sensors used for research on C and water cycles have multiplied many times over since the first sensor launched into orbit. Remote sensing provides consistency of coverage and repeat measurements through time are now indispensable in the C and hydrological scientist's toolbox.

3.3 Remote sensing of GPP

Satellite-based studies have used the light-use efficiency (ϵ) approach to estimate GPP (Prince & Goward, 1995; Running et al., 2000, 2004; Behrenfeld et al., 2001) or net primary production (NPP) (Field et al., 1995; Ruimy et al., 1999). Significant effort and progress have been made in developing the satellite-based GPP algorithms (Running et al., 2004; Xiao et al., 2004; 2005). The algorithm relies on ϵ approach relating GPP to the amount of absorbed photosynthetically active radiation (APAR) (Monteith, 1966, 1972), such that,

$$GPP = \varepsilon \times fPAR_{chl} \times PAR , \qquad (1)$$

where PAR is the photosynetically active radiation (in µmol photosynthetic photon flux density, PPFD), *f*PAR_{chl} is the fraction of PAR absorbed by leaf chlorophyll in the canopy, and ε is the light use efficiency (µmol CO₂/µmol PPFD). Light use efficiency (ε) is affected by leaf phenology, temperature, and water:

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$$\varepsilon = \varepsilon_0 \times P_m \times W_m \times T_m , \qquad (2)$$

where ε_0 is the apparent quantum yield or maximum light use efficiency (µmol CO₂/µmol PPFD) for a given land cover type or vegetation function type, and P_m , W_m and T_m are the modifiers for the effects of leaf phenology, water and temperature on light use efficiency of vegetation, respectively.

Different parameters and inputs for the satellite-based algorithm were estimated in different ways: (i) the fraction of PAR absorbed by leaf chlorophyll in the canopy (*f*PAR_{chl}) and the modifiers (P_m , W_m); (ii) PAR and temperature modifier (T_m) were calculated using climate data (either from tower measurements or climate models); and (iii) the maximum light use efficiency (ϵ_0) was referred to the land-cover-related look-up table and then modified/optimized using EC tower C measurements and footprint climatology.

To accurately estimate *f*PAR_{chl} in forests is a challenge to both radiative transfer modeling and field measurements. Significant efforts and progress have been made in developing advanced vegetation indices that are optimized for retrieval of *f*PAR from individual optical sensors (Gobron et al., 1999; Govaerts et al., 1999). The *f*PAR_{chl} within the photosynthetically active period of vegetation was estimated as a linear function of the the Enhanced Vegetation Index (EVI),

$$fPAR = f(EVI).$$
(3)

EVI is similar in design to NDVI but uses spectral information from the blue band (ρ_{blue}). Following Huete et al. (1997) it was computed,

$$EVI = G \times (\rho_{nir} - \rho_{red}) / (\rho_{nir} + C_1 \times \rho_{red} - C_2 \times \rho_{blue} + L), \tag{4}$$

where G = 2.5, $C_1 = 6$, $C_2 = 7.5$, and L = 1. EVI is found to be significantly correlated with the fraction of the photosynthetically active radiation absorbed by leaf chlorophyll in the canopy providing a good surrogate of the spatial variability index for photosynthesis rate.

The parameter P_m was estimated using the Normalized Difference Vegetation Index (NDVI) and the Land Surface Water Index (LSWI) and was calculated at two different phases, depending upon life expectancy of leaves (deciduous versus evergreen):

$$P_m = \begin{cases} \frac{1+LSWI}{2} & Duirng \ bud \ burst \ to \ leaf \ full \ expansion}{After \ leaf \ full \ expansion} \end{cases}$$
(5)

NDVI (Tucker 1979; Field et al., 1995) was calculated as,

$$NDVI = (\rho_{nir} - \rho_{red}) / (\rho_{nir} + \rho_{red}), \tag{6}$$

where ρ_{nir} , and ρ_{red} are the reflectance in the near infrared and red bands, respectively. NDVI is generally related to green vegetation cover or vegetation canopy density and has been shown to be well correlated with green LAI and biomass (e.g., Sellers, 1985; Myneni et al., 1995).

LSWI (Xiao et al. 2002) is a useful water index and was calculated as the normalized difference between the NIR (0.78-0.89 μ m) and AWIR (1.58-1.75 μ m) spectral bands:

$$LSWI = (\rho_{\text{nir}} - \rho_{\text{swir}}) / (\rho_{\text{nir}} + \rho_{\text{swir}}),$$
(7)

where ρ_{nir} and ρ_{swir} are the reflectance of near infrared bands, red bands and short infrared bands, respectively.

The timings of bud burst and leaf full expansion can be identified using NDVI. The effect of water on plant photosynthesis (W_m) has been estimated as a function of available soil content in plant root zone and water vapor pressure deficit (VPD) in a number of processbased ecosystem models (e.g. Chen et al., 2007) and remote-sensing based models (e.g. Running et al., 2000). Soil moisture represents water supply to the leaves and canopy, and VPD represents evaporative demand in the atmosphere. Leaf and canopy water content is largely determined by the dynamics of both soil moisture and VPD. As the first order of approximation, here following the alternative and simple approach that uses a satellite-derived water index (Xiao et al., 2004), the seasonal dynamics of W_m was estimated,

$$W_{\rm m} = \alpha \times (1 + \rm LSWI) / (1 + \rm LSWI_{\rm max}), \tag{8}$$

where α is a magnifier (its default value equals 1.0) and LSWI_{max} is the maximum LSWI within the plant growing season for individual pixels. The temperature modifier T_m was estimated at each time step, using the equation developed for the terrestrial ecosystem model (Raich et al., 1991),

$$T_m = \frac{(T - T_{\min})(T - T_{\max})}{[(T - T_{\min})(T - T_{\max})] - (T - T_{out})^2}$$
(9)

where T_{min} , T_{max} and T_{opt} are the minimum, maximum and optimal temperature for photosynthetic activities, respectively. Their default values are respectively set to be 0, 35 and 20 °C in this study. If air temperature falls below T_{min} , T_m is set to be zero.

The ε_0 values vary with vegetation types, and the information about ε_0 for individual vegetation types can be obtained from a survey of the literature (Ruimy et al., 1995) and optimized using EC tower measurements. According to the work (Zhang et al. 2006), the default ε_0 value was estimated to be 0.032 µmol CO₂/µmol PPFD in this study stand in 2004.

3.4 Remote sensing of ET

We follow a drop of water traveling through a watershed from input, storage, and finally output and assess how RS can be used to track water fluxes and reservoirs. Table 3 summarizes the potential application of RS to study of hydrology. ET, the largest component of water loss from ecosystems, plays an important role in affecting soil moisture, vegetation productivity, C cycle, and water budgets in terrestrial ecosystems (Dirmeyer, 1994; Hilker et al. 2008; Chen et al., 2009). In this section, I mainly discuss application of RS to ET.

Verstraeten (Verstraeten et al., 2008) provided a comprehensive review of remote sensing methods for assessing ET and soil moisture content across different scales and Kalma (Kalma et al., 2008) reviewed satellite-based algorithms for estimating ET and land surface temperatures at local, regional and continental scales, with particular emphasis on studies published since the early 1990s.

In general, water evapotranspired from ecosystems into the atmosphere will reduce the land surface temperature (T_a). Reduction in soil moisture will decrease plant transpiration and evaporation from soil and plant surfaces. Reduction in ET will increase T_a . T_a can be derived from remotely-sensed thermal-infrared (TIR) band (8-14 microns) from various operational satellites. Based on the relationship between T_a and ET, remotely sensed T_a has been used to estimate regional ET (Gillies et al., 1997; Kite et al., 2000; Su et al., 2000., Coops et al., 2002). The existing thermal imaging sensors provide adequate coverage of thermal dynamics that are useful for operational monitoring applications of ET. For example, thermal images at 15 minutes intervals and at a spatial resolution of 5 kilometers can be obtained from the NOAA Geostationary Operational Environmental Satellites (GOES), and TIR data at a fine spatial resolution (60 m or 120 m) with a much longer time interval (16 days) have been provided by the Thematic Mapper (TM) and ETM+ instruments on Landsat 5 and Landsat 7.

4. Modeling of C and water dynamics in terrestrial ecosystems based on remote sensing

The land surface of the Earth represents significant sources, sinks, and reservoirs of C, heat and moisture to the atmosphere. C and energy fluxes and water cycles at soil-atmosphere and plant-atmosphere interfaces are therefore important land surface processes. Due to the complexity and non-linearity of C, N and water dynamics in terrestrial ecosystems, various modeling tools are needed for better understanding of these biogeochemical and hydrological processes and their feedback mechanisms with the land surface climate system (Rannik et al., 2006). The rapidly proliferating volume of spatial data generated by RS has created a significant challenge in terms of designing model algorithms. A spatially distributed processbased model uses spatial data for computing ecohydrological and biophysical processes. The model algorithms represent hypotheses that can be assessed and potentially revised after confrontation with RS and land surface-based observations. It is well known that realistic simulations of C and water dynamics in terrestrial ecosystems is of critical importance, not only for the surface microclimate, but also for the large-scale physics of the atmosphere (Cox et al., 1999; Gedney et al., 2006; Dickinson et al., 2002). Depending on the scientific objectives or applications, C and water cycle models have been designed with varying degrees of aggregation with respect to ecosystem processes, components, and RS data as model inputs. Such models can be flagged by land surface, ecosystem and hydrological models based on their objectives and emphases. The former focus on ecosystem processes and the interactions between ecosystems and the atmosphere; while the latter place emphasis on the land surface hydrology processes, including lateral flow resulting from catchment topography.

4.1 Land surface and ecosystem modeling

Global climate and the global carbon cycle are controlled by exchanges of water, carbon, and energy between the terrestrial biosphere and atmosphere. Thus land surface models (LSMs) are essential for the purpose of developing predictive capability for the Earth's climate on all time scales (Matthews et al., 1998). Most current LSMs can be associated with three broad types (Seth et al., 1994): soil-vegetation-atmosphere transfer schemes (SVATS), potential vegetation models (PVMs), and terrestrial biogeochemistry models (TBMs).

The first generation of SVATS evolved from simple bucket schemes focusing on soil water availability (Manabe et al., 1969), through the schemes of Deardorff (Deardorff et al., 1978).

Marked improvements of the second generation (e.g., BATS (Seth et al., 1994), SiB (Sellers et al., 1997; Sellers et al., 1986), and CLASS (Verseghy et al., 1999; Verseghy et al., 1993) from the first generation are the separation of vegetation from soil and the inclusion of multiple soil layers for dynamic heat and moisture-flow simulations (Chen et al., 2007). The second generation SVATS firstly modeled plant physiology in an explicit manner in GCMs (General Circulation Model or Global Climate Model) (Henderson et al., 1993). For most second-generation SVATS, land cover was fixed, with seasonally-varying prescriptions of parameters such as reflectance, leaf area index or rooting depth (Wang et al., 2002; Kickert et al., 1999; Kley et al., 1999; Schwalm et al., 2001). Some SVATS incorporated satellite data to characterize more realistically the seasonal dynamics in vegetation function (Kickert et al., 1999; Bonan et al., 1994). The latest (third generation) SVATS used more recent theories relating photosynthesis and plant water relations to provide a consistent description of energy exchange, ET, and C exchange by plants (Chen et al., 2007; Sellers et al., 1996). In our effort in understanding the impact of climate change on terrestrial ecosystems, energy, water, and C cycles need to be modelled simultaneously (Sellers et al., 1996; Williams et al., 2001). Recently, most of SVATS have thus been enhanced to include the CO₂ flux between the land surface and the atmosphere, such as SiB2 (Sellers, P.J et al, 1996), IBIS (Foley et al., 1996), NCAR-LSM (Bonan et al., 1995), BATS (Dickinson et al., 2002), CLASS-C (Wang et al., 2002) and EASS (Chen et al., 2007).

The earlier generation of PVMs comprised a suite of schemes that focus on modeling distributions of vegetation as a function of climate (Holdridge et al., 1947; Prentice et al., 1990) without influences of anthropogenic or natural disturbance. The second generation of PVMs included more sophisticated modules to account for factors controlling vegetation distributions, such as competition, varying combinations of plant functional types, and physiological and ecological constraints (Prentice et al., 1992).

TBMs developed from scaling up local ecological models, are process-based models that simulate dynamics of energy, water, and carbon and nitrogen exchange among biospheric pools and the atmosphere (Seth et al., 1994). Few of the existing TBMs incorporate PVMs. These models are not applicable to transient climate change experiments without coupling with PVMs.

In recent decades, the interactions among soil, vegetation and climate have been studied intensively and modeled successfully on the basis of water and energy transfer in the soil-vegetation-atmosphere system (Seth et al., 1994; Sellers et al., 1986; Verseghy et al., 1999; Verseghy et al., 1993; Zhang et al., 2003). Also the construction and refinement of LSMs have received increasing attention (Sellers et al., 1996; Viterbo et al., 1995; Christopher et al., 2004). Combination of these three different LSMs and utilization of remotely sensed land surface parameters are critical in the future LSM development, because of (1) the tight coupling of exchanges of water, energy and carbon between the land surface and the atmosphere; (2) the sophisticated impact/feedback mechanisms between climate change and terrestrial ecosystems; and (3) increasingly strong anthropogenic alterations to land cover. On-line coupling of a LSM with a GCM is needed for studying interannual to multi-decadal climate variations.

Several model intercomparisons have focused on evaluating SVATS and TBMs with particular objectives. For instance, the Project for Intercomparison of Land-surface Parameterization Schemes (PILPS) was initiated to evaluate an array of LSMs existing in GCMs (General Circulation Model or Global Climate Model) (Henderson et al., 1993); while

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the AMMA (African Monsoon Multidisciplinary Analysis) Land Surface Model Intercomparison Project (ALMIP) is being conducted to get a better understanding of the role of soil moisture in land surface processes in West Africa (de Rosnay et al., 2009). Coordinated land surface modeling activities have improved our understanding of land surface processes (de Rosnay et al., 2009).

4.2 Spatially-distributed hydrological processes modeling

Hydrology and ecosystem have, for the most part, been studied independently. Most LSMs and ecosystem models make an assumption of "flat Earth" with the absence of lateral redistribution of soil moisture. On the other hand, hydrological models have mostly been concerned with runoff production. Spatially-distributed models are needed, especially for hydrological simulation objective, because of heterogeneity of land surface and non-linearity of hydrological processes. Spatially-distributed hydrological models are not only able to account for spatial variability of hydrological processes, but enable computation of internal fluxes and state variables. Such kinds of models are increasingly applied to simulate spatial variability of forcing variables (*e.g.* precipitation), physiographic characteristics, detailed processes and internal fluxes within a catchment (Liang et al., 1994; Liang et al., 2004; Beldring et al., 2003; Brath et al., 2004; Christensen et al., 2007; Reed et al., 2004).

4.3 Modeling dynamics of stable C isotopic exchange between ecosystem and the atmosphere

It is recognized that the atmospheric measurements are still too sparse, relative to its spatial variability, to be used for inferring the surface flux at high spatial resolution (Ciais et al., 1995). The use of the isotope ratio as an additional constraint to identify various C sources and sinks can contribute to a significant reduction in the uncertainty. Though available isotopic datasets are being accumulated quickly (Griffis et al., 2005; Ponton et al., 2006; Lai et al., 2006; Lai et al., 2005) isotope measurements are still lacking considering land surface diversity and heterogeneity. This shortage of long-term measurements and of sampling frequency still limits C isotopic studies.

Mechanistic ecosystem models that couple micrometeorological and eco-physiological theories have the potential to shed light on how to extend efforts and applications of stable isotopes of CO₂ to global C budgeting, because biophysical models have the capacities of simulating isotope discrimination in response to environmental perturbations and can produce information on its diurnal, seasonal and interannual dynamics. Few biophysical models, however, have been developed to assess stable C discrimination between a plant canopy and the atmosphere (Suits et al., 2005; Oge'e et al., 2003; Baldocchi et al., 2003). Most existing biophysical models are based on individual leaf level discrimination equations given by Farquhar et al. (Farquhar et al., 1989; Farquhar et al., 1982) and only focus on the land surface layer (ignoring vertical and horizontal advection effects beyond 50~100 m above the ground (Baldocchi et al., 2003). However, in nature, the convective boundary layer (CBL) integrates the effects of photosynthesis, respiration, and turbulent transport of CO₂ over the landscape (Lloyd et al., 1996; Pataki et al., 2003). The influence of the CBL cannot be ignored when using isotope composition of CO₂ to investigate biological processes (Bowling et al., 1999), because the effect of atmospheric stability on turbulent mixing/diffusion has an important impact on scalar fluxes and concentration fields within

and above canopies (Baldocchi et al., 1995; Leuning et al., 2000). Few such models considering the CBL effects on isotope fractionation have been developed to date (Lloyd et al., 1996; Lloyd et al., 2001; Chen et al., 2006; Chen et al., 2006; Chen et al., 2007).

4.4 Modeling coupled C and water dynamics – An ecohydrological approach

C and N dynamics and hydrological processes are closely linked. The stomatal conductance (g_s) is the key linkage between C assimilation (photosynthesis) and transpiration. An empirical equation is used in the second-generation LSMs to calculate g_s , which is hypothesized to be controlled by the environmental conditions (Jarvis et al., 1976). While field and laboratory studies have documented that leaf photosynthesis also affects g_s . Therefore, Ball *et al.* (Ball et al., 1987) proposed a semi-empirical stomatal conductance formulation (Ball-Woodrow-Berry model), in which g_s is controlled by both photosynthesis and the environmental conditions. Most of third-generation LSMs (Ecological models, *e.g.* SiB2 (Sellers et al., 1997; Sellers et al., 1996); CN-CLASS (Arain et al., 2006); *Ecosys* (Grant et al., 2007; Grant et al., 1999; Chen et al., 2007) fully couple photosynthesis and transpiration processes by employing the Ball-Woodrow-Berry stamatal conductance formulation.

In addition to the coupling of hydrological condition and C assimilation through the linkage of g_{sr} C assimilation is also coupling with N dynamics through another biochemical parameter, V_{cmax}^{25} --- maximum carboxylation rate at 25 °C. In the photosynthesis model proposed by Farquhar *et al.* (1980), the net photosynthetic rate A_{net} at leaf level is a function of two tightly-correlated parameters V_{cmax}^{25} and J_{cmax}^{25} (the maximum electron transport rate at 25 °C), and is calculated as,

$$A_{net} = \min(A_c, A_j) - R_d \tag{10}$$

where A_c and A_j are Rubiso-limited and light-limited gross photosynthesis rates, respectively, and R_d is the daytime leaf dark respiration and computed as $R_d = 0.015 V_{c max}$. A_c and A_j are expressed as,

$$A_{c} = V_{c \max} \frac{C_{c} - \Gamma^{*}}{C_{c} + K_{c} (1 + O_{c} / K_{o})}$$
(11a)
and,
$$A_{j} = J_{\max} \frac{C_{c} - \Gamma^{*}}{4(C_{c} + 2\Gamma^{*})}$$
(11b)

where C_c and O_c are the intercellular CO₂ and O₂ mole fractions (mol mol⁻¹), respectively; Γ^* is the CO₂ compensation point without dark respiration (mol mol⁻¹); K_c and K_o are Michaelis-Menten constants for CO₂ and O₂ (mol mol⁻¹), respectively. In the nutrient-limited stands, A_{net} is generally limited by A_c , while A_c is dominantly controlled by a parameter V_{cmax} (see Eq. 11a). Many research results showed V_{cmax}^{25} is very sensitive to leaf N status (more specifically leaf Rubisco-N) (Dickinson et al., 2002; Wilson et al., 2000; Wilson et al., 2001; Warren et al., 2001). As a result in some ecosystem models (*i.e.* C&N-CLASS (Arain et al., 2006)), V_{cmax}^{25} is calculated as a nonlinear function of Rubisco-N following observations made by Warren and Adams (Dickinson et al., 2002):

$$V_{c\,\max}^{25}(N) = \alpha \left[1 - \exp(-1.8N_{r0}) \right]$$
(12)

where α is the maximum value of $V_{c \max}^{25}$ and N_{r0} is the leaf Rubisco-N (g N m⁻² leaf area) in the top canopy.

The coupled C, N and water processes have been carefully considered in most of the thirdgeneration LSMs (*e.g.* SiB2 (Sellers et al., 1997; Sellers et al., 1986; Sellers et al., 1996); CN-CLASS (Arain et al., 2006) and *Ecosys* (Grant et al., 2007; Grant et al., 1999), the models' grids, however, are isolated from their neighboring grids mainly due to the availability of input data. Vertical soil hydrological processes are hard to be realistically simulated if the lateral flows are ignored by assuming that the Earth is "flat". However, Simulations of the topographically-driven lateral water flows are important components in most of spatiallydistributed models, while the detailed ecophsiological processes are weakly represented (Govind et al., 2009). Much effort to bridge these two different models has been increasingly made (Rodriguez et al., 2001; D'odorico et al., 2004;Govind et al., 2009; Creed et al., 1998; Band et al., 2001; Porporato et al., 2002; Porporato et al., 2003; Daly et al., 2004; Chen et al., 2005). However, a model coupling approach --- a full combination of ecosystem model and hydrological model, *i.e.* ecohydrological modeling, is still lacking.

4.5 Applications of remotely-sensed data in ecohydrological modeling

Remote sensing techniques, which inherently have the ability to provide spatially comprehensive and temporally repeatable information of the land surface, may be the only feasible way to obtaining data needed for land surface and ecological modeling (Sellers et al., 1986; Gurney et al., 2003; Kite et al., 1996; Engman et al., 1996; Melesse et al., 2008). The most common rationale for interfacing remote sensing and land surface-ecosystem models is using remotely sensed data as model inputs (Plummer et al., 2000). These input data, corresponding to forcing functions or state variables in ecological modeling, include LC, LAI, normalized difference vegetation index (NDVI), and the fraction of photosynthetically active radiation (f_{PAR}) (Sellers et al., 1986; Running et al., 1998; Chiesi et al., 2002; Loiselle et al., 2001). Another effort is the direct estimation of GPP and net primary productivity (NPP) (Goetz et al., 1999; Seaquist et al., 2003) of biomass (Seaquist et al., 2003; Bergen et al., 1999) and of plant growth (Maas et al., 1988; Kurth et al., 1994), by making use of f_{PAR} and NDVI. It has been shown that the direct estimation has lower accuracy than the integration of remotely sensed data with process based models (Goetz et al., 1999).

Remote sensing data have also been used to parameterize hydrological models (Chen et al., 2005; Kite et al., 1996; Boegh et al., 2004). For instance, a hydrological model (TerrainLab) was further developed using remote sensing as inputs (Chen et al., 2005). TerrainLab is a spatially distributed, process-oriented hydrological model using the explicit routing scheme of Wigmosta et al. (Wigmosta et al., 2004). This model has been applied to flat areas such as boreal and wet land region, (Govind et al., 2009; Chen et al., 2005; Govind et al., 2009), but it has not yet been applied to mountainous areas.

Different from traditional hydrological models, which have coarse spatial resolutions, the grid-based-distributed ecohydrological models have a high demand for spatial data (Kite et al., 1996; Montzka et al., 2008). Some researchers highlight that the main obstacles in current distributed ecohydrological modeling is the lack of sufficient spatially distributed data for

input and model validation (Stisen et al., 2008). Remote sensing can potentially fill in some of the gaps in data availability and produce means of spatial calibration and validation of distributed hydrological models. As a result the application of remote sensing techniques in hydrological studies and water resources management has progressed in the past decades (see review by (Kite et al., 1996)).

In general, the applications of remotely sensed data in ecohydrological modeling can be in the two ways (Kite et al., 1996; Chen et al., 2005; Boegh et al., 2004; Montzka et al., 2008; Stisen et al., 2008; Ritchie et al., 1996; Schultz et al., 1996; Melesse et al., 2007; Schmugge et al., 2002; Jain et al., 2004; Pietroniro et al., 2005; French et al., 2006): (i) multispectral remote sensing data are used to quantify surface parameters, such as vegetation types and density. Although the usefulness of remote sensing data is widely recognized, there remain few cases where remote sensing data have been actually used in ecohydrological simulations. Difficulties still exist in choosing the most suitable spectral data for studying hydrological processes as well as in interpreting such data to extract useful in formation (Chen et al., 2005; Kite et al., 1996; Engman et al., 1996); and (ii) processed remote sensing data are used to provide fields of hydrological parameters for calibration and validation of ecohydrological models, such as precipitation (Kite et al., 1996; Wang et al., 2001), and soil moisture (Jackson et al., 1993; Hollenbeck et al., 1996., 1996; Kim et al., 2002; Koster et al., 2006). Koster et al. (Koster et al., 2006) pointed out that remote sensing data take the form of emitted and reflected radiances and thus are not the type of data traditionally used to run and calibrate models. Hence, it is important to understand and develop relationships between the electromagnetic signals and hydrological parameters of interest (Chen et al., 2005). Kite and Pietroniro (Kite et al., 1996) stated that the use of remote sensing in hydrological modeling was limited. Even though a number of new sensors have been launched since then and research has documented that remote sensing data have promising perspectives, operational uses of satellite data in hydrological modeling still appear to be in its infancy (Stisen et al., 2008).

5. Research gaps in C and water flux estimates and scaling approaches

A variety of methods are being used in the C and water cycles studies. As shown in Figure 3, different approaches have different temporal and spatial scales. The most direct measurements of the terrestrial C flux are made either at the plot scale $(10^{-2}-10^{1} \text{ m}^{2})$, *e.g.* using biometric methods and various forms of chamber, or at the ecosystem (patch) scale $(10^{4} - 10^{6} \text{ m}^{2})$, using the EC technique. Ecohydrological / ecosystem modeling and remote sensing estimations are generally available across variable spatiotemporal scales. These estimates are normally available within a nested framework that permits a progressive comparison of measurements made by surface instrumentation (scale: 1 to 10 m), surface flux equipment (10 m to 1 km), airborne remote sensing equipment (100 m to several km), satellite remote sensing (30 m to global scale) and EC tower (1-3 km),

The atmosphere integrates surface fluxes over many temporal and spatial scales and links scalar sources and sinks with concentrations and fluxes. This principle has been successfully used to develop inverse models to estimate annual C budgets (Tans et al., 1990; Enting et al., 1995; Fan et al., 1998; Bousquet et al., 1999; Gurney et al., 2002; Gurney et al., 2003). However, due to model limitations and paucity of continental CO₂ observations these

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studies have yielded C fluxes only at coarse resolution, over large spatial regions (Gurney et al., 2004; Gurney et al., 2005; Gurney et al., 2008).

Progress in C balance studies has been achieved at both ends of the spatial scale spectrum, either large continents (larger than 10⁶ km², e.g. global inverse modeling) or small vegetation stands (less than 1-3 km², e.g. EC-measurements). Methods to estimate CO₂ sources and sinks at the intermediate scale (i.e. landscape to regional scales) between continental and local scales are less well advanced. Moreover, the C cycle in different regions can vary markedly in response to changing climate (Friedlingstein et al., 2003). Reliable estimates of terrestrial C sources and sinks at landscape to regional spatial scales (finer than those used in global inversions and larger than local EC flux measurements and roughly defined as the range between 10² and 10⁶ km²) are required to quantitatively account for the large spatial variability in sources and sinks in the near-field of a measurement location (Gerbig et al., 2003), as well as fundamental to improving our understanding of the C cycle (Crevoisier et al., 2006).



Fig. 3. Temporal and spatial scales of different approaches

It is generally considered unreliable to upscale stand-level fluxes (i.e. EC measurements) to a region by simple spatial extrapolation and interpolation because of the heterogeneity of the land surface and the nonlinearity inherent in ecophysiological processes (Levy et al., 1999). It is also challenging to apply atmospheric inversion technique to regional scales for quantifying annual C budgets because at such intermediate scales the atmosphere is often poorly constrained (Matross et al., 2006; Gloor et al., 1999). Moreover, aggregation errors and errors in atmospheric transport, both within the PBL and between the PBL and free troposphere, can also be obstacles to using these approaches to obtain quantitative estimates of regional C fluxes (Lin et al., 2004). Hence, there is a strong motivation to develop methods

to quantify and validate estimates of the C balance at these intermediate scales (Lin et al., 2004; Chen et al., 2008; Bakwin et al., 2004; Matross et al., 2006). Observations of CO₂ over the continent within the PBL reflect exchange processes occurring at the surface at a regional scale ($10^2 - 10^5$ km²). The flux information contained in CO₂ concentration data represents footprints of up to 10^5 km² (Gloor et al., 2001; Lin et al., 2004), which are several orders of magnitude larger than the direct EC-flux footprint. This information is therefore needed in our effort to upscale from site to region. Moreover, the number of CO₂ mixing ratio measurements above the land surface, made by either tower or aircraft, is steadily increasing. Previous efforts to interpret the signal of regional CO₂ exchange making use of tower concentration data have focused on simple one-dimensional PBL budgets that rely on gradients in CO₂ concentrations between the PBL and the free troposphere (Bakwin et al., 2004; Helliker et al., 2004). These methods are limited to monthly resolution because of the need to smooth and average over several synoptic events (Matross et al., 2006).

6. Future research directions

A synthetic research framework is needed to strength the less well researched areas as reviewed in Section 5: bottom-up and top-down approaches integrating scalable (footprint and ecosystem) models and a spatially nested hierarchy of observations which include multispectral RS, inventories, existing regional clusters of eddy-covariance flux towers and CO_2 mixing ratio towers and chambers.

The current research trends and the future directions in this field include: (i) A synthesis aggregation method --- integrating ecohydrological and isotopic models, remote sensing and component flux data, is becoming a pragmatic approach towards a better understanding of the coupled C, N and water dynamics at landscape/watershed scales; and (ii) The landscape- and regional-scale C fluxes are being estimated using an integrated approach involving direct land surface measurements, RS measurements, and ecosystem-, footprint- and inversion- modeling.

7. Summary

After comprehensive reviewing of a variety of approaches being used in research on the C/water cycles, the concluding remarks are summed the following:

Research gaps in this field are (i) The coupled terrestrial C and hydrological dynamics are far from well understood, especially at landscape (watershed) and regional scales; (2) Much progresses have been achieved at the extreme ends of the spatial-scale spectrum, either large regions/continents or small vegetation stands. Because of the heterogeneity of the land surface and the nonlinearity inherent in ecophysiological and ecohydrological processes in response to their driving forces, it is difficult to upscale stand level results to regions and the globe by extrapolation. Budgets of C and water at landscape intermediate regional scales (10^2-10^5 km^2) have large uncertainties.

A coupled spatially-explicit ecohydrological model is a powerful tool for quantitative and predictive understanding of the coupled C and water mechanism. This modeling framework can be used to infer aspects of the land surface system that are difficult to measure, and will be critical to improving the accuracy of forecasts of landscape change and C dynamics in the real world.

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Combining and mutually constraining the bottom-up and top-down methods to reduce their uncertainties using data assimilation techniques is a practical and effective means to derive regional C and water fluxes with reasonably high accuracy. In the future upscaling framework, spatially nested hierarchy of observations, including multispectral RS, inventories, existing regional clusters of EC flux towers and CO₂ mixing ratio towers and chambers, are able to integrated using scalable (footprint and ecosystem and ecohydrological) models and data-model fusion techniques.

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