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FIELDS AND RADIATION

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Definition

Remote sensing is the technique to retrieve information about an object without being in physical contact with it (Elachi, 1987). This information is acquired by detecting and measuring changes that the object under investigation imposes on the surrounding field.

The interacting field can be an electromagnetic, acoustic, or gravitational field. The *electromagnetic field* is due to space–time variations of the electric and the magnetic fields (Ulaby et al., 1981; Ishimaru, 1991). Static electric and magnetic fields can be originated by a stationary electric charge distribution or by stationary currents or ferromagnetic materials, respectively. The electromagnetic methods, which are the most frequently used in remote sensing, cover the whole electromagnetic spectrum from radio-frequency waves to gamma rays through microwaves, submillimeter waves, and far infrared, near infrared, visible, ultraviolet, and x-ray waves. Acoustic *fields* are due to the continuous exchange between the fluid kinetic energy and the potential energy store during fluid compression (Lighthill, 1978). The acoustic refraction of Earth atmosphere depends on temperature, wind, and, to a lesser extent, on humidity. *Gravitational fields* are due to gravitational forces, typically exerted by a planetary mass. The gravitational fields determine the dynamics of objects embedded in the field itself.

Radiation represents the field propagation through waves. Amplitude, phase, polarization, and power are typical features of a field radiation (Elachi, 1987). The latter can be generated by transformation of energy from other sources such as kinetic, chemical, thermal, electrical, magnetic, or nuclear. Several transformation mechanisms can lead to field waves over different regions of the frequency spectrum. Generally speaking, the more organized the transformation mechanism is, the more coherent is the generated radiation. From a theoretical point of view, radiation can be stated through the wave equation which describes the wave propagation phenomenon for electromagnetic, acoustic, and gravitational fields (Ishimaru, 1991). Physical properties of the media where the field is generated, such as temperature, humidity, shape, and composition, determine the medium properties which govern the field–matter interaction. The refractive index of the atmosphere is a typical example of electric properties which influence electromagnetic propagation.

Due to their inherent remote operation, remote sensing systems must exploit a *propagation mechanism*. The capability to infer the characteristics of the object under remote observation are derived from the properties of the wave field that has interacted, through emission, absorption, scattering, reflection, or transmission, with the object itself (Ishimaru, 1981). The retrieved field interactions are mainly due to reflection, scattering, and transmission in case of active remote sensing systems, whereas to absorption and emission in case of passive systems. The reflected or scattered radiation has generally the same frequency of the incident one; however, there exist processes which can produce irradiation at frequencies different from the incident wave one, such as Raman scattering and fluorescence, in case of electromagnetic waves. Transmission properties of media determine the capability of radiation to penetrate the medium itself.

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Cross-references

Electromagnetic Theory and Wave Propagation
Media, Electromagnetic Characteristics
Radiation, Multiple Scattering
Radiation, Volume Scattering
Radiative Transfer, Theory

FISHERIES

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Definition

Catch per unit effort. CPUE standardizes fish catch data based on the amount of the effort (total time or area sampled) exerted.
Fishery stock. A subpopulation of a particular species in a given area. Unlike a fish population, a stock is defined as much by management concerns (such as jurisdictional boundaries or harvesting location) as by biology. There are three different types of stocks: commercial (exploited) species, unexploited species, and protected species. Stocks are not restricted to just fish, but also include marine mammals and invertebrates.
Fisheries stock assessment. An estimate of either the total population or total biomass of a fisheries stock. Stock assessments are a crucial component of fisheries management.
Fisheries management. The protection and management of fishery stocks to maintain sustainable exploitation for commercial species, and to recover the populations of protected and endangered species.
Fisheries oceanography. The study of oceanic processes affecting marine ecosystems and the relationship of these ecosystems to the abundance and availability of fish (Harrison and Parsons, 2001).
Living marine resources (LMR). A term to refer to all types of stocks, which is not restricted to just fish, but also includes marine mammals and invertebrates.
Operational fisheries. Utilizing oceanographic information to maximize the efficiency of fishing efforts.
Recruitment. The amount of fish added to the stock each year due to reproduction and/or migration into the stock area.

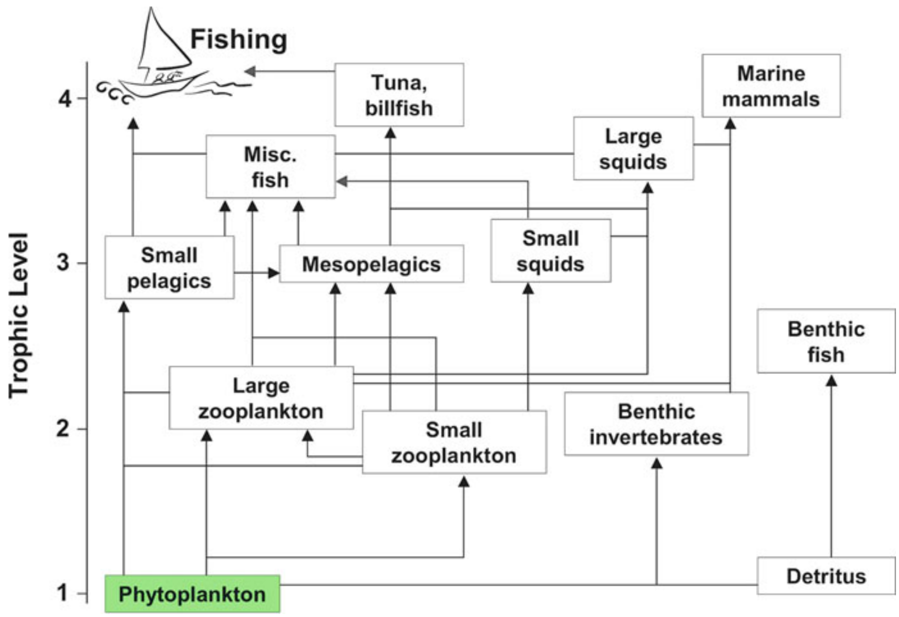
Fisheries and remote sensing

Introduction

In the broadest sense, fisheries encompass not just commercial fish stocks, but all living marine resources (LMRs), which for threatened and endangered species involve efforts to help the populations recover. There are three distinct aspects of fisheries: harvesting, assessment, and management, all of which have different goals. Harvesting efforts focus on increasing the catch per unit effort (CPUE), that is methods of finding, and more efficiently catching, more fish. Assessment involves both the species and its habitat. Stock assessments estimate either the total population or the total biomass of a fisheries stock in a given region, whereas habitat assessments characterize the environmental conditions favored by a species. Fisheries management uses both stock assessments and habitat assessments to set harvesting limits and guidelines on commercial stocks to maintain sustainable exploitation, and also to develop regulations to help recover the populations of protected and endangered species.

In the last half century, the world fish harvest has increased more than fourfold from 20 million tons in 1950 to over 90 million tons in 2000 (FAO Fisheries Department, 2004). At the same time the number of overexploited and depleted stocks has increased, and an expanding human population and problems with food supply have increased the pressure on fisheries resources. Better management and understanding of fisheries are needed to both maximize the utility of the current resources, and to ensure their sustainability into the future. However, these issues are complicated by the significant interannual variations that occur in fish populations, and sorting out fluctuations caused by anthropogenic effects (overexploitation, habitat alteration, pollution, etc.) from those caused by natural environmental variability is not trivial. The fundamental question of what drives the interannual variability of fish stocks was first posed over 100 years ago with the formation of the International Council for the Exploration of the Seas (ICES) in 1902, and still has not been adequately resolved (Kendall and Duker, 1998; Bakun and Broad, 2003).

Satellite data provide an environmental context within which to examine these issues, by measuring parameters of the habitat and ecosystems that influence marine resources at high temporal and spatial scales. There are two primary ways that satellite data are used within fisheries. One is to find populations, usually a commercial fish stock to increase CPUE, but also in some cases for conservation, for example, trying to identify locations of endangered cetaceans in order to minimize the number of lethal interactions with ships. A second application is characterizing and monitoring the habitat that influences living marine resources (LMRs). Most of the dynamic features that are important to ecosystems, that is, oceanfronts, eddies, convergence zones, river plumes, and coastal regions, cannot be adequately resolved without satellite data. Similarly,



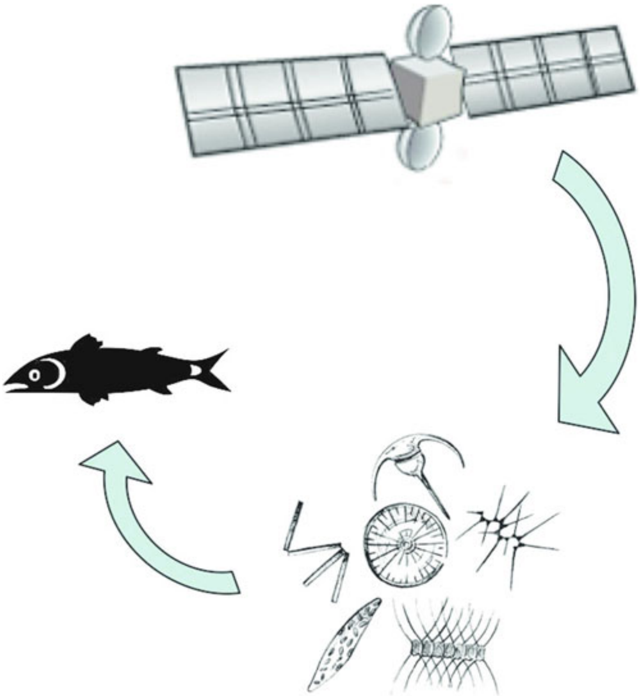
Fisheries, Figure 1 Schematic representation of the ocean food web.

satellite data are crucial for resolving the timing of processes such as upwelling, harmful algal blooms, seasonal transitions, and El Niño events. Remotely sensed variables such as sea surface temperature (SST), sea surface height, ocean color, ocean winds, and sea ice are all used to characterize relevant environmental conditions (SSH, ocean color, ocean winds and sea ice, here and elsewhere). Additionally, environmental satellite data are used to monitor a number of issues that impact fisheries, such as coastal pollution and coral reef bleaching events. For some coastal applications, particularly aquaculture, high-resolution imagery data has been a useful tool. Many of these applications are described in more detail in the IOCCG's (International Ocean Colour Coordinating Group) report on remote sensing in fisheries and aquaculture (IOCCG, 2009) and in the proceedings of an international symposium on remote sensing and fisheries held in 2010 (Stuart et al., 2011).

Satellite ocean color is particularly important to fisheries, since it is the only remotely sensed parameter that directly measures a biological component of the ecosystem (Wilson et al., 2008). Satellite chlorophyll provides an index of phytoplankton biomass, which is the base of the oceanic food chain, or food web, as depicted in simplified form in Figure 1. The relationship between satellite chlorophyll data and a specific fish stock depends upon the number of linkages between phytoplankton and the higher trophic level. For some species, such as anchovies and sardines, which eat phytoplankton at some points in their life cycle, the linkage can be direct (Ware and Thomson, 2005), whereas for other species there are many trophic levels in between and the relationship can be nonlinear. There can also be spatial disconnects between satellite measurements of the ocean surface and demersal and deepwater species. Nonetheless, chlorophyll is the only biological component of the marine ecosystem accessible to remote sensing, and as such it provides a key metric to measuring ecosystems on a global scale. Satellite chlorophyll measurements are the primary component in algorithms to calculate the primary productivity (PP) of the ocean. Global PP measurements, in conjunction with fish catch statistics and food web models, such as shown in Figure 2, can be used to estimate the carrying capacity of the world's fisheries. In the open ocean 2 % of the PP is needed to support the fishery catch, but in coastal regions the requirement ranges from 24 % to 35 %, suggesting that these systems are at or beyond their carrying capacity (Pauly and Christensen, 1995), which is a cause for concern as the bulk of the world's fish catch comes from coastal areas. In a similar manner, discrepancies between the values of satellite-derived PP and reported fish catches have been used to demonstrate spurious trends in global fish catches as reported by the Food and Agriculture Organization (FAO) of the United Nations (Watson and Pauly, 2001). In this instance satellite ocean color data provide an important objective baseline against which to gauge data that can have socioeconomic biases.

Operational fisheries (harvesting)

Locating and catching fish is becoming more challenging as fish stocks dwindle and move further offshore, thus increasing the search time, cost, and effort. Satellite data can help to increase CPUE by identifying oceanographic features that are often the sites of fish stock congregation and migration such as temperature fronts, meanders,



Fisheries, Figure 2 Cartoon of the connection between satellite measurements to fisheries through measurements of chlorophyll-bearing phytoplankton.

eddies, rings, and upwelling areas (Laurs et al., 1984; Fiedler and Bernard, 1987; Chen et al., 2005). Assuming adequate catch limitations are in place, increasing the CPUE is not incompatible with maintaining a sustainable fish stock population.

Both satellite ocean color and SST data have been used for increasing fishing efficiency. SST and ocean color often have similar patterns as generally warm, nutrient-depleted water has low chlorophyll concentrations and cold, nutrient-rich water has high chlorophyll. SST can also be an important factor for determining potential fishing grounds since different fish species have different optimal temperature ranges. Generally SST data have been used more often than ocean color data in fisheries applications. There are two main reasons for this. One, satellite SST is a more established data source, with data going back to 1981, whereas SeaWiFS, the first satellite to consistently provide satellite chlorophyll data on a global basis, was not launched until 1997. Second, SeaWiFS was a privately owned satellite, and while its data was always freely available, with a time delay, to the research community, the availability of near real-time (NRT) data needed by fishers for identifying potential fishing areas was only available on a commercial basis. For economic reasons that resulted in SeaWiFS data being unavailable to many fishers in the world, as the commercial costs of the real-time data can be prohibitive, particularly for those in underdeveloped countries, which is where 70 % of the fish for human consumption comes from (FAO Fisheries Department, 2004). Ocean color data from the MODIS instrument on Aqua, launched in 2002, is available at no cost on an NRT basis.

For use in increasing the CPUE, satellite data must be available in a near real-time basis. There are international differences in how satellite data are disseminated to fishers, as national agencies serve different constituencies (Wilson, 2011). The mandate of NOAA Fisheries in the USA, for example, is to manage and conserve marine resources, and they are not allowed to provide services such as distributing "fish finding maps" that would compete with commercial interests. However in other countries, notably Japan and India, the national fisheries agencies are actively involved with helping increase the efficiency of their fishing fleets. For example, data from the Indian Ocean color satellite (in conjunction with satellite SST) are used by the Indian National Center for Ocean Information Services (INCOIS) to make maps of potential fishing zones (PFZ), which are freely disseminated several times a week throughout coastal India by fax, phone, Internet, electronic display boards, newspaper, and radio broadcasts. Studies on the effectiveness of the PFZ advisories have suggested that they have helped reduce search time by up to 70 % and have significantly increased the CPUE (Solanki et al., 2003; Zainuddin et al., 2004).

Stock assessment

While satellite remotely sensed data are now widely used in operational fisheries, their use in stock assessments is just beginning (Koeller et al., 2009). The incorporation of environmental data of any kind into stock assessment models has rarely been achieved successfully, for several reasons. Assessments have traditionally taken classical single species approaches which deal only with the numeric population dynamics of the stock under review – the fish stock as "bank account," with principal (abundance), interest (growth), deposits (recruitment), and withdrawals (natural and fishing mortality) determined by research vessel surveys and fishery (catch, effort) data. The environmental factors forcing change to the bank account are complex, poorly understood, and difficult to measure; consequently, they have largely been excluded from traditional assessment models, greatly limiting their accuracy and effectiveness (Koeller et al., 2009). Additionally, radical changes to methodology, such as incorporating environmental data, would compromise the interannual time series of a stock population derived from stock assessments.

However, the advent of the "ecosystem approach to fisheries" (EAF) has given new impetus to better understand the environmental factors influencing fish stock dynamics and to try to include environmental variability as an integral part of the assessment process. It is particularly important to develop an understanding of the factors determining recruitment of commercially important fish and shellfish stocks, for two reasons: first, the adverse effects of fishing cannot be separated from "normal" environmentally driven changes unless the latter are thoroughly understood. Second, environmental factors modify underlying stock-recruitment relationships, arguably the most important information necessary to define reference points and achieve fisheries sustainability. Until recently, defining stock-recruitment relationships and identifying the environmental factors modifying them have been the "holy grail" of fisheries research, largely unresolvable with traditional oceanographic methods because of the complex, large- and small-scale spatial/long- and short-term temporal processes involved. However, the availability of environmental satellite data such as ocean color, SST, and altimetry is now making these objectives achievable.

Recruitment

A fundamental issue in fisheries oceanography is understanding how environmental variability affects annual recruitment, the number of new individuals entering a stock. Recruitment is an important parameter because the bulk of mortality occurs in the development of larvae from eggs. Most fish have planktonic larval stages that are strongly influenced by ocean circulation and can have narrow ranges of optimal thermal conditions. Availability of a good food source is important for successful recruitment and hence many fish reproduce near the seasonal peak in phytoplankton abundance. A long-standing hypothesis in fisheries has been that recruitment success is tied to the degree of timing between spawning and the seasonal phytoplankton bloom, the Cushing-Hjort or match-mismatch hypothesis (Cushing, 1969, 1990). This hypothesis has been difficult to address with traditional shipboard measurements that have limited spatial and temporal resolution, but with satellite ocean color data, interannual fluctuations in the timing and extent of the seasonal bloom can be clearly seen. In an application on the Nova Scotia Shelf, the timing of the spring bloom determined from satellite ocean color was compared with available in situ data on larval survival of haddock, an important commercial fish species. Comparison of these two independent data sets indicated that highly successful year classes of haddock are associated with exceptionally early spring blooms of phytoplankton, confirming the match-mismatch hypothesis (Platt et al., 2003). A comparable study has also documented a relationship between the timing of the spring bloom and the growth rate of shrimp (Fuentes-Yaco et al., 2007). These studies demonstrate that it can be possible to separate ecosystem-associated variability in fish stocks from other components such as human exploitation or predation effects. The satellite time series permits the extraction of value-added products, in this case the timing of the seasonal biological cycle. Understanding these processes will lead to improved and longer term fisheries forecasts, that is, for the period between birth and capture, which for some species can be as much as a decade.

Habitat assessment

Coral reef monitoring

Coral reef ecosystems support a high diversity of coral, fish, and benthic species, with corals forming the structural and ecological foundation of the reef system. Coral reefs are sensitive to their environment (temperature, light, water quality, and hydrodynamics), and as a result of both anthropogenic and climate impacts (Kleypas et al., 2001), they are among the most threatened coastal ecosystems worldwide (Pandolfi et al., 2003; Hoegh-Guldberg et al., 2007). Corals have a symbiotic relationship with a microscopic organism, zooxanthellae, which provides the corals with oxygen and a portion of the organic compounds they produce through photosynthesis. When stressed, many reef inhabitants expel their zooxanthellae en masse. The polyps of the coral are left bereft of pigmentation and appear nearly transparent on the animal's white skeleton, a phenomenon referred to as coral bleaching.

Severe bleaching events can have dramatic long-term effects on the coral. Recovery rates appear to differ with species, and the time required to attain full recovery of symbiotic algae varies from as little as 2 months to as much as 1 year. When the level of environmental stress is high and sustained, the coral may die. Since the late 1980s, coral bleaching related to thermal stress has become more frequent and more severe. High SSTs associated with the 1997–1998 El Niño caused bleaching in much of the world's oceans, particularly in the Indian Ocean and in the western Pacific. Other major bleaching events occurred around the Great Barrier Reef and Northwestern Hawaiian Islands in 2002 and in the Caribbean in 2005.

With the capability of providing synoptic views of the global oceans in near real time and the ability to monitor remote reef areas, satellite remote sensing has become a key tool for coral reef managers and scientists (Mumby et al., 2004; Maina et al., 2008; Maynard et al., 2008). Since 1997, NOAA has been producing near-real-time, web-accessible, satellite-derived SST products to globally monitor conditions that might trigger coral bleaching from thermal stress. Currently NOAA's Coral Reef Watch Program provides operational products such as SST anomalies, bleaching hot spot anomalies, Degree Heating Weeks, and Tropical Ocean Coral Bleaching Indices to the global coral reef community (Strong et al., 2006). These products provide an effective early warning system globally, but are not always accurate in predicting the severity of a bleaching event at a regional scale (McClanahan et al., 2007; Maynard et al., 2008). In Australia, CSIRO's (Commonwealth Scientific and Industrial Research Organisation) ReefTemp project produces satellite-derived bleaching risk indices specifically for the Great Barrier Reef (Maynard et al., 2008).

Tagging

Electronic tagging of LMRs is a key methodology to gather information needed for accurate and responsible fisheries management. Satellite data is crucial to place track data in an environmental context, in order to fully understand foraging and migration patterns, fish behavior and feeding ecology, habitat selection, and individual and population-level responses to environmental and climate variability. This approach has been used to characterize the environment of a wide variety of tagged species – turtles, penguins, seals, salmon, etc. – to better understand both their behavior and their habitat (Block et al., 2003; Hinke et al., 2005; Ream et al., 2005 ; Polovina et al., 2006; Weng et al., 2007). An example of this is described in fuller detail under the "Sea Turtles" subheading in the "Management of Protected Species" section.

Survey support

Fishery independent surveys are a crucial part of stock assessment. Just as satellite data can be used to increase fishing CPUE by identifying front locations and other features where fish tend to congregate, these data are also routinely used by fisheries cruises doing survey assessments for management and stock assessment. The near real-time data are valuable for locating fronts and other relevant features to sample across, as well as placing the results in a larger spatial context.

Fisheries management

Vessel monitoring system (VMS)

A standard fishery management tool is to close certain areas to fishing or to establish restricted fishing in certain areas, but ensuring that regulations and laws are being adhered to can be difficult for enforcement agencies. Satellite-based vessel monitoring systems (VMS) enable vast expanses of the ocean to be effectively monitored. By using a transmitter aboard commercial fishing vessels, paired with traditional global positioning satellites, vessels can be monitored while at sea to determine if they are fishing in closed areas or out of season. An obvious limitation of VMS is that vessels without installed VMS units, or vessels with faulty VMS units, are not monitored. In many fisheries, fishing vessels are required to carry an operational VMS transmitter, but illegal fishing is still possible by noncompliant fishing vessels. Recently synthetic aperture radar data have been used to successfully identify noncompliant fishing vessels, that is, vessels operating without VMS units (Kourti et al., 2005). In addition to their aid in enforcement of fisheries regulations, VMS data can provide valuable information to managers about both fish stock distributions and patterns of fishing activities (Deng et al., 2005; Mills et al., 2007; Bertrand et al., 2008).

Management of protected species

Monk seals

In the late 1980s, field programs monitoring monk seal pup survival, sea bird reproductive rates, and reef fish densities in the Northwestern Hawaiian Islands (NWHI) indicated ecosystem changes had occurred. However, due to a lack of oceanographic data at sufficient space and time scales, it was difficult to construct environmental indicators, or envision how environmental variation might be coupled with the higher trophic level changes (Polovina et al., 1994). The launch of the SeaWiFS ocean color sensor in 1997 allowed assessment of basin-wide biological variability across the Pacific. The SeaWiFS imagery shows that during the winter, the northern atolls of the Hawaiian Archipelago, Kure, Midway, and Laysan Atolls are located at the boundary between the cool, high surface chlorophyll, vertically mixed water on the north and the warm, low surface chlorophyll, vertically stratified subtropical water on the south. This boundary has been termed the transition zone chlorophyll front (TZCF) (Polovina et al., 2001).

In some years, the TZCF remains north of these northern atolls throughout the year, while in other years, the TZCF shifts far enough south during the winter to encompass these atolls with higher chlorophyll water. Hence, the ecosystem of the northern atolls is more productive after the TZCF is located more southerly relative to its long-term winter position. Specifically during a winter when the TZCF was shifted south of its average position, monk seal pup survival increased 2 years later (Baker et al., 2007). The 2 year time lag probably represents the time needed for enhanced primary productivity to propagate up the food web to monk seal pup prey. Should management action, such as a head start program, be developed to improve pup survival, a 2 year forecast based on satellite ocean color can be used to predict the years when low survival is likely and hence when management intervention is needed.

Right whales

With fewer than 400 individuals left, the North Atlantic right whale is one of the most endangered whale populations (International Whaling Commission, 1998; Kraus et al., 2005). This population spends much of its time in US and Canadian waters, with the winter calving grounds off of Florida, Georgia, and South Carolina, and feeding grounds in the Gulf of Maine. The recovery of this population is limited by high mortality, especially due to ship strikes and entanglements in fishing gear. Because its habitat overlaps with lucrative fishing grounds and shipping lanes of major US ports, reducing mortality is politically and economically challenging (International Whaling Commission, 1998; Kraus et al., 2005). The current management strategy involves limiting adverse impacts by requiring modifications to fishing gear or vessel speeds in regions and time periods when whales are likely to be present. Thus, all management options require knowing when and where whales are likely to be. The question is how to identify these likely regions within a dynamic ocean environment.

A new approach to locating right whales combines synoptic information from satellites with a model of the right whales' main prey. Right whales feed on small crustaceans called copepods, especially the large and abundant species *Calanus finmarchicus*. High numbers of whales are typically found in regions of high copepod concentrations (Pendleton et al., 2009). Many important rates in *Calanus*'s life cycle can be estimated using satellite data. The time required for an egg to develop into an adult is related to temperature, with shorter generation times in warmer water. Using satellite chlorophyll as a proxy for phytoplankton, the main food of *Calanus*, determines how quickly a female copepod can produce eggs. By combining the rate information derived from satellite data with reconstructions of the ocean currents from a computer model, estimated maps of *Calanus* abundance can be produced and related to right whale distributions (Pershing et al., 2009a, b). An initial test of this system forecasted that due to the cold winter in 2008, the *Calanus* population would be delayed, and that whales would arrive on their main spring feeding ground east of Cape Cod 3 weeks later than normal. While a full analysis of the data is underway, it appears that the whales arrived close to when the model predicted. These forecasts are currently being expanded to include a wider area of space and time and will soon be able to incorporate observations of both copepods and whales.

Sea turtles

A pelagic longline fishery based in Hawaii occasionally catches several species of sea turtles, with the threatened loggerhead sea turtle historically accounting for the majority of the turtle bycatch. Since 1997, Argos-linked transmitters have been attached to loggerhead sea turtles caught and released by longline vessels (Polovina et al., 2000), in order to characterize migration and forage areas of loggerheads, with the aim of spatially separating the fishery from the loggerheads. In recent years, the number of tracked turtles has been augmented by releasing hatchery reared loggerheads provided by the Port of Nagoya Aquarium, Nagoya, Japan. To characterize turtle habitat it is necessary to place their tracks within an environmental context. The use of satellite SST, ocean color, altimetry, and wind data have all been important in defining the oceanographic habitat of turtles within the North Pacific (Polovina et al., 2000, 2004, 2006; Kobayashi et al., 2008), allowing determination of seasonal habitat maps (Kobayashi et al., 2008). By combining this information with fisheries and fisheries bycatch data, it is now possible to predict the locations of areas with a high probability of loggerhead and longline interactions (Howell et al., 2008). In 2006, NOAA launched an experimental product called TurtleWatch, which uses satellite oceanographic data to map, in near real time, areas with a high probability of loggerhead and longline interactions, so that fishers can avoid them. This information benefits both the turtles and the fishers, who operate under strict limits on the number of turtle interactions allowed. The TurtleWatch tool is generated and distributed daily in near real time since the zone with the high probability of loggerhead bycatch is a temporally dynamic feature. The TurtleWatch product is also provided to fishers onboard via a commercial fisheries information system.

Aquaculture

Many aquaculture species (e.g., bivalves, shrimp) are suspension feeders and derive nutrition from particulates, the most nutritious being phytoplankton. Bivalve aquaculture can have a significant impact on the local environment by reducing both the levels of particulates in the water, and of anthropogenic eutrophication (Lindahl et al., 2005). Given its ability to measure both phytoplankton and also turbidity (Hoepffner et al., 2008), which is determinal for some species, satellite ocean color data can be a valuable tool in aquaculture development, but currently it is underutilized in this capacity (Grant et al., 2009). The primary reason for this underutilization is resolution – many aquaculture sites are below the spatial detection of single pixels, for example, small estuaries and bays 1 km wide (see *Coastal Ecosystems*). Various high-resolution commercial satellites have been used for aquaculture applications such as mapping mussel farms (Alexandridis et al., 2008), and site selection for nearshore aquaculture sites has been routinely based on the use of multispectral images from high spatial-resolution sensors (e.g., Landsat, Spot) which more recently have been complemented with the application of sensors such as Aster or IRS LISS/PAN (Dwivedi and Kandrika, 2005). However, medium resolution environmental satellite data can be used for open ocean applications. For example, site selection of sea bream and sea bass cages near the Canary Islands (Spain) made extensive use of SST data for the identification of suitable culture temperatures in the region (Pérez et al., 2003). Radar imagery (ERS-2 and RADARSAT) has been used to inventory and monitor milkfish cage culture in the Philippines (Travaglia et al., 2004).

Fisheries and climate

The SeaWiFS ocean color sensor was launched in August of 1997, just prior to the 1997/1998 El Niño which was one of the strongest ENSO (El Niño-Southern Oscillation) events of the century. This satellite data, in synergy with data from an extensive array of moorings across the equatorial Pacific, has contributed enormously to our understanding of ENSO dynamics and their ecosystem impacts. Deepening of the thermocline, and cessation of upwelling along the equator and in the coastal ecosystems, lowers ocean productivity and causes significant drops in the anchovy fisheries of Peru and Chile (Alamo and Bouchon, 1987; Escribano et al., 2004). However, other species are positively impacted by El Niño, for example, increases are observed in the biomass of sardine and mackerel (Bakun and Broad, 2003; Ñiquen and Bouchon, 2004). Satellite ocean color data have demonstrated that the effects of El Niño are not constrained to just the equatorial and coastal upwelling regions, but extend throughout most of the Pacific Ocean. For example, during the 1997/1998 event the TZCF was shifted ~5° south of its regular position (Bograd et al., 2004), and lower chlorophyll values occurred across most of the subtropical Pacific (Wilson and Adamec, 2001).

Since we only have continuous ocean color data from 1997 onward, it is not possible to detect decade-scale variability with just these data (see *Climate Monitoring and Prediction*). However, it is possible to observe long-term changes by comparing climatological SeaWiFS data with data from the Coastal Zone Color Scanner (CZCS), which operated between 1979 and 1985. For example, the present wintertime position of the TZCF in the Pacific is about 5° further north than it was during CZCS time period, and this shift has also been seen in SST data used as a proxy for the TZCF (Bograd et al., 2004). Data from these two different satellites have also been used to demonstrate regions of the ocean which have experienced significant changes in the amount of chlorophyll and primary productivity in the past 20 years (Gregg and Conkright, 2002; Gregg et al., 2003).

There is significant long-term temporal variability in fish stocks, and for over 150 years, scientists have been trying to differentiate the effects of interannual variability, overfishing, and long-term changes such as regime shifts, which are characterized by relatively rapid changes in the baseline abundances of both exploited and unexploited species (Polovina, 2005). Long-term variations in ecosystems often follow trends or patterns also observed in ocean and atmosphere parameters (Mantua et al., 1997; Hare, and Mantua, 2000; Peterson and Schwing, 2003). For example, a shift in the North Pacific in the 1970s between a shrimp-dominated ecosystem to one populated primarily by several species of bottom-dwelling groundfish species coincided with a regional change from a cool to a warm climate (Botsford et al., 1997; Anderson and Piatt, 1999). While similar phenomena have been seen for many different stocks, and in all ocean basins, the mechanisms that link large-scale ocean and atmosphere dynamics to changes in population abundances are not always clear (Botsford et al., 1997; Baumann, 1998) and the relationships are not always constant over time (Solow, 2002). Ecosystem changes related to regime shifts are not in themselves harmful to the ecosystems as a whole (Bakun and Broad, 2003), but in order to maintain sustainability, management practices must be flexible enough to recognize and accommodate them (Polovina, 2005). One of the current limitations of satellite data is their relatively short time-spans. For fisheries applications it is crucial that climate quality records of ocean color be maintained so that existing satellite records will be able to serve as a benchmark against which to gauge future changes and to track historical variations.

Summary

Satellite data characterize oceanic properties of habitat and ecosystems that influence living marine resources at spatial and temporal resolutions that are impossible to achieve any other way. The high spatial resolution provides an important geographical context for interpreting other data. The daily-to-weekly temporal resolution allows for effective monitoring of many oceanic features and permits the extraction of value-added products such as the timing of seasonal events. For fisheries applications it is crucial that climate quality records of ocean color be maintained so that existing satellite records will be able to serve as a benchmark against which to gauge future changes and to track historical variations. These time series of science-quality satellite data are needed to understand linkages between climate and ecosystems, and to characterize and monitor ecosystems as part of an ecosystem-based approach to fisheries management.

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Cross-references

Climate Monitoring and Prediction
Coastal Ecosystems
Ocean Measurements and Applications, Ocean Color
SAR-Based Bathymetry
Sea Ice Concentration and Extent
Sea Surface Temperature
Sea Surface Wind/Stress Vector

FORESTRY

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Synonyms

Forest conservation; Forest management/forest ecosystem management; Non-timber forest products; Silviculture; Sustainable forest management; Timber management

Definition

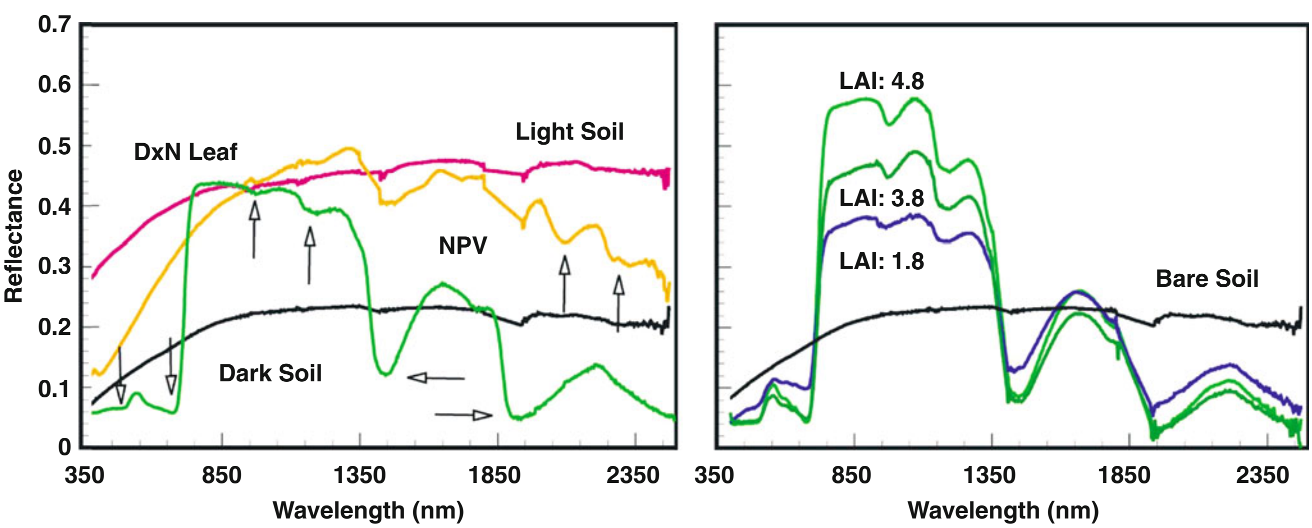
Forestry. The science of planting, monitoring, describing, and managing forests and forest systems and tree plantations for their goods and services, often for commercial production, natural resource use, and habitat preservation. More recently, consideration of the role of forests in carbon cycling and cultural and spiritual values is included.

Introduction

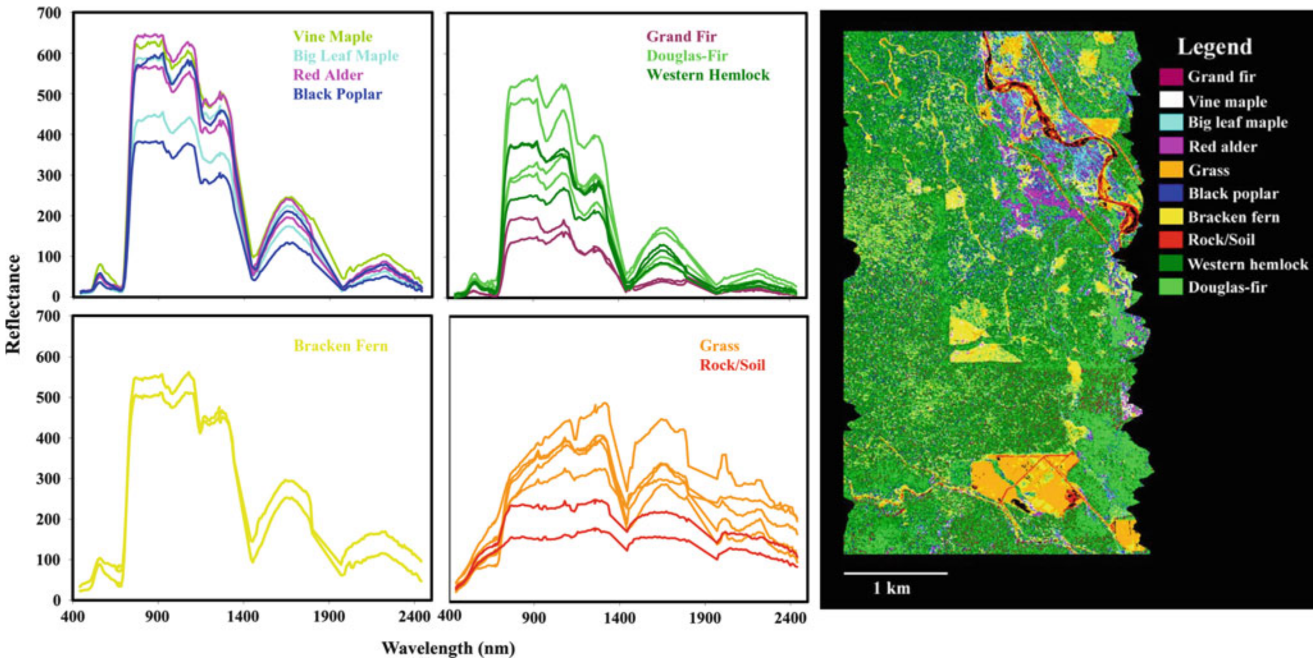
Remote sensing has a long history in forestry, starting with the use of aerial photography in the early 1900s and progressing to more advanced satellite and airborne sensors today. While photointerpretation of aerial photography remains an important tool (Wulder, 1998), the launch of Landsat in 1972, and proliferation of numerous digital airborne and spaceborne sensors since then have broadened the types of research questions that can be asked, and the spatial area over which forests can be mapped and monitored.

The wavelength-dependent intensity of electromagnetic radiation reflected or emitted from vegetation is a product of light scattering and absorption processes occurring at multiple scales. At the finest scales at or below the scale of an individual leaf or branch, the interaction varies depending on anatomy (i.e., thickness, internal structure, optical discontinuities between cell membranes) and biochemistry (molecular absorptions due to water, pigments, and other biochemical compounds and chlorophyll fluorescence; Gates et al., 1965). At canopy scales, the interaction depends upon the number of scatterers and absorbers and their physical arrangement, such as the number of leaves per unit volume and their angular distributions, the ratio of leaves to branches, crown geometry, and tree height. At stand scales, important stand attributes include tree density (trees/unit area), species composition, and stand area. In the reflected solar spectrum (0.350–2.5 μm), the manner in which these multiscale processes modify reflected light can be used to infer important plant biochemical or structural properties, such as the number of leaves per unit ground area, known as Leaf Area Index (LAI: Figure 1). Biochemical, anatomical, and structural differences can also be used to discriminate tree species (Figure 2), map invasive tree species or forest pathogens (Wulder et al., 2006), and infer species diversity (Asner et al., 2009). In the Mid- and Thermal infrared (IR: 2.5–14 μm), emission depends on the temperature of individual canopy components (leaves and branches) and wavelength-dependent emission efficiency, called emissivity (Salisbury and Milton, 1988). Emissivity is very high for water-filled leaves and lower for branches and stems. Given knowledge of emissivity, canopy temperatures can be estimated and used to infer important plant physiological processes, such as rates of evapotranspiration. In the microwave (>1 mm), scattering and absorption depend on the physical size of canopy components, their orientation, and their dielectric properties, which are largely controlled by water content. Large, water-filled branches are highly reflective in the microwave.

Remote sensing systems can be broadly divided into active and passive sensors. Active remote sensing systems emit a directional energy pulse that interacts with a surface and then returns to the sensor. Information is determined about the surface based on the length of time it takes for the pulse to return, the strength of the returned pulse, and other attributes such as a change in polarization. The two



Forestry, Figure 1 Poplar leaf (*left*) and canopy reflectance (*right*). Leaf scale spectra are shown for a *Populus. deltoides* x *Pinus. nigra* hybrid and compared to two soils and Poplar wood (labeled NPV). Important biochemical absorptions are marked with arrows including chlorophyll (480 and 680 nm), water (980, 1,200, 1,450, and 1,900 nm), and lignocellulose (broad regions at 2,100 and 2,300 nm). Spectra on the right show how reflectance changes with increasing LAI, including an increase in NIR and decrease in red reflectance. Liquid water bands at 980 and 1,200 nm are enhanced as light encounters more leaves with an increase in LAI (Roberts et al., 2004) (Adapted from Davis and Roberts, 1999).



Forestry, Figure 2 Spectra of four broadleaf tree species, three conifers, bracken fern, senesced grass, and rock/soil, including multiple spectra of several of the species (*left*). Spectral differences within a plant species illustrate that spectra are often not unique, but vary with architecture, illumination, or other factors. Map of plant species at Wind River, Washington, generated using 2003 AVIRIS data (*right*).

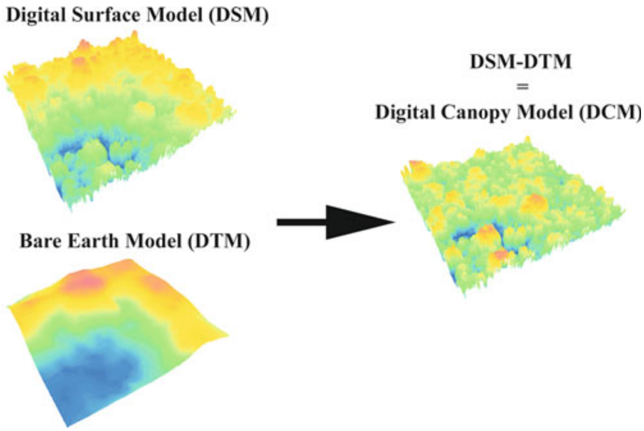
primary active remote sensing systems used for forestry applications are radio detection and ranging (radar), which uses wavelengths of electromagnetic radiation longer than a millimeter, and light detection and ranging (lidar), which most often uses NIR lasers (0.9–1.064 μm). Active remote sensing is the primary tool used for mapping forest structure (e.g., tree height, crown properties, cover, and aboveground biomass). Passive remote sensing systems measure electromagnetic radiation that is either reflected solar radiation or emitted from the surface. Passive remote sensing systems include aerial photography and airborne or spaceborne scanners that measure a few to many wavelengths of light. Passive remote sensing systems play a greater role in mapping changes in forest cover, forest health, and plant chemistry. Both passive and active remote sensing methods are employed at the ground level, including the use of hemispherical photographs to estimate crown closure and LAI and laser range finders and ground-based lidar to estimate tree height (Davis and Roberts, 1999).

Remote sensing applications

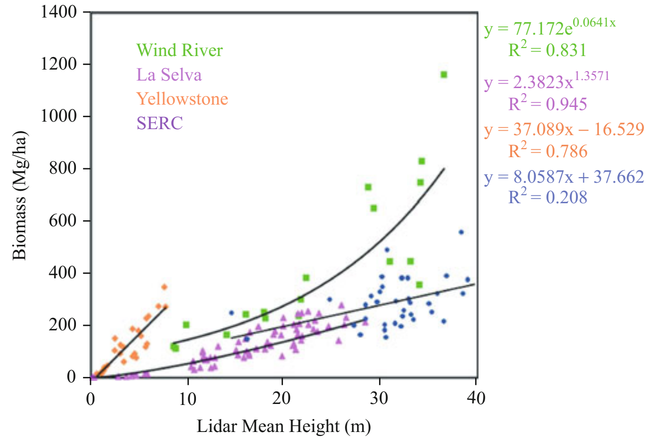
Forest inventories

One of the primary remote sensing forestry applications has been to aid in the development of forest inventories. Forest inventories are designed to quantify important properties of forest stands, including stand density (the number of trees per unit area), crown closure, average crown diameters, tree heights, and species composition (Avery and Burkhart, 1983). Species composition can be determined using dichotomous photointerpretation keys based on such measures as branching patterns, crown shape, the presence or absence of leaves, and color for color or color-infrared film (Heller and Ulliman, 1983). Tree height can be estimated using stereoscopic techniques, or geometrically from information on sun angles, viewing geometries, and shadows cast by trees. Stand volume and aboveground biomass can be estimated given accurate estimates of height, crown closure, and species composition using relationships derived from field methods. Aerial photographs also aid in improved field sampling by providing forest cover area and through improved stratified random sampling. Several national-scale inventory programs have relied extensively on stratified random sampling from aerial photography, including the forest inventory (Analysis Program: FIA: http://fia.fs.fed.us/) in the United States. Species-level differences in leaf optical and structural properties make it possible to discriminate individual tree species, using sensors such as the Advanced Visible/Infrared Imaging Spectrometer (AVIRIS: Roberts et al., 2004; Figure 2).

While coarser spatial resolution, spaceborne sensors can provide many important components of a forest



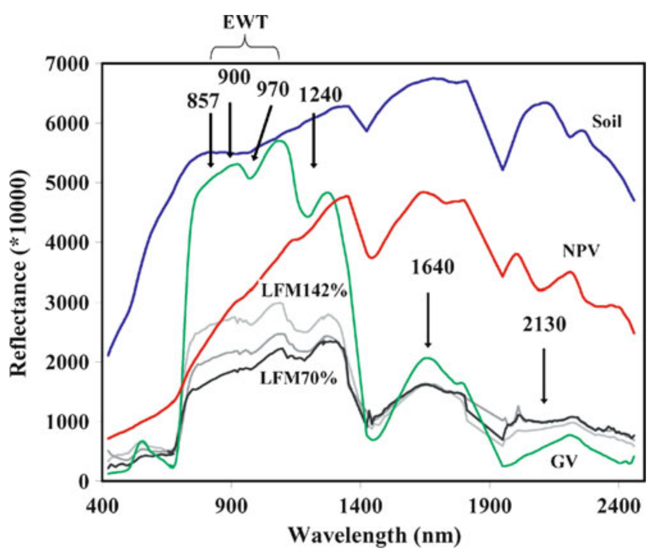
Forestry, Figure 3 Showing how a digital canopy model (DCM) is calculated from a digital surface model (DSM) and bare earth model (digital terrain model: DTM). This DSM was generated from a first return lidar system flown over La Selva, Costa Rica. The DTM was calculated using the same data by searching for ground returns within a fixed search window (Adapted from Clark et al., 2004).



Forestry, Figure 4 Plot of biomass (y) against mean lidar height (x) from four different forests: Wind River (mixed western hemlock and Douglas fir), La Selva (tropical rain forest), Yellowstone (Lodgepole pine), and SERC (mixed broadleaf deciduous). SERC included courtesy of Keely Roth of UC Santa Barbara.

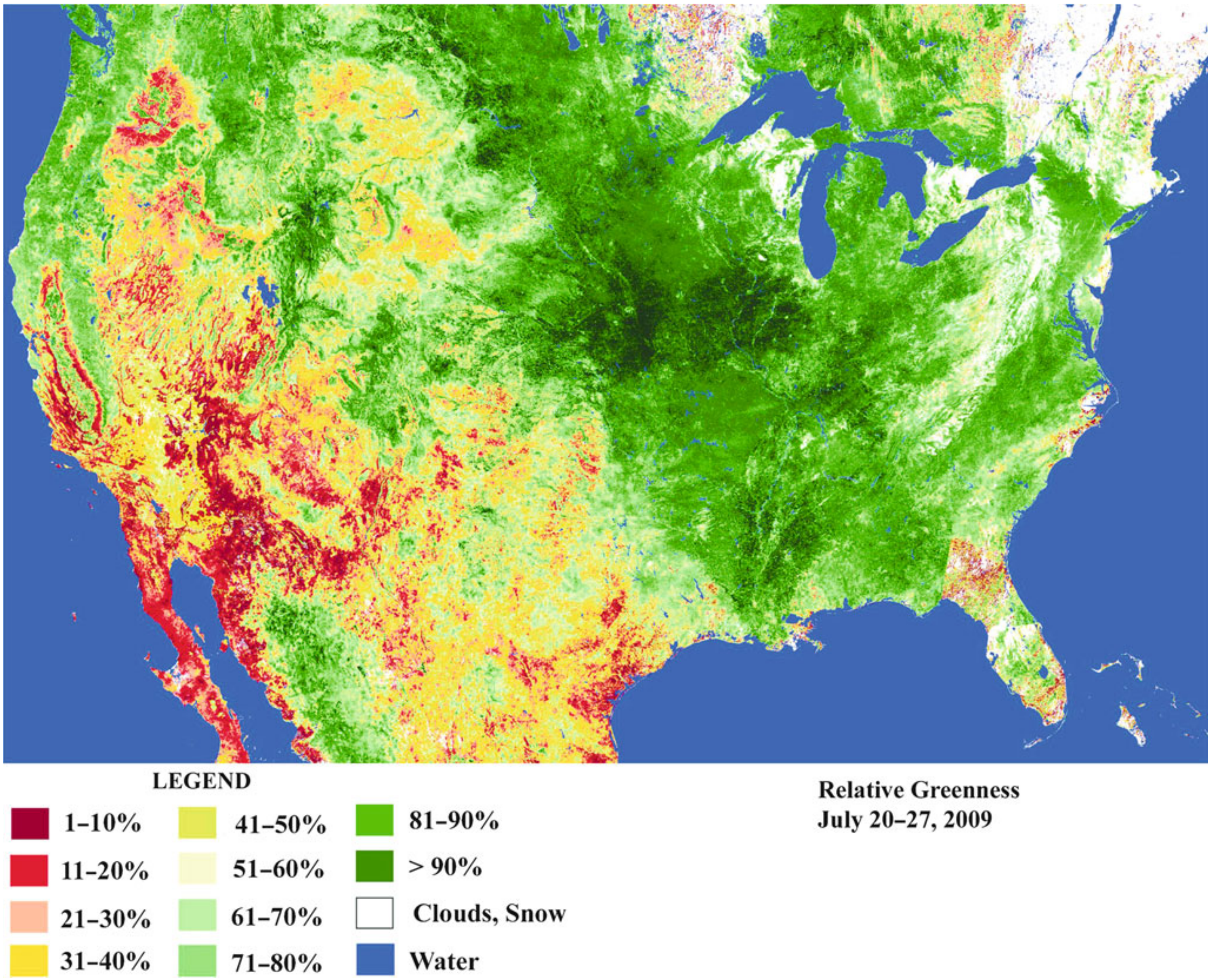
inventory, the greatest advances have been made in the use of lidar. Lidar systems are typically classified as either discrete return or waveform (Lefsky et al., 2002). Discrete-return lidar systems typically illuminate a small area of ground and divide the returning laser pulse into one or more returns defined by major energy peaks in the returned signal (Lefsky et al., 2002). The returned signal typically includes a distance measure and the strength of return (intensity). Waveform lidar systems divide the returning pulse into a large number of predefined height bins, thus capturing changes in the intensity of reflected energy at a uniform vertical height interval. A majority of forestry applications rely on discrete-return lidar due to greater data availability and established utility.

Discrete-return lidar, by measuring vertical canopy structure, provides many of the structural elements critical for forest inventories. Examples include crown closure, calculated as the percentage of crown returns to total area imaged and canopy height, estimated as the difference between a ground return and the highest return for a specific pixel (digital canopy model, or DCM: Figure 3). Crown diameter can be determined provided individual crowns can be identified and tree height can be estimated from the highest return within an identified crown. Crown base height can be determined from lidar (Riaño et al., 2003) and used to estimate crown volume and bulk density (leaves/branches per unit volume). However, one of the most important uses of lidar has been in improved estimates of forest aboveground biomass (Figure 4). Poor knowledge of tropical forest biomass is one of the most important sources of uncertainty in estimating carbon emissions from deforestation (Houghton et al., 2001). Strong correlations between tree height and biomass make



Forestry, Figure 5 Plot showing spectra of important canopy fuels including green leaves (GV) and litter, branches and stems (NPV). Plant litter, branches and stems are readily distinguished from soils based on their spectral shape. As LFM declines, NIR canopy reflectance decreases, chlorophyll absorption becomes muted, and SWIR reflectance increases. *Arrows* point to important wavelengths used to estimate changes in canopy moisture.

it possible to estimate biomass from lidar height returns. Lidar intensity can also be used to provide species compositional information, especially when given a combination of leaf-on and leaf-off data (Kim et al., 2009). While

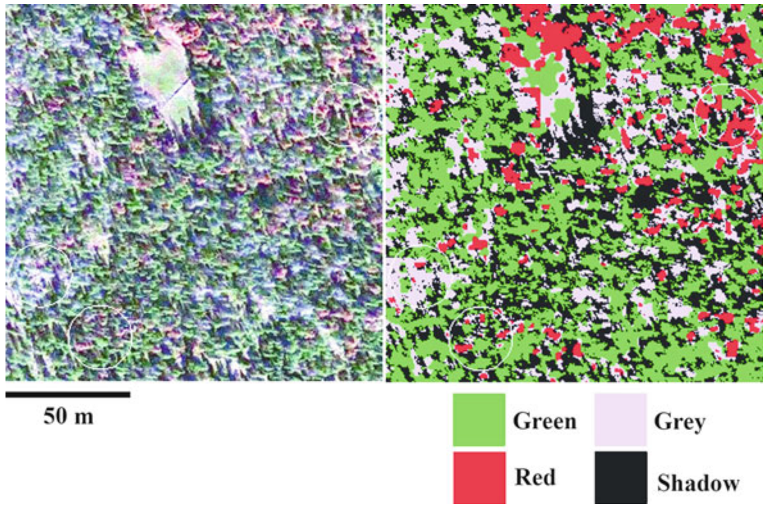


Forestry, Figure 6 Relative greenness for July 20–27, 2009. Areas of below average greenness are shown in various *shades of red*, and areas with above average greenness are shown in various *shades of green* (Data from ftp://ftp2.fs.fed.us/pub/ndvi/, retrieved from http://wfas.fire.org/content/view/30/47/).

a majority of forestry applications have relied on discrete-return lidar, similar high-quality height and biomass estimates have been derived from waveform lidar systems, such as the airborne Laser Vegetation Imaging Sensor (LVIS) (Drake et al., 2002) and the Geoscience Laser Altimeter System (GLAS) onboard ICESAT (Lefsky et al., 2005). Waveform lidar is particularly important because it can be deployed in space and used to estimate biomass from forests that cannot be imaged using airborne systems.

Wildfire fuels and forest fires

Another major remote sensing application in forestry is fire, where remote sensing provides information on fuels, fire danger, fire occurrence, and fire impacts. Improved knowledge of changing fuel properties and the global incidence of fire is widely considered one of the greatest weaknesses in current global climate models and the ability to quantify fluxes of carbon between the biosphere and atmosphere (Running, 2008). Fires require fuels to burn and are limited by the presence of water; thus, important fuel properties include the mass of fuel, their arrangement in space (depth and packing), their size distribution and geometry, and the amount of water in living and dead tissue (Pyne et al., 1996). Forests can be divided into two important fuel classes, crown and surface fuels. The most extreme fires burn through crown fuels. A common practice is to assign fuel properties using a fuel model, which is typically mapped using image classification. Two of the most common systems used in the United States were proposed by Anderson (1982) and



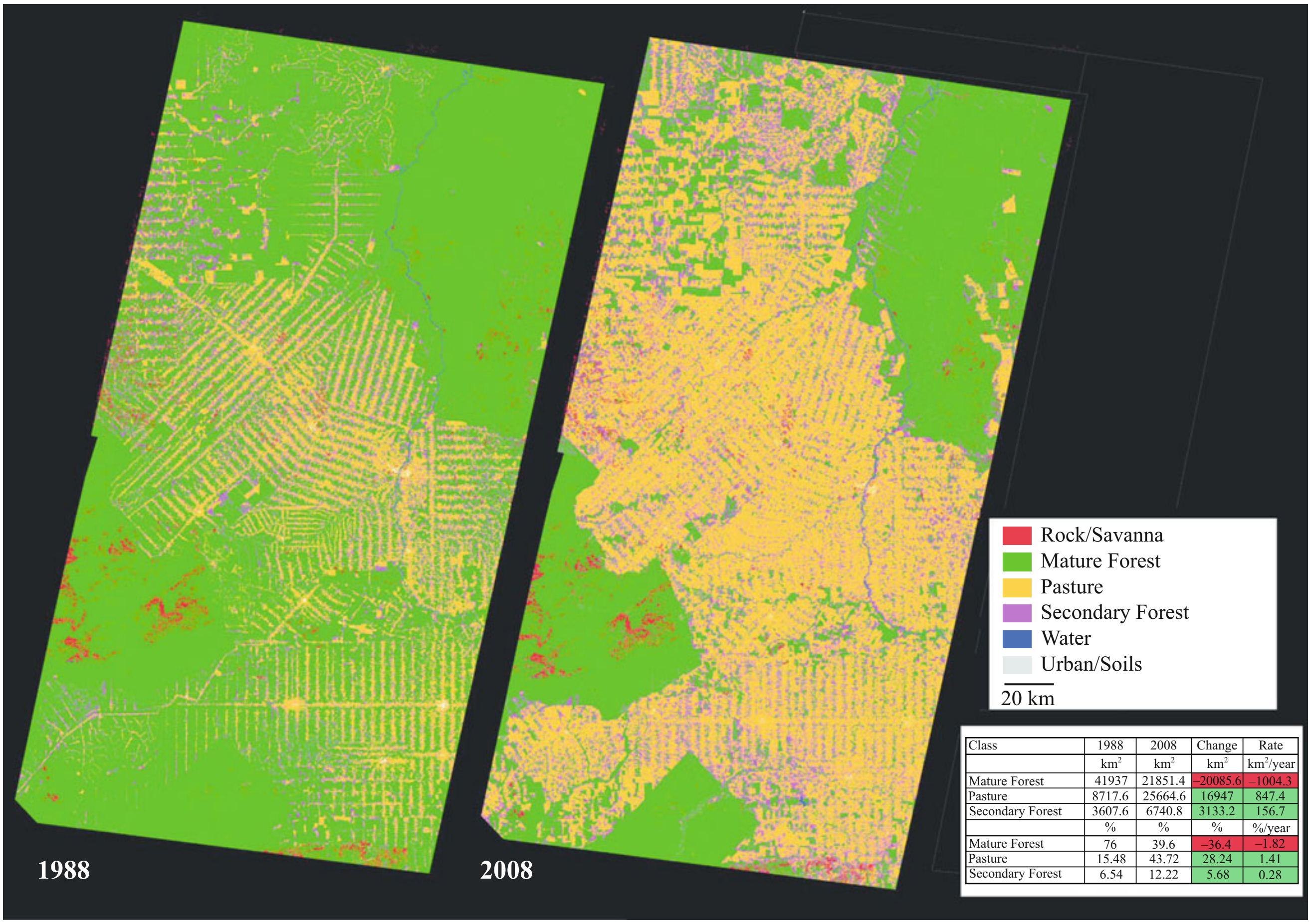
Forestry, Figure 7 Showing a high-resolution true color pan-sharpened image from Geo-Eye-1 (*left*) and a map of *green*, *red*, and *gray* attack phases of mountain pine beetle generated using a maximum likelihood classifier (*right*) (Adapted from *Dennison* et al., (2010)).

Scott and Burgan (2005), consisting of 13 and 40 models, respectively. These models can be mapped using a variety of passive optical remote sensing systems but have most often been mapped using Landsat Thematic Mapper (TM) data. Because passive optical systems only image canopy tops, they cannot measure surface fuels obscured by the canopy or other important structural variables. However, these can be estimated statistically (Keane et al., 2001). This is the approach currently used by the Landfire program (http://www.landfire.gov/) to estimate understory fuels, canopy bulk density, tree height, and crown base height from Landsat TM and biophysical gradients (i.e., aspect, elevation), trained using field data and fire history.

In shrubland systems, many important fuel properties can be estimated directly from remote sensing because the canopy is the primary fuel (Roberts et al., 2003a; Figure 5), including live fuel moisture (LFM: Dennison et al., 2003) and fuel condition (live to dead fuel ratio, Roberts et al., 2003a). A number of sensors have been used to estimate LFM, including Landsat TM (Chuvieco et al., 2002), AVIRIS (Dennison et al., 2003), and the Moderate Resolution Imaging Spectrometer (MODIS: Peterson et al., 2008). MODIS is particularly important in that these data provide information on how LFM changes seasonally.

Prefire fuels are static, typically assigned to a fuel model where the only dynamic element is dead fuel moisture estimated from meteorology. Fire danger, however, is dynamic, varying with changing vegetation and atmospheric conditions. Most fire danger indices, such as the Keetch-Byrum Index (Keetch and Byrum, 1968), rely exclusively on meteorology. However, dynamic changes in fuels can be determined using remote sensing. One example is the use of MODIS to estimate seasonal changes in LFM (Peterson et al., 2008). Another is relative greenness (RG: Burgan et al., 1998), in which the greenness of a pixel at a specific time is compared to its historical range derived from a long time series. RG is routinely calculated by the US Forest Service using the Normalized Difference Vegetation Index (NDVI) applied to Advanced Very High Resolution Radiometer (AVHRR) as part of its Wildfire Assessment program (WFAS: http://wfas.fire.org/content/view/30/47/: Figure 6). RG is also used as an input into the Fire Potential Index (FPI), a danger index calculated from RG and fuel model derived 10 h fuels and dead fuel moisture of extinction (Burgan et al., 1998).

An important element of fire fighting and forest-carbon accounting is the ability to map the presence of fire. Active fire mapping includes fire detection and estimation of important fire properties, such as fire temperature, area, or fire radiative power (FRP). Satellite-based fire detection relies primarily on the Mid-IR, in which fires emit substantially more electromagnetic radiation than cooler background pixels or reflected solar radiation. Example Mid-IR fire detections include daily 1 km observations using AVHRR (3.55–3.93 μm: Setzer and Malingreau, 1996), sub-hourly 4 km observations using Geostationary Operational Environmental Satellite (GOES, 3.9 μm band; Menzel and Prins, 1996), and two or more daily observations from MODIS, an active fire product similar to AVHRR that takes advantage of additional wavelengths and spatial information to reduce false detections (Giglio et al., 2003). Another important MODIS fire product is FRP, an index correlated to biomass consumption (Wooster et al., 2005), calculated using a modified form of Stefan-Boltzmann's equation applied to the difference between background radiance and fire-elevated radiance in the MODIS 4 μm band (Kaufman et al., 1998). Fire temperature and area can be estimated based on the



Class	1988	2008	Change	Rate
	km²	km²	km²	km²/year
Mature Forest	41937	21851.4	–20085.6	–1004.3
Pasture	8717.6	25664.6	16947	847.4
Secondary Forest	3607.6	6740.8	3133.2	156.7
	%	%	%	%/year
Mature Forest	76	39.6	–36.4	–1.82
Pasture	15.48	43.72	28.24	1.41
Secondary Forest	6.54	12.22	5.68	0.28

Forestry, Figure 8 Maps showing changes in mature forest, pasture, and secondary forest in a portion of Rondonia, Brazil, between 1988 and 2008. Landsat TM data were classified using an approach described by Roberts et al., 2002, modified to reduce errors in secondary forest due to illumination and confusion between mature forest and old secondary forest. The 2008 image is included, courtesy of Michael Toomey of UC Santa Barbara. In these two Landsat scenes, mature forest declined from 76 % (41,940 km^2) to 39.6 % (21,851 km^2), while pasture increased from 15.5 % (8,720 km^2) to 43.7 % (25,665 km^2) of the area shown. Secondary forests nearly doubled from 6.5 % (3,600 km^2) to 12.2 % (6,740 km^2) over this same period.

spectral shape of fire-emitted radiance measured by several sensors, including AVIRIS (Dennison et al., 2006).

Immediately following a wildfire, critical questions include how much area was burned and the severity of damage. Measures of burned area and fire severity are critical in that exposed soil following wildfire is prone to erosion and mass movement, while the potential of recovery may vary depending on the intensity and frequency of fire (Barro and Conard, 1991; Zedler et al., 1983). Common fire severity measures are typically calculated using sensors such as Landsat and include the Difference Normalized Burn Ratio (DNBR) as an example (Key and Benson, 2006; Van Wagtendonk and Lutz, 2007). DNBR responds to spectral changes due to an increase in exposed soil, surface ash, and dead plant material. Global estimates of burned area are also critical in that they capture the global incidence of fire disturbance and provide a means for estimating carbon emissions from burned areas. A number of global burned area products exist including one produced using MODIS (Roy et al., 2005).

Forest health

Spectroscopic changes in leaf reflectance (i.e., pigment damage, water loss), and forest structural changes, such as leaf shedding or defoliation, offer the potential of using remote sensing to map the presence of forest pathogens (Pu et al., 2008). Remote sensing has a long history of use for mapping forest health, initially through the use of aerial photography, but more recently using airborne and spaceborne passive remote sensing systems (Wulder et al., 2006). Examples include the use of multispectral remote sensing to map defoliation due to various species of budworms (Radeloff et al., 1999), adelgids (Franklin et al., 1995), bark beetles (Wulder et al., 2006; Dennison et al., 2010: Figure 7), and gypsy moth (Townsend et al., 2004). Multispectral and hyperspectral remote sensing have been used to map the distribution of forest pathogens such as *Phytopthora*, which causes diseases such as sudden oak death syndrome (Pu et al., 2008) and Swiss needle cast.

Land-cover mapping, forest degradation, and forest conversion (deforestation)

One of the most important roles of remote sensing for forestry has been in tracking changes in the world's forests, either through forest removal (deforestation), degradation, regrowth, afforestation (tree planting), or natural disturbance (i.e., Hurricane Katrina). Forest areas, consisting of at least 40 % canopy cover by woody plants taller than 5 m, increased an average of three million ha/year between 1990 and 2000 in temperature regions, but declined by an average of 12 million ha/year between 1980 and 2000 in tropical regions (Millenium Ecosystem Assessment, 2005). Much of this information has come from passive remote sensing systems, such as the Landsat TM, MODIS, AVHRR, and SPOT-4. Loss of forest cover underestimates actual human impacts because it does not take into account forest degradation, in which forest integrity is reduced by fire, selective logging, or fragmentation. In the Amazon, annual increases in degraded forests are estimated to exceed deforestation (Nepstad et al., 1999).

One of the most intensively studied areas of the humid tropics is the Amazon Basin, which contains the largest remaining tracts of undisturbed tropical rainforest globally and in which a majority of the deforestation has occurred during the era of routine satellite observations (Roberts et al., 2003b). Tropical rain forests are particularly important because they house some of the world's highest biodiversity and store more carbon than any other terrestrial ecosystem (Dixon et al., 1994). Within the Amazon Basin, some of the highest deforestation rates have occurred in the state of Rondonia, which began to undergo rapid conversion as early as the mid-1970s and continues to experience rapid forest loss today (Figure 8).

Summary

Remote sensing has numerous applications in forestry. Older, historical applications relied primarily on interpretation of aerial photography for forest inventories. More recently, newer airborne and spaceborne active and passive sensors have greatly expanded the utility of remote sensing in forestry. Examples include lidar, which can provide forest structural parameters such as tree height, crown volume, and stand biomass at accuracies that are equal to, or exceed, ground-based measures. Regional to global estimates of changes in forest cover have also been made possible by remote sensing, providing critical measures of changes in carbon stocks and fluxes needed to better understand human environmental impacts and better manage resources. Several operational remote sensing products contribute to improved assessment of fire danger, fire management, fire severity, and postfire recovery.

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Cross-references

Data Processing, SAR Sensors
Lidar Systems
Microwave Radiometers
Optical/Infrared, Radiative Transfer
Radars
Radiation, Electromagnetic
Reflected Solar Radiation Sensors, Multiangle Imaging