Appendix B – Summary of Existing Methods for Estimating Biospheric Carbon Stocks & Fluxes

Carbon Stocks

Biospheric carbon stock assessment has become the standard method for valuing forest carbon offsets, and is a foundation for the UN's REDD program (Gibbs et al. 2007). These provide critical baseline measures for evaluation of offset programs. Repeated stock assessments provide an indicator of actual carbon loss or gain (integrated fluxes). Several methods are used, including plot-based field methods, forest inventory approaches, and remote sensing, and these methods have been reviewed in Gibbs et al. 2007.

Direct stock assessment is challenging due to the many components involved, several of which are not directly accessible. Terrestrial biospheric carbon stocks incorporate several live and dead components, both above and below-ground. Biospheric carbon fractions include living trees, other live vegetation, roots (fine and course), and dead carbon pools, which include large woody debris, plant litter, and soil organic matter.

Field based inventory methods can be accurate for small regions, but are time-consuming, hard to verify without independent sampling, and easily subject to human error or fraud. Biome averages based on inventory methods are commonly used, but these are typically based on extrapolation from inadequate sampling or inconsistent methods, so vary widely in their estimates (Gibbs et al. 2007).

Since inventories and other field sampling methods are typically limited to small plots or local regions, remote sensing has been used to extrapolate stock estimates to larger regions through calibration and allometric approaches. Use of remote sensing can increase consistency and cost-efficiency over manual field methods. However, to be defensible, remote sensing and automated sampling methods must at some point be tied to field assessments. High spatial resolution imagers and new technologies like LiDAR and imaging spectrometers may improve the type of information that can be derived about stocks from remote sensing and may reduce dependence on manual measurements in the field.

Field Measurements: Inventory methods

Forest inventory methods are derived from forest mensuration programs to estimate tree growth and traditionally do not estimate all forest carbon fractions. Forest biomass can be estimated by destructively harvesting trees, drying and weighing the biomass, and applying a correction factor to express the portion present as carbon (Westlake 1996, Kitani and Hall1989). Harvest methods are considered to be accurate but impractical because they require forest destruction and are expensive in terms of the time required to obtain the measurements over all pools of carbon (Gibbs et al., 2007).

Inventory programs often use look-up tables or correlations with aboveground biomass to fill in the smaller carbon pools. Allometric models scale relationships between tree properties and biomass, often using DBH or combined with tree height to estimate carbon stocks (see review by Gibbs et al., 2007). Inventory data are extrapolated to larger areas using either empirical or statistical methods. Brown et al. (1993) were early users of GIS models that incorporated spatially explicit data layers (climate, topography, environmental information, and inventory data) to produce maps of carbon stocks.

Because forest inventories were originally done to support the forest products industry, they don't directly assess carbon. Many of these programs now have formalized protocols for assessments at the state and national levels. For example, the U.S. Forest Service Forest Inventory and Assessment (FIA) database consists of ~125,000 plots collected with consistent methodologies (Woudenberg et al., in press) that include information about forest type, tree density, size class, habitat descriptions, tree diameter at breast height (DBH), soil litter layers, etc. and information about areal extent of forest lands. Current USFS enhanced FIA data include annual estimates of tree crown conditions, coarse woody debris, tree carbon and biomass. The FIA program uses three levels of data collection, which systematically sample US forest lands: Phase 1 stratifies land cover using remote sensing to identify forests, Phase 2 samples one field site for every 6,000 acres and collects data on forest type, site attributes, tree species, tree size, and overall tree condition and Phase 3 measures forest health attributes, including canopy condition (over and understory), lichen composition, woody debris, and soil properties. The Forest Health Monitoring (FHM) program samples about 7,800 plots, which are scaled up to larger regions using aerial photo interpretation.

Remote sensing Methods

In recent years, remote sensing has been applied to biospheric carbon stock assessment, providing a level of objectivity and consistency that is difficult to attain with field sampling alone. Satellite and airborne remote sensing systems have been used to provide synoptic estimates of forest carbon stocks. Almost all carbon biomass studies to date have depended on statistical relationships between ground-based measurements and satellite-observed vegetation indices. Monitoring of carbon stocks at national or regional scales still needs additional research and multisource data inputs to increase confidence in the estimates (Gibbs et al., 2007). However, these methods provide a rich array of data sources that, particularly when checked against field measurements, allow regional and global monitoring of biosequestration. Some of the key methods are described below.

Optical remote sensing data

Most remote sensing methodologies use red and near-infrared reflectance to scale canopy biomass. However, because chlorophyll absorbs so strongly in the red part of the spectrum, measurements often saturate at leaf area indexes of 3-4, making these methods more reliable where vegetation is sparse (Roberts et al., 2004). Optical systems tend to underestimate carbon stocks when canopies are dense, especially when using standard vegetation indexes like the Normalized Difference Vegetation Index (NDVI), which saturates at LAIs well below most mature forests. Optical systems are also limited to measurements under "ideal" illumination conditions, usually a cloud-free period from late morning to early afternoon. Cloud cover is a serious problem in many tropical and arctic regions, thus limiting the use of remotely sensed data in areas that are of greatest concern for degradation by human activity and/or climate change. As discussed below, radar provides a good alternative for use in areas with persistent cloud cover.

The AVHRR satellite, which has a spatial resolution of approximately 1.1 km, has provided a consistent 30-year record for monitoring global forests. The long term AVHRR data set has been used to follow long term trends in forest cover at the global scale (Gutman, 1999). Similarly, we have a 25-year record of Landsat Thematic Mapper data (starting in 1984) that provides global coverage. Up until recently, Landsat has been mostly used at the regional scale of forests and site conditions, although the USGS has used it to produce a National Land Cover Map for the U.S (http://landcover.usgs.gov/usgslandcover.php). The recent advances in Landat data access at USGS makes it possible to use Landsat globally, although the data base does not have a full archive of international images over the entire record. Also, Landsat has limited spectral bands, reducing its value for biospheric carbon assessment relative to newer sensors. Launched in 2000, NASA's MODIS sensors provide global coverage, although the MODIS products are generally thought to be too coarse for most local-scale stock assessments or offset projects. Thenkabail et al. (2004) has shown that MODIS does not accurately estimate carbon stocks in tropical forests because of its large pixel size.

Newer high spatial resolution satellites like the Worldview-2 instrument (Digital Globe's satellite sensor, http://www.satimagingcorp.com/satellite-sensors/worldview-1.html), with eight spectral bands in the visible and near-infrared and sub-meter pixels could provide higher spatial resolution coverage. The trade-off of such small pixels is that the extent of the area covered is small, making nadir observations of specific locations difficult. This presents a challenge in obtaining large area coverage, and if you could amass the data, the expense would become prohibitively high given current costs. The German RapidEye constellation of five satellites, launched in 2008, provides frequent repeat data combined with 5m pixels and 5 spectral bands (3 visible, 1 far red and one near-infrared band). At this spatial scale the local land cover patterns is apparent and the added spectral band at the "red edge" (boundary between visible and infrared bands formed by the long wavelength edge of the chlorophyll absorption feature) provides additional information on photosynthetic pigments and leaf area density.

Hyperspectral sensors, with many narrow spectral bands, offer additional advantages for carbon stock assessment over broadband sensors. The advantage of having more infrared bands than these instruments have is that the data are less correlated with visible bands and so more information on structure and composition can be retrieved. If the bands are placed at key absorption features like water absorption, cellulose absorption, mineral and clay absorptions, etc., they can contribute to quantifying those materials. Thenkabail et al. (2004) obtained much better carbon estimates using hyperspectral data from the Hyperion imaging spectrometer, confirming that the spectral limitation is the most critical since the pixel size is the same as Landsat's.

Very high-resolution aerial imagery

The advantage of airborne sensors is the potential to make high spatial and high spectral resolution measurements. Data from airborne instruments can then be used to train coarser satellite sensors with wider coverage. Imagery as fine as 20 cm pixels is available from some airborne imagers (e.g., AISA, Specim, Oulu Finland; and Hyperpec, Headwall, Fitchburg, Massachusetts, USA). At this scale, data can be used to measure the number of trees, tree crown areas or crown diameters in addition to using the spectral information to quantify the state of health or vigor of the vegetation. Maps of tree crown areas from these high spatial resolution sensors can be used to estimate carbon stocks with high accuracy (e.g., Greenberg et al., 2005). These data are collected over relatively limited spatial extents (100-1000 km), but could be used for mapping inaccessible areas or used in a sampling scheme where coarser satellite data are trained from these smaller sampling systems. Nonetheless, using mosaics of several flight lines it is possible to build up large area coverage.

A great variety of airborne imagers are and have been flown. Most of these imagers have either 3 or 4 bands, operating in the visible to near-infrared (VIS-NIR) region or are imaging spectrometers, which have large numbers of narrow adjacent wavebands ("hyperspectral"), thus when analyzed produce a spectrum for each pixel. These can either be of the VIS-NIR type or measure across the reflected infrared spectrum, typically from 400-2500 nm. These are generally flown so that they acquire very high spatial and spectral resolution. Most of the imaging spectrometers flown today are available in North America and Europe (although HyMap is Australian) but are not yet widely available elsewhere. Dr. Gregory Asner, from the Department of Global Ecology at the Carnegie Institution, is flying a full spectrum ITRES airborne imaging spectrometer and a full waveform Optec LiDAR over tropical forests (Asner et al. 2010) with the goal of species and functional type mapping all tropical forests globally within five years.

Satellite microwave or radar data

Radar (radio detecting and ranging) sensors emit photon pulses and measure the time for the pulses to return from the vegetation canopies and the ground. Radar pulses penetrate clouds and are insensitive to atmospheric water vapor, thus they can be used in any season and location. While radar bands can be used in land cover classifiers similar to methods common to optical remote sensing instruments, the physical basis underlying the measurements is different, so the information is different. Radars are sensitive to the amount and phase of water (vapor, liquid, solid) and the three-dimensional structure of the canopy and land surface.

The Synthetic aperture radar (SAR) can be used to quantify forest carbon stocks in relatively homogeneous or young forests but saturate at low biomass (50-100 tC/ha), so may not be sufficiently sensitive for high-biomass forests (Paris and Ustin 1990, Le Toan et al. 2004, Patenoude et al. 2004). SAR sensors are on board several satellites (ERS-2, PALSAR on ALOS, and ASAR on Envisat). These are used for biomass estimation in areas where optical remote sensing is difficult and in woodlands and less dense forests.

The difference between signals returned from the ground and the canopy are used to estimate tree height, which is then converted to estimates of forest carbon stocks using allometry. Flying multiple SAR instruments with different frequencies (particularly S, L, and P bands) provides more information about the 3D structure of the vegetation than shorter wavelengths (e.g., X, C), which tend to saturate and mainly provide information about the upper surface. Longer wavelength radars (e.g., S, L, P-bands) can penetrate the canopy to the understory and the ground surface, although this also depends on vegetation density (Paris and Ustin, 1990). The pulses are polarized and different instruments may have horizontal or vertical polarizations. The return signals can be polarized and this can be used to generate "cross-polarization" images (where the radar sends signals in one polarization and receives in another). These different polarized images respond differently to the orientation of vertically oriented forests compared to the more horizontally oriented land surface, thus these data provide more information about 3D forest structure than a single polarization, thus improving the ability to produce accurate carbon maps.

Airborne LiDAR (light detection and ranging)

LiDAR is an alternative form of active remote sensing technology that emits laser pulses in the near-infrared. Because of this LiDAR systems are subject to the same water vapor saturation as other optical sensors. However, LiDARs produce datasets that are easier to interpret than radar, are more routinely available from commercial sources. The demand for LiDAR data has been rapidly growing because of its ability to collect spatially detailed 3-D monitoring of forest structure. Radar and LiDAR systems can both provide day and night coverage, expanding the time window available for data collection beyond sunlit hours.

Like radar, LiDAR instruments measure the return time to estimate the height and vertical structure of forests (Dubayah and Drake 2000). When the light pulse contacts the forest canopy and ground surfaces, it is then reflected back to the instrument. As with other methods described above, LiDAR data can be calibrated against field data to develop allometric relationships to estimate carbon stocks (Hese et al. 2005). While these methods work well for trees during their expansive height growth stage, they don't work well in tropical forests that rapidly reach their maximum height while continuing to accumulate carbon for many decades. Large-footprint LiDAR is reported to exceed the capabilities of radar and optical sensors to estimate carbon stocks for all forest types (Means et al. 1998, Lefsky et al. 1999, Drake et al. 2003), and is now the "method of choice" for remote estimates of forest carbon stocks. Unfortunately, most commercial, airplane-mounted LiDAR instruments remain costly to use for anything more than small areas, largely due to pricing structures in the airborne geomatics industry. Recent studies show that it is possible to systematically collect LiDAR data over extensive areas that is cost-effective from automation and economies of scale (Asner et al. 2010). A satellite-based LiDAR system could provide global coverage but none are currently funded and continued development of NASA's DESDynI was terminated in the White House 2012 budget. Consequently, the goal of global LiDAR coverage remains elusive at this time.

Linking measurements of carbon stocks and disturbance

Accurately quantifying disturbance and linking it to changing carbon stocks remain key challenges in biospheric carbon assessment (Running 2008). Changes in carbon stocks and related emissions can be monitored from satellite-based observations of deforestation once the broad spatial distribution of carbon stocks is well established and the calibrations or allometric relationships are understood and validated. To calculate carbon emissions using stock methods, it is essential to determine the area disturbed - often in the form of area logged, burned (wildfire), or lost through other disturbance events (e.g. drought or insect infestation) - and the amount of carbon contained in those forests before and after the disturbance. Clear cuts can be readily assessed from remote sensing, but more diffuse disturbance (e.g. selective logging) requires additional approaches (e.g. Asner et al. 2005) that are not as straightforward as baseline stock assessments. For this reason a variety of approaches based on more direct *flux* assessment can be used, and are considered below.

Carbon Fluxes

Several methods of assessing fluxes (biospheric gains and losses) are now in wide use by carbon cycle scientists. Fluxes can be measured and expressed over short (daily or weekly) time spans, or integrated over long time spans (one year or more) to estimate changes in stocks. When integrated spatially, particularly in a multi-scale framework (top-down or bottom-up scaling, discussed below), they can provide insight into spatial patterns of changing biospheric carbon stocks.

One advantage of flux assessments over traditional stock methods lies in their ability to detect short-term ecosystem losses or gains in carbon, for example due to disturbance. Often, these perturbations can be readily tied to underlying processes causing these changes, including drought, insect infestations, wildfire, or land use land cover change (LULCC) (Fuentes et al. 2006, Reichstein et al 2007, Kurz et al. 2007 & 2008, Beer et al. 2011) In this way, they provide a "sharper tool" for understanding the *dynamics* of biospheric carbon over finer time scales than can be provided by periodic stock assessments. Many flux methods are based on automated monitoring, ranging from remote sensing to automated field methods, lending a degree of objectivity hard to attain with manual sampling. However, most equipment used for flux assessment tends to be expensive and requires ongoing maintenance and regular calibration, adding to the costs of these methods.

Flux assessments include "top-down" methods, where atmospheric CO_2 data are used to estimate regional fluxes using model inversions (Tans et al. 1990, Fan et al. 1998). Top-down methods are good for providing constraints on fluxes and can contribute to regional or global monitoring. However, due to their coarse spatial scales, these methods cannot typically resolve local or plot-level estimates, so have not been able to contribute to current carbon markets. This may improve as high-resolution satellites and better atmospheric measurements become more available (Crisp et al. 2004). The MODIS satellite sensor provides several global data products that are used to produce coarse-scale global NPP (Net Primary Production) products (Running et al. 2004), but these coarse-scale products often do not match local- and regional -scale measurements very well (Heinsch et al. 2006, Turner et al. 2005), and may miss subtle or fine-scale disturbance. Better integration with airborne and ground-based methods is needed to improve these top-down products for local and regional assessments.

Flux assessments also include a large variety of "bottom-up" methods, where local fluxes (typically measured by eddy covariance) are linked to remote sensing to extrapolate to larger regional or global scales (Rahman et al. 2001, Fuentes et al. 2006, Reichstein et al. 2007, Xiao et al. 2008, 2010). Recently, with the help of improved cyberinfrastructure and cloud computing, bottom-up methods are advancing dramatically (Ryu et al. 2010), offering novel solutions at a range of scales matching policy and carbon market needs.

Direct Flux measurement

Eddy covariance calculates net biospheric-atmospheric carbon fluxes for entire ecosystems from direct measurements of carbon dioxide concentrations and air movement (wind speed and direction). Chamber methods can also be used, but these are typically restricted to very small ($<1m^2$) areas, so are of limited use for carbon markets. Similar methods involving chambers or eddy covariance for measuring ecosystem methane fluxes are also becoming available, but have not been as widely applied as the methods for carbon dioxide, largely due to high costs and technical limitations of early methane sensors (Smeets et al. 2009).

The eddy covariance method can be used to collect data automatically and continuously over extended periods, allowing direct measurements of fluxes for entire vegetation stands, something unattainable by any other method. Typically, this method is reported in 30-minute or daily time intervals, and can be integrated to provide annual sums. While eddy covariance records the exchange of gases between the atmosphere and the biosphere, providing a direct measure of carbon dioxide sequestration, this method is expensive and limited to certain conditions. Instruments must be calibrated and maintained, and are limited to areas of minor topographic relief where the vegetation composition and structure is relatively uniform over large areas (Baldocchi 2008). The methods do not provide reliable data where the fetch is inadequate or during periods of low wind speed, and often fail during harsh weather, leading to frequent data gaps. Because eddy covariance methods are restricted in geographic coverage to level, homogenous landscapes, large parts of the world are not suitable for this method, and extrapolation from single-site measurements to larger regions is a challenge. Alternate "inverse dispersion" methods (Wilson et al. 1982, 2010, Flesch et al. 1995 & 2005, Leuning et al. 2000) are capable of monitoring surface-atmosphere exchanges for more complex landscapes, but are not yet in wide use. Meanwhile, eddy covariance has emerged as a standard method for quantifying surface-atmosphere gas fluxes.

Currently, there are hundreds of eddy covariance sites around the world, and many of these are part of the global FLUXNET network (http://www.fluxnet.ornl.gov/fluxnet/). Particularly when combined with aircraft, satellite, or field optical data that can help extrapolate from local points to larger regions or fill in missing data, the flux network provides a potent system for monitoring biospheric carbon fluxes at multiple scales, and for understanding the factors controlling these fluxes for different representative ecosystems (Reichstein et al. 2007, Xiao et al. 2008, 2010). Recent applications of cloud computing have greatly assisted in the power of extrapolating to regional and global levels (Ryu et al. 2010). Combining flux measurements with remote sensing is also critical to validation of remote sensing driven models (Turner et al. 2005, Heinsch et al. 2006). Optical sampling networks (e.g. SpecNet) coupled to flux networks (FLUXNET) can help fill in gaps due to missing data, and can provide key "calibrations" needed to enable proper interpretation of optical measurements from aircraft and satellite (Gamon et al. 2006, 2011).

Optical remote sensing

Most current applications of remote sensing to biospheric carbon focus on the visible and near-infrared ("optical sensing") because the technology is mature with good quality data. A particular benefit of optical sensing is that it can be applied at many scales, from an individual point to the whole globe (Gamon and Qiu 1999). Sampling reflected solar radiation at multiple wavelengths (including visible, near-infrared, and short-wave infrared) reveals information on vegetation structure and physiological state useful for assessing biospheric carbon stocks and fluxes. Vegetation is spectrally distinctive and discriminating healthy green vegetation from senescent vegetation, soils, and other materials is relatively straightforward. Instruments are available that measure spectra from field-based, airborne or sampled from satellite platforms, with spatial resolutions ranging from centimetres to kilometres (Gamon and Qiu 1999). These data can readily verify the presence/absence of vegetation, percent canopy cover, evaluate whether cover has increased when comparing data from two or more dates, and can be used to measure a variety of key parameters related to carbon stocks and fluxes.

Structural parameters include estimates of aboveground biomass, % cover, leaf area index, and the fraction of photosynthetically active radiation (F_{APAR}) absorbed by green vegetation. Assessing below-ground structure or carbon storage from remote sensing is more challenging and cannot be done directly by optical means since optical remote sensing cannot penetrate soil. Instead, remote sensing can be used to extrapolate from field measurements involving below-ground monitoring to obtain large-area estimates of carbon. While certain structural metrics can be related to carbon stocks (see above), they can also be used to estimate fluxes, since they help define the capacity for photosynthetic carbon uptake. Consequently, vegetation structural measurements, along with other measurements, are essential to the estimate of carbon stocks and fluxes described in the next paragraph.

Optical remote sensing can estimate photosynthetic carbon uptake (photosynthetic rates, net ecosystem exchange, gross primary production, or net primary production). Usually, some form of a "light-use efficiency" (LUE) model (Monteith 1977) is used, and many variations of this model have been developed, ranging from "instantaneous" leaf- and canopy-scale models (Gamon et al. 2001) to annual integrations applied at regional or global scales (Field et al. 1998, Goetz and Prince 1999, Lobell et al. 2002, Running et al.

2004). In this sense, the LUE model is readily "scaleable" and easily driven by remote sensing inputs at many spatial scales.

The LUE model combines an estimate of light absorption (APAR or "absorbed PAR") with an "efficiency" factor (ε) that describes the proportion of absorbed light converted to fixed carbon (biospheric carbon). APAR is closely related to structural parameters (fPAR or LAI) and represents the vegetation's capacity for light absorption, and therefore its potential photosynthesis, assuming no physiological restrictions due to stress. The efficiency (ε) term indicates changes in the efficiency of light usage due to environmental restrictions or physiological constraints. In the past, efficiency has often been defined as a constant or biome-specific parameter, and this is often still used as a first approximation. Recent satellite-driven models either use meteorological data (Running et al. 2004) or direct remote sensing measurements (Hilker et al. 2009) to estimate efficiency as a model variable, recognizing that environmental conditions and plant physiological responses can cause considerable variation in light-use efficiency.

To calculate the net carbon uptake (e.g. net photosynthesis, net primary production), a respiration term must be added to the LUE model. Alternatively, since ecosystem respiration can be closely tied to recently fixed carbon (Högberg et al. 2001), the LUE model often provides a remarkably good estimate of net ecosystem exchange (NEE) or net primary production (NPP) even without an explicit respiratory term. In this case, respiration becomes an implicit part of the "efficiency" term of the LUE model (Gamon and Qiu 1999), and respiration can be estimated from remote sensing using the same structural parameters used to drive APAR in the LUE model (Gamon et al. 2006). If respiration is to be calculated explicitly, a variety of modeling approaches can be used. Most respiratory models require estimation of temperature and moisture, both of which can be detected remotely (Gamon and Qiu 1999). Disturbance is one of the main confounding factors when estimating ecosystem respiration, as it can cause the abrupt release of otherwise stable biospheric carbon pools (Kurz et al. 2007, 2008). Consequently, attempts to model fluxes from remote sensing should be cognizant of the degree and nature of disturbance.

In recent years, optical remote sensing have expanded in scope to provide far more detailed physiological information that previously thought possible with remote sensing. Newer methods include estimation of chlorophyll and carotenoid pigments levels (Gitelson et al., 2002, 2003; Feret et al., 2008, Zarco-Tejada et al., 2001), photosynthetic light-use efficiency (Gamon et al. 1992, Hilker et al. 2009), and water content (Hunt and Rock 1989, Hunt 1991, Peñuelas et al. 1993, Ustin et al. 1998). Together, these new optical remote sensing methods are providing many ways to assess vegetation "health" that can be useful in assessing carbon fluxes and can further refine regional estimates of biospheric carbon uptake.

Satellite sensors

A rich array of platforms are available for optical remote sensing, ranging from satellite to airborne and field sensors. Currently, the MODIS satellite sensor uses a light-use efficiency (LUE) model to produce global estimates of annual biospheric carbon uptake (Net Primary Production) for most of the world's surface (Running et al. 2004). In this case, the efficiency and respiratory terms are driven largely from a global network of meteorological stations. Other forms of the LUE model driven entirely from satellite data sources have also been tested, with promising results (Rahman et al. 2004, Sims 2006). While generally too coarse for local carbon offset projects, these satellite products clearly demonstrate that technical capability exists to estimate biosequestration rates from satellite for large regions of the globe. When supplemented by finer-scale observations, we now have a rich selection of tools for monitoring biospheric carbon fluxes at a range of spatial scales. For example, airborne imaging spectrometry and field sensors can be useful for estimating carbon flux using a LUE model.

Airborne sensors

A number of airborne imaging spectrometers can be used to estimate carbon fluxes with the light-use efficiency model. For example, the AVIRIS sensor has been used to estimate regional patterns of carbon flux using the light-use efficiency model (Rahman et al. 2001, Fuentes et al. 2006). Since many airborne imaging spectometers provide sub-meter spatial resolution (as well as high spectral resolution), they provide a much finer scale product than most satellite sensors, and provide an "intermediate scale" platform for linking satellite data to field observations. Because aircraft deployments can be more flexible than satellite orbital constraints, aircraft sensors are well-suited for experimental tests. Due to the new generation of inexpensive airborne sensors, airborne platforms present are now presenting new opportunities for monitoring carbon fluxes at local to regional scales

Field optical sensors

Recent years have seen the emergence of a wide array of field optical sampling methods that closely match the scale of the eddy covariance measurements (Gamon et al. 2006, Leuning et al. 2006, Hilker et al. 2007) while providing much-needed ground validation for aircraft and satellite sensors (Cheng et al. 2006). When properly calibrated, field optical sensors can estimate ecosystem carbon uptake by providing the APAR and efficiency terms of the light-use efficiency model (Gamon et al. 2011). Principal advantages are 1) their reliability, 2) their relatively low cost compared to other methods discussed above, 3) their flexibility and expandability, and 3) their ability to be directly compared to aircraft and satellite data providing similar metrics but from different scales (Cheng et al. 2006, Hilker et al. 2009).

Optical methods now exist at many levels of technology and cost, and range from simple, inexpensive, two-band radiometers to more expensive field spectrometers and imaging spectrometers. These can be arrayed on a variety of platforms, and can be networked with radio or satellite links. Recent advances in wireless technology facilitate sampling schemes that allow improved sampling of representative ground regions, including flux tower footprints and satellite pixels. In this way, optical sensors provide a convenient "bridge" linking direct flux measurements (chambers or eddy covariance) to aircraft or satellite sensors.

Recent studies are showing that simple radiation sensors can be configured into low-cost automated monitoring stations ("phenology stations," Huemmrich et al. 1999). These provide proxy measures of canopy light absorption (APAR) that often scale closely with whole-ecosystem carbon fluxes (Huemmrich et al. 2010) or biomass gain (Gamon et al. 2011). In this way, simple, low-cost optical sensors can be used to estimate ecosystem carbon storage, often with remarkable accuracy. Current work is improving this accuracy by improving estimates of light-use efficiency (ε) and ecosystem respiration from remote sensing. For example, Garrity et al. (2010) recently demonstrated an inexpensive optical sensor for automated monitoring the Photochemical Reflectance Index (PRI), an indicator of photosynthetic light-use efficiency (Gamon et al. 1992). Other studies have applied this index to aircraft (Rahman et al. 2001, Fuentes et al. 2006) or satellite (Rahman et al. 2004, Drolet et al. 2005, Hilker et al. 2009) data, providing a path for improved estimates of photosynthesis and vegetation carbon uptake from space (Grace et al. 2007).

While inexpensive optical sensors are now in limited use as research tools, expanded application of these sensors, development of wireless sensor networks, and competition among several manufacturers is likely to reduce the costs. Recent advances in optical sensor design and application, including robotic, multi-angle sampling methods, and wireless sensor networks, offer further opportunities for sampling eddy covariance footprints (Gamon et al. 2011). By enabling the comparison of whole-ecosystem optical properties to flux measurements these sensors are improving our ability to monitor carbon uptake and validate airborne and satellite data (Cheng et al. 2006, Drolet et al. 2008, Hilker et al. 2009). Properly calibrated and integrated networks of field optical sensors represent a major un-tapped opportunity for biospheric carbon monitoring.

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