Liu, Geoinfor Geostat: An Overview 2016, 4:4
DOI: 10.4172/2327-4581.1000151

Geoinformatics & Geostatistics: An Overview

Short Communication

A SCITECHNOL JOURNAL

Opportunities of Mapping Forest Carbon Stock and its Annual Increment Using Landsat Time-Series Data

Liangyun Liu*

Keywords

Remote sensing; Forest carbon stock; Above ground biomass (AGB); Time-series; afforestation; Deforestation

Introduction

Forest biomass is a major store of carbon, and plays an important role in the carbon cycle. Since the net carbon flux of the forest and the magnitude of carbon loss and uptake are determined by the rate of biomass change (reduction or accumulation) at fine spatial and temporal scales, only satellite data can adequately capture its dynamics over larger areas [1,2].

The Landsat program has experienced seven successful missions that have contributed to an unprecedented more than 4 decades' (1972-) record of Earth Observations that capture global land conditions and dynamics. Incremental improvements in imaging capabilities continue to improve the quality of Landsat science data, while ensuring continuity over the full instrument record [3]. The longstanding Landsat program goal has been to acquire, archive, and distribute repetitive global multi-spectral imagery of the Earth's land surfaces at a scale where natural and human-induced changes can be detected, characterized, and monitored over time [4]. Global 30 m observations have been provided by the Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI) from 1984 to present. The free Landsat data policy opens a new era for mapping land cover changes [5]. The NASA funded Web Enabled Landsat (WELD) project has demonstrated the capability to generate near-continental scale Landsat composited mosaics with a weekly, monthly, seasonal and annual reporting frequency [6].

Forests are a comparatively easy cover type to map as well as a current focus of environmental monitoring concerning the global carbon cycle and biodiversity loss. Remote sensing is widely used to acquire information on forest biomass and its dynamics. Here, we aim to review the opportunities and methods of mapping forest carbon stock and its annual increment using Landsat data.

***Corresponding authors:** Liangyun Liu, Institute of Remote Sensing and Digital Earth | Chinese Academy of Sciences No.9 Dengzhuang South Road, Haidian District, Beijing 100094, China, Tel: +86-10-8217-8163; Fax: +86-10-8217-8177; E-mail: liuly@radi.ac.cn

Received: May 16, 2016 **Accepted:** August 02, 2016 **Published:** August 06, 2016

Discussion

Accurate forest carbon sequestration assessment requires estimation of both forest biomass and forest biomass dynamics over time. There is close relation between forest aboveground biomass (AGB) and total biomass or total carbon stock [7]. Numerous studies showed that forest AGB could be successfully mapped from multi-spectral satellite images. Landsat data may be most suitable for estimation of forest carbon stock and also its annual increment, because it provides a balance between the requirements for localized high-spatial resolution studies and global monitoring [8].

Forest biomass mapping using Landsat multispectral data

Woody biomass is a significant indicator of carbon storage for woody vegetation, which is a part of the terrestrial carbon cycle. Remote sensing of biomass predominantly depends on empirical models because there is no direct physical links between biomass and the canopy reflected radiance in optical spectral regions [9]. However, some forests' structural parameters, sensitive to spectral reflectance or vegetation indices, are related to biomass allometrically [10,11,12]. Some literatures showed the significant relationship between forest AGB and spectral reflectances in shortwave infrared (SWIR) band [13] near-infrared (NIR) band [14,15], vegetation indices [16].

Regression approaches have been widely applied for prediction of aboveground forest biomass [9]. Foody et al. [17] found that multiple regressions with raw Landsat bands explained at least as much, and generally more of the variation in tropical forest biomass as did derived vegetation indices in three different sites in Brazil, Malaysia and Thailand, and the strongest relationships between the biomass predicted and that measured from field survey was obtained with a neural network (r>0.71). In Yellowstone National Park, Jakubauskas and Price [18] found that multiple regression models of biomass from spectral indices did not significantly improve predictions of AGB over models using only Landsat bands. In contrast, many other studies reported improved estimates of forest AGB using vegetation indices [16,19]. Due et al [16] investigated the performance of different Landsat bands and vegetation indices for Moso bamboo AGB, and they found other vegetable indices such as Perpendicular Vegetation Index (PVI), Enhanced Vegetation Index (EVI), and Soil Adjust Vegetation Index (SAVI) are better than the Normalized Difference Vegetation Index (NDVI). These AGB estimate methods were also applied for large area forest region, and linked to the inventory data with a significant correlation coefficient of 0.41. For example, Tomppo et al. [20] combined Landsat-TM data and IRS-1C Wide Field Sensor (WiFS) data, together with field data of National Forest Inventories (NFIs) to map forest AGB in Finnish, with a mean relative RMSE value of 61%, which varied with different species from 58.3% to 128.5%. Gallaun et al. [21] combined national forest inventory data and Moderate Resolution Imaging Spectroradiometer (MODIS) data to produce pan-European maps of growing stock and above-ground woody biomass, with a mean absolute error of 25 m^3/ha for coniferous, 20 m^3/ha for broadleaved and 25 m^3/ha for total growing stock. Labrecque et al. [22] found that AGB estimates for hardwood forests were strongly related to stand age and near-infrared reflectance (R^2=0.95) while the AGB for pine forests was strongly related to the corrected NDVI (R^2=0.86) in northern Wisconsin, USA. Although numerous studies

doi: 10.4172/2327-4581.1000151

showed that forest AGB were retrieved from spectral reflectance or vegetation indices with varying degrees of success, there were always big problems in transferring predictive relations over space or time. The relative contribution of different Landsat TM wavebands or vegetation indices to predictive relations differed between sites, years and seasons, and the accuracy of predictive relations declined when they were applied to a region other than that upon which they had been developed, or to other seasons [17,19].

However, complex forest stand structures and biophysical environments often result in a major source of uncertainty in biomass estimation, especially for dense forest [23,24,25]. In mature forest, aboveground biomass and vegetation density may vary greatly depending on soil conditions, species, and local topography. The Landsat spectral signatures cannot effectively reflect the biomass differences between distinct mature forest sites although their biomass amounts vary significantly. The texture information calculated from Landsat data may be related to tree height and canopy diameter [26]. Lu and his colleagues found that the combination of spectral response and textural signals could effectively improve biomass estimation performance, especially in the areas with complex forest stand structures [23,27]. And they also showed that most textures derived from Landsat data are weakly correlated with successional forest biomass, while Landsat spectral signatures are significantly correlated with successional forest biomass.

Mapping tree heights with multi-spectral imagery is a relatively new application and is dependent on integrating synoptic coverage optical data with samples of height data, often from LiDAR-derived reference data. Although optical data are considered to be sensitive to forest cover properties in the horizontal plane and relatively insensitive to vertical structure, there is a growing literature on integrating samples of LiDAR data with synoptic optical data coverage [28]. Tyukavina et al. [29] employed annual Landsat 7 growing season composite images and height data from the Geoscience Laser Altimeter System (GLAS) to estimate pan-tropical forest height [28]; improved upon the Landsat inputs, moving from a single growing season composite to a set of multi-temporal metrics derived from Landsat 7 and 8 data, and they reported an overall mean absolute error (MAE) for tree height estimation of 2.45 m.

Exploiting both the temporal and spectral information domains offers the possibility of use of Landsat in the characterization of forest vertical structure and biomass. Recently, some studies showed the potential of time-series satellite images for forest AGB mapping. Andersen et al. [30] indicated that spectral trajectories developed from a time series of Landsat TM imagery can be used to accurately predict various inventory parameters, including biomass. Main-Knorn et al. used the LandTrendr algorithm to detect and describe biomass trends with near-annual time-series data, and produced yearly biomass maps based on the spectral empirical model validated by field data. Liu et al. [31] developed a method to retrieve tree age of planted forest from the Landsat time-series stacks in the last forty years, and the validation result showed to be consistent with the surveyed tree ages, with a RMSE value of 4.32 years and a determination coefficient (R^2) of 0.824. Then, Liu et al. [32] presented an AGB regression model by integrating vegetation indices and tree age, and the forest AGB model was significantly improved with an R^2 values from 0.50 to 0.727. Both the forest biomass and its annual increment were mapped based on the yearly ground surface images and afforestation age information, and a noticeable carbon increment for the planted artificial forest was observed with an annual rate of about 1 t/ha over the last four decades [32].

Semi-arid ecosystems also significantly contribute to interannual variability of the global carbon cycle. Poulter et al. [34] find that the global carbon sink anomaly was driven by growth of semi-arid vegetation in the Southern Hemisphere. For open forest in such semi-arid area, such as woodland, savanna, and shrubland with high heterogeneity, the influence of underlying background (soil and herbaceous vegetation) on the remote sensing signals would influence the estimation ability of optical data for biomass mapping. Numerous studies showed that woody cover was significant variable for estimating woody above-ground biomass [34,35] .Wang et al. [27] designed a linear spectral mixture analysis to estimate the woody cover for Landsat imagery, and they found that woody cover from multi-temporal Landsat data was much more suitable for estimating woody AGB than the than traditional reflectance or vegetation indices for this arid region covered with low-cover shrubs.

Forest changes mapping using Landsat time-series data

Human-induced or natural forest changes, such as reforestation, deforestation, fire, also represent major sinks and sources of CO_2 and other greenhouse gases. Landsat data provide a unique data source for reconstructing forest change history at regional or global scale. Time-series analysis to determine forest change are preferred, as applications based on two-dates or multi-dates of Landsat images may be strongly affected by phenology differences and bidirectional reflectance distribution function effects [36].

The availability of dense time series of Landsat images provides a chance to reconstruct forest disturbance and change history with higher temporal resolution (such as 1 year) and higher precision. Both continuous and subtle (associated with afforestation, forest degradation, recovery) as well as discontinuous and sudden (e.g., clear-cuts) forest change phenomena can be assessed, quantified, and monitored using time series of remote sensing data [37,38]. For example, Lehmann et al. [39] used time-series Landsat imagery from 1972–2013 to identify changes in forest extent and trend respectively for the Australian continent at multiple epochs for the purpose of estimating forest changes associated with carbon accounting. A vegetation change tracking algorithm was presented by Huang et al. [40,41,42] to detect forest changes from a time-series of Landsat images. Li et al. [43] analyzed the forest change patterns in Mississippi during the time period 1987–2005 from 132 Landsat TM and ETM+ scenes using a vegetation change tracker (VCT) algorithm and revealed a gradually decelerating forest fragmentation during the time period 1987–1993 and an accelerating fragmentation during the period 1994–2005. Other application of VCT included that in Alabama, USA [43]; Mississippi [44]; eastern United States [40].

In the semi-arid and sparsely forested regions strongly influenced by human activities, forest change mapping, especially afforestation, may be more challenging. Liu et al. [31] developed a vegetation change tracking method to reconstruct the forest change history (afforestation and deforestation) from the time-series Landsat GSR images based on the integrated forest z-score (IFZ) model by Huang et al. [40], which was improved by multi-phenological IFZ models and the smoothing processing of IFZ data for afforestation mapping. The mapping result showed a large increase in the extent of forest, from 380,394 ha (14.8 % of total district area) in 1974 to 1,128,380 ha (43.9 %) in 2010. Their results confirmed a great achievement of the ecological revegetation projects in Yulin district, a key region of the Three-North Shelter Forest Program (TNSFP), over the last 40 years [31].

doi: 10.4172/2327-4581.1000151

Conclusion

Forest ecosystem plays a complex role in regulating our climate, and there is great global interest in quantifying forest changes and the associated interchange between atmospheric and terrestrial carbon pools. Landsat time-series multi-spectral data provide valuable opportunities for mapping of forest dynamic, including forest biomass and forest changes. Numerous studies clearly show that both forest biomass and its annual increments can be mapped by the spectral, spatial and temporal information from the time-series Landsat dat.

Acknowledgement

The authors gratefully acknowledge financial support provided for this research by the high-resolution earth observation project of China (30-Y20A29-9003-15/17), and National Key Research and Development Program of China from MOST(2016YFB0501501)

Reference

1. Hansen MC, Loveland TR (2012) A review of large area monitoring of land cover change using Landsat data. Remote sensing of Environment 122: 66-74.
2. Main-Knorn M, Cohen BW, Kennedy ER, Grodzki W, Pflugmacher D, et.al. (2013). Monitoring coniferous forest biomass change using a Landsat trajectory-based approach. Remote Sensing and Environment 139: 277-290.
3. Loveland TR, Dwyer JL (2012) Landsat: Building a strong future. Remote Sensing of Environment 122: 22-29.
4. Goward SN, Williams DL (1997) Landsat and earth systems science: Development of terrestrial monitoring. Photogrammetric Engineering and Remote Sensing 63: 887-900.
5. Wulder MA, Masek JG, Cohen WB, Loveland TR, Woodcock CE (2012) Opening the archive: How free data has enabled the science and monitoring promise of Landsat. Remote Sensing of Environment 122: 2-10.
6. Roy DP, Ju JC, Kline K, Scaramuzza PL, Kovalskyy V, et al. (2010) Web-enabled Landsat data (WELD): Landsat ETM+ composited mosaics of the conterminous United States. Remote Sensing of Environment 114: 35-49.
7. Litton CM, Raich JW, Ryan MG (2007) Carbon allocation in forest ecosystems. Global Change Biology 13: 2089-2109.
8. Goward SN, Masek JG, Williams DL, Irons JR, Thompson RJ (2001) The Landsat-7 mission: Terrestrial research for the 21st century. Remote Sensing of Environment 78: 3-12.
9. Powell S, Cohen WB, Healey SP, Kennedy RE, Moisen GG, et al. (2010) Quantification of live aboveground forest biomass dynamics with Landsat time-series and field inventory data: a comparison of empirical modeling approaches. Remote Sensing of Environment 114: 1053-1068.
10. Heiskanen J (2006) Estimating aboveground tree biomass and leaf area index in a mountain birch forest using ASTER satellite data. International Journal of Remote Sensing 27: 1135-1158.
11. Hall RS, Skakun RJ, Arsenault EJ, Case BS (2006) Modeling forest stand structure attributes using Landsat ETM+ data: Application to mapping of aboveground biomass and stand volume. Forest Ecology and Management 225: 378-390.
12. Song C (2013) Optical remote sensing of forest leaf area index and biomass. Progress in Physical Geography 37: 98-113.
13. Steininger MK (2000) Satellite estimation of tropical secondary forest above-ground biomass: data from Brazil and Bolivia. International Journal of Remote Sensing 21: 1139-1157.
14. Mäkelä H, Pekkarinen A (2004) Estimation of forest stand volumes by Landsat TM imagery and stand-level field inventory data. Forest Ecology and Management 196: 245-255.
15. Kumar P, Rani M, Pandey PC, Majumdar A, Nathawat MS (2010) Monitoring of deforestation and forest degradation using remote sensing and GIS: A case study of Ranchi in Jharkhand (India). Report and opinion 2: 55-67.
16. Du H, Cui R, Zhou G (2010) The responses of Moso Bamboo (Phyllostachysheterocycla var. pubescens) forest aboveground biomass to Landsat TM spectral reflectance and NDVI. Acta Ecologica Sinica 30: 257-263.
17. Foody GM, Boyd DS, Cutler MEJ (2003) Predictive relations of tropical forest biomass from Landsat TM data and their transferability between regions. Remote Sensing of Environment 85: 463-474.
18. Jakubauskas ME, Price KP (1997) Empirical relationships between structural and spectral factors of Yellowstone lodgepole pine forests. Photogrammetric Engineering and Remote Sensing 63: 1375-1381.
19. Foody GM, Cutler ME, McMorrow J, Pelz D, Tangki H, et al. (2001) Mapping the biomass of Bornean tropical rain forest from remotely sensed data. Global Ecology and Biogeography 10: 379-387.
20. Tomppo E, Nilsson M, Rosengren M, Aalto P, Kennedy P (2002) Simultaneous use of Landsat-TM and IRS-1C WiFS data in estimating large area tree stem volume and aboveground biomass. Remote Sensing of Environment 82: 156-171.
21. Gallaun H, Zanchi G, Nabuurs GJ, Hengeveld G, Schardt M, Verkerk PJ (2010) EU-wide maps of growing stock and above-ground biomass in forests based on remote sensing and field measurements. Forest Ecology and Management *260*: 252-261.
22. Labrecque S, Fournier RA, Luther JE, Piercey D (2006) A comparison of four methods to map biomass from Landsat-TM and inventory data in western Newfoundland. Forest Ecology and Management 226: 129-144.
23. Lu D (2005) Above ground biomass estimation using Landsat TM data in the Brazilian Amazon International. Journal of Remote Sensing 26: 2509-2525.
24. Gleason CJ, Im J (2011) A review of remote sensing of forest biomass and biofuel: options for small-area applications. GIScience & Remote Sensing 48: 141-170.
25. Lu D, Chen Q, Wang G, Moran E, Batistella M (2012) Aboveground forest biomass estimation with Landsat and LiDAR data and uncertainty analysis of the estimates. International Journal of Forestry Research.
26. Lu D, Batistella M (2005) Exploring TM image texture and its relationships with biomass estimation in Rondônia, Brazilian Amazon. Acta Amazonica 35: 249-257.
27. Wang Z, Bastin GN, Liu L, Caccetta PA, Peng D (2015) Estimating woody above-ground biomass in an arid zone of central Australia using Landsat imagery. J Appl Remote Sens 9: 1.
28. Hansen MC, Potapov PV, Goetz SJ, Turubanova S, Tyukavina A, et al. (2016) Mapping tree height distributions in Sub-Saharan Africa using Landsat 7 and 8 data. Remote Sensing of Environment.
29. Tyukavina A, Baccini A, Hansen MC, Potapov PV, Stehman SV, et al. (2015) Aboveground carbon loss in natural and managed tropical forests from 2000 to 2012. Environmental Research Letters 10: 7.
30. Andersen HE, Strunk J, Temesgen H, Atwood D, Winterberger K (2011) Using multilevel remote sensing and ground data to estimate forest biomass resources in remote regions: a case study in the boreal forests of interior Alaska. Canadian Journal of Remote Sensing 37: 1-16.
31. Liu L, Tang H, Caccetta P, Lehmann EA, Hu Y, et al. (2013) Mapping afforestation and deforestation from 1974 to 2012 using Landsat time-series stacks in Yulin District, a key region of the Three-North Shelter region, China. Environmental monitoring and assessment 185: 9949-9965.
32. Liu L, Peng D, Wang Z, Hu Y (2014) Improving artificial forest biomass estimates using afforestation age information from time series Landsat stacks. Environmental monitoring and assessment 186: 7293-7306.
33. Poulter B, Frank D, Ciais P, Myneni RB, Andela N, et al. (2014) Contribution of semi-arid ecosystems to interannual variability of the global carbon cycle. Nature 509: 600-603.
34. Fensham RJ, Fairfax RJ, Holman JE, Whitehead PJ (2002) Quantitative assessment of vegetation structural attributes from aerial photography. International Journal of Remote Sensing 23: 2293-2317.
35. Suganuma H, Abe Y, Taniguchi M, Tanouchi H, Utsugi H, et al. (2006) Stand biomass estimation method by canopy coverage for application to remote sensing in an arid area of Western Australia. Forest Ecology and Management 222: 75-87.
36. Townshend JR, Masek JG, Huang C, Vermote EF, Gao F, et al. (2012) Global characterization and monitoring of forest cover using Landsat data: Opportunities and challenges. International Journal of Digital Earth 5: 373-397.

37. Kennedy RE, Cohen WB, Schroeder TA (2007) Trajectory-based change detection for automated characterization of forest disturbance dynamics. Remote Sensing of Environment, 110: 370-386.

38. Kennedy RE, Yang ZG, Cohen WB (2010) Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1 LandTrendr — Temporal segmentation algorithms. Remote Sensing of Environment, 114: 2897-2910

39. Lehmann EA, Wallace JF, Caccetta PA, Furby SL, Zdunic K (2013) Forest cover trends from time series Landsat data for the Australian continent. International Journal of Applied Earth Observation and Geoinformation 21: 453-462.

40. Huang C, Goward SN, Masek JG, Gao F, Vermote EF, et al. (2009a) Development of time series stacks of Landsat images for reconstructing forest disturbance history. International Journal of Digital Earth 2: 195-218.

41. Huang C, Goward SN, Schleeweis K, Thomas N, Masek JG, et al. (2009b) Dynamics of national forests assessed using the Landsat record: Case studies in eastern United States. Remote Sensing of Environment 113: 1430-1442.

42. Huang C, Goward SN, Masek JG, Thomas N, Zhu Z, et al. (2010) An automated approach for reconstructing recent forest disturbance history using dense Landsat time series stacks. Remote Sensing of Environment 114: 183-198.

43. Li M, Huang C, Zhu Z, Shi H, Lu H, et al. (2009a) Assessing rates of forest change and fragmentation in Alabama, USA, using the vegetation change tracker model. Forest Ecology and Management 257: 1480-1488.

44. Li M, Huang C, Zhu Z, Wen W, Xu D, et al. (2009b) Use of remote sensing coupled with a vegetation change tracker model to assess rates of forest change and fragmentation in Mississippi, USA. International Journal of Remote Sensing 30: 6559–6574

Author Affiliation

Top

Key Laboratory of Digital Earth Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing 100190, China