Leaf area index (LAI)

Subjects: Environmental Sciences
Contributor: Jin Xu

Leaf area index (LAI) is an important vegetation leaf structure parameter in forest and agricultural ecosystems. Remote sensing techniques can provide an effective alternative to field-based observation of LAI. Different system configurations (passive, active, and multisource sensors on different collection platforms) has been used to estimate forest and crop LAI. The ease of use of empirical models supports these as the preferred choice for forest and crop LAI estimation. In terms of scale issues, both spectral and spatial scales impact the estimation of LAI. Uncertainty coming from various sources results in reduced accuracy in estimating LAI.

Keywords: LAI estimation ; remote sensing ; forest and agricultural applications

1. Introduction

Forest and agricultural systems are dominant components of the global ecosystem[1], and understanding how management actions impact their growth patterns[2][3] and their effect on global climate is important[4][5][6]. Leaf area index (LAI) is one of many biophysical parameters that play a significant role in monitoring plant nutritional and health status and can serve as an indicator of stress and damage[7][8]. Moreover, LAI is an important input to many climate[9][10], ecological[11], terrestrial primary production[12][13] and crop growth[14] models. Since the 1990s, LAI estimation has been widely studied in forest[15][16] and agricultural[17][18] systems. Breda[19], Jonckheere et al. [20], Weiss et al.[21], Chen[22], and Qu[23] reviewed experiment design, sampling methods, instruments, and estimation theories for ground-based measurements of LAI. Ground LAI measurement methods are generally divided into two major categories: direct and indirect[24]. Direct measurements include destructive sampling and litterfall collection and are more accurate than indirect methods[20]. Indirect measurements include using optical instruments and estimation models[20][25]. Several devices have been created to improve the efficiency of ground-based measurements of LAI[26]. Based on the gap fraction, which describes light penetration and the amount and distribution of openings in the canopy[27], indirect ground measurements quantify effective LAI (eLAI). Effective LAI is a reduction of true LAI based on the clumping index, which characterizes the effect of nonrandom spatial distribution of foliage on LAI measurements[25]. Therefore, eLAI is smaller than true LAI[25]. Yan et al.[26] describe popular methods, recent advances, challenges, and perspectives of indirect optical ground measurement of LAI, and present clumping correction methods to explain the conversion from eLAI to true LAI. However, ground LAI measurements are labor-intensive, time-consuming, and may only be appropriate for small areas and small stature crops rather than the large extents typical of forests and many agricultural applications.

The development of remote sensing techniques has provided powerful and effective tools for estimating the spatial distribution of LAI for large areas and how LAI changes over time[15][16][28][29]. The increased availability of a large number of sensors with diverse spatial, spectral, temporal, and radiometric characteristics has led to consideration of spatial and spectral scale effects becoming a crucial focus for effectively applying remote sensing data[30]. Furthermore, the impact of these scale effects varies from model to model[31] when remote sensing data is used for LAI estimation. Prior studies have explored the field of LAI estimation from remotely sensed data. Baret and Buis[32] described methods and challenges with canopy characteristic estimation from remote sensing observations, and suggested ways to improve retrieval performance, including using prior information, and incorporating spatial or temporal constraints. Zheng and Moskal[27] reviewed inversion theories and methods of LAI estimation from different sensors and concluded that lidar data could provide accurate, timely, and meaningful information to improve LAI estimation. Song[33] reviewed the use of optical remote sensing in mapping LAI and discussed empirical approaches using spectral and spatial information, as well as semi-empirical and biophysical approaches. Song[33] anticipated that new algorithms using complementary information from different sensors would lead to the generation of better global LAI products. Chen[22] presented LAI principles and algorithms and highlighted issues associated with LAI retrieval using remote sensing data, including the differences among existing global LAI products and distorted seasonal variations of LAI.

2. Leaf Area Index Estimation Using Remote Sensing

Improving forest and crop LAI estimation from remotely sensed data depends on greater utilization of diverse data sources, continued model enhancement, and further exploration of scale effects. There are few studies that report the use of lidar remote sensing for crop LAI estimation, while radar remote sensing has limited application for forest LAI estimation. The expanded use and fusion of different data sources and data types provides opportunities to improve LAI estimation accuracy, consistency, and efficiency.

Beyond the data applied, there are opportunities to improve LAI estimation through continued development of empirical, physical, and hybrid models. In the short-term, without general models, empirical models that require local validation are currently recommended for forest and crop managers. However, continued work is needed to focus on using new inversion algorithms based on machine learning methods to develop general models that mitigate the “ill-posed” problem associated with physical model inversion. This will require the study of physical mechanisms of radiative transfer to integrate local physiology and biochemistry parameter datasets from different sites and temperature zones.

A challenge in creating more generally applicable LAI estimation models is quantifying the scale effects arising from application of images with various resolutions that lead to variable accuracy for LAI estimation. Quantitative exploration of the scale relationship from different sensors can facilitate the utilization of multiple data sources. Spatial scale effects appear to play a more important role for forest LAI estimation as compared to agricultural applications, which is likely related to the impact of the greater pixel heterogeneity typical in forests.

More extensive use of methods to quantify uncertainty is needed to improve rigor in forest and crop LAI estimation and validation. Bayesian approaches have been demonstrated as an effective method to quantify the uncertainty of LAI estimation based on the uncertainty of the input parameters that affect LAI estimation. Further analysis is needed in order to better analyze the quantitative effects of remote sensing data source, ground measurements, and related environmental factors on LAI estimation.

The theoretical uncertainty of ground measurements, influence of scale mismatches, and the uncertainty of LAI estimation are all interrelated. It is necessary to establish an appropriate experimental design to explore scale effects, while taking into account the quantitative uncertainty of input factors in order to better understand and mitigate these challenges. Through enhancing data applications, models, and uncertainty source analysis, remote sensing-based forest and crop LAI estimation models will have greater potential to provide critical support of forest and agricultural management practices.

References

1. Hansen, M.C.; Potapov, P.V.; Moore, R.; Hancher, M.; Turubanova, S.; Tyukavina, A.; Thau, D.; Stehman, S.; Goetz, S.; Loveland, T. High-resolution global maps of 21st-century forest cover change. Science 2013, 342, 850–853.
2. Vanclay, J.K. Modelling Forest Growth and Yield: Applications to Mixed Tropical Forests; CABI: Wallingford, UK, 1994; p. 537.
3. Ryan, M.G.; Binkley, D.; Fownes, J.H.; Giardina, C.P.; Senock, R.S. An experimental test of the causes of forest growth decline with stand age. Ecol. Monogr. 2004, 74, 393–414.
4. Saxe, H.; Cannell, M.G.; Johnsen, Ø.; Ryan, M.G.; Vourlitis, G. Tree and forest functioning in response to global warming. New Phytol. 2001, 149, 369–399.
5. Flannigan, M.D.; Amiro, B.D.; Logan, K.A.; Stocks, B.; Wotton, B. Forest fires and climate change in the 21st century. Mitigation Adapt. Strat. Glob. Chang. 2006, 11, 847–859.
6. Liu, Y.; Stanturf, J.; Goodrick, S. Trends in global wildfire potential in a changing climate. For. Ecol. Manag. 2010, 259, 685–697.
7. Myneni, R.B.; Hoffman, S.; Knyazikhin, Y.; Privette, J.; Glassy, J.; Tian, Y.; Wang, Y.; Song, X.; Zhang, Y.; Smith, G. Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data. Remote Sens. Environ. 2002, 83, 214–231.
8. Zarco-Tejada, P.; Sepulcre-Cantó, G. Remote sensing of vegetation biophysical parameters for detecting stress condition and land cover changes. In Proceedings of the Jornadas de Investigación de la Zona no Saturada del Suelo, VIII, Cordoba, Spain, 14–16 November 2007; pp. 37–44.
9. Neilson, R.P.; Drapek, R.J. Potentially complex biosphere responses to transient global warming. Glob. Chang. Biol. 1998, 4, 505–521.

10. Ruimy, A.; Saugier, B.; Dedieu, G. Methodology for the estimation of terrestrial net primary production from remotely sensed data. J. Geophys. Res. Atoms. 1994, 99, 5263–5283.
11. Bonan, G.B. Importance of leaf area index and forest type when estimating photosynthesis in boreal forests. Remote Sens. Environ. 1993, 43, 303–314.
12. Running, S.W.; Nemani, R.R.; Heinsch, F.A.; Zhao, M.; Reeves, M.; Hashimoto, H. A continuous satellite-derived measure of global terrestrial primary production. AIBS Bull. 2004, 54, 547–560.
13. Wang, R.; Chen, J.M.; Liu, Z.; Arain, A. Evaluation of seasonal variations of remotely sensed leaf area index over five evergreen coniferous forests. ISPRS J. Photogramm. Remote Sens. 2017, 130, 187–201.
14. Curnel, Y.; de Wit, A.J.; Duveiller, G.; Defourny, P. Potential performances of remotely sensed LAI assimilation in WOFOST model based on an OSS Experiment. Agric. For. Meteorol. 2011, 151, 1843–1855.
15. Treitz, P.M.; Howarth, P.J. Hyperspectral remote sensing for estimating biophysical parameters of forest ecosystems. Prog. Phys. Geogr. 1999, 23, 359–390.
16. Chen, J.M.; Cihlar, J. Retrieving leaf area index of boreal conifer forests using Landsat TM images. Remote Sens. Environ. 1996, 55, 153–162.
17. Carlson, T.N.; Ripley, D.A. On the relation between NDVI, fractional vegetation cover, and leaf area index. Remote Sens. Environ. 1997, 62, 241–252.
18. Wu, C.; Niu, Z.; Wang, J.; Gao, S.; Huang, W. Predicting leaf area index in wheat using angular vegetation indices derived from in situ canopy measurements. Can. J. Remote Sens. 2010, 36, 301–312.
19. Breda, N.J. Ground-based measurements of leaf area index: A review of methods, instruments and current controversies. J. Exp. Bot. 2003, 54, 2403–2417.
20. Jonckheere, I.; Fleck, S.; Nackaerts, K.; Muys, B.; Coppin, P.; Weiss, M.; Baret, F. Review of methods for in situ leaf area index determination: Part I. Theories, sensors and hemispherical photography. Agric. For. Meteorol. 2004, 121, 19–35.
21. Weiss, M.; Baret, F.; Smith, G.; Jonckheere, I.; Coppin, P. Review of methods for in situ leaf area index (LAI) determination: Part II. Estimation of LAI, errors and sampling. Agric. For. Meteorol. 2004, 121, 37–53.
22. Chen, J.M. Remote sensing of leaf area index of vegetation covers. In Remote Sensing of Natural Resources; CRC Press: Boca Raton, FL, USA, 2013; pp. 375–398.
23. Qu, Y. Leaf Area Index: Advance on the Ground-Based Measurement. In Observation and Measurement of Ecohydrological Processes; Li, X., Vereecken, H., Eds.; Springer: Berlin/Heidelberg, Germany, 2018; pp. 1–20.
24. Gower, S.T.; Kucharik, C.J.; Norman, J.M. Direct and Indirect Estimation of Leaf Area Index, fAPAR, and Net Primary Production of Terrestrial Ecosystems. Remote Sens. Environ. 1999, 70, 29–51.
25. Chen, J.M.; Rich, P.M.; Gower, S.T.; Norman, J.M.; Plummer, S. Leaf area index of boreal forests: Theory, techniques, and measurements. J. Geophys. Res. Atmos. 1997, 102, 29429–29443.
26. Yan, G.; Hu, R.; Luo, J.; Weiss, M.; Jiang, H.; Mu, X.; Xie, D.; Zhang, W. Review of indirect optical measurements of leaf area index: Recent advances, challenges, and perspectives. Agric. For. Meteorol. 2019, 265, 390–411.
27. Zheng, G.; Moskal, L.M. Retrieving leaf area index (LAI) using remote sensing: Theories, methods and sensors. Sensors 2009, 9, 2719–2745.
28. Green, E.P.; Mumby, P.J.; Edwards, A.J.; Clark, C.D.; Ellis, A.C. Estimating leaf area index of mangroves from satellite data. Aquat. Bot. 1997, 58, 11–19.
29. Wulder, M.A. Optical remote-sensing techniques for the assessment of forest inventory and biophysical parameters. Prog. Phys. Geogr. 1998, 22, 449–476.
30. Weng, Q. Scale Issues in Remote Sensing; John Wiley & Sons: Hoboken, NJ, USA, 2014.
31. Wu, H.; Li, Z. Scale issues in remote sensing: A review on analysis, processing and modeling. Sensors 2009, 9, 1768–1793.
32. Baret, F.; Buis, S. Estimating canopy characteristics from remote sensing observations: Review of methods and associated problems. In Advances in Land Remote Sensing; Springer: Dordrecht, The Netherlands, 2008; pp. 173–201.
33. Song, C. Optical remote sensing of forest leaf area index and biomass. Prog. Phys. Geogr. 2013, 37, 98–113