森林垂直结构参数实测与遥感研究进展: 以叶面积指数和聚集指数为例

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摘要 森林垂直结构参数指的是森林冠层孔隙率、郁闭度、叶面积指数(leaf area index, LAI)和聚集指数(clumping index, CI)等关键结构参数在垂直方向的分布特征. 获取森林垂直结构参数是深入研究森林碳氮水循环和遥感辐射传输过程的关键环节. 本文聚焦LAI和CI, 探讨森林垂直结构参数地面实测与遥感反演研究进展. 地面测量的常用仪器有LAI-2200、数字半球相机和光合有效辐射(photosynthetically active radiation, PAR)测量仪等, 不同高度的测量可以通过破坏采样、塔基测量和移动升降机等手段来进行. 地面测量方法虽然较为准确, 但通常比较费时费力, 不利于获取大范围信息. 遥感方法主要通过经验的植被指数估算或物理模型反演来进行. 激光雷达(LiDAR)作为一种主动式遥感方法, 具有反演垂直结构参数的独特优势. 虽然遥感方法能够进行大范围连续观测, 但目前还没有成熟的全球遥感产品能满足实际需求, 少数区域产品也缺乏充分的质量检验. 森林垂直结构参数已经在陆面过程模型、冠层辐射传输模型和森林经营管理中展现了巨大的应用价值. 未来的研究应进一步探索新的地面测量和遥感反演方法, 分析参数的垂直分布特征, 同时开展垂直结构参数的验证研究, 为森林垂直结构参数在模型机理研究和森林管理中提供科学依据.

关键词 垂直结构参数, 叶面积指数, 聚集指数, 地面测量, 遥感反演, 激光雷达

由于森林植被对阳光、养料和水分等自然选择的结果, 森林不同植被种群分别占据了不同空间, 形成了独特的垂直分层分布结构, 自上而下可分成乔木树冠层、下木层、灌木层、草本植物层和苔藓等不同层次^[1]. 森林垂直分层直接影响太阳辐射和水分蒸散在林冠中传递, 造成树冠不同部位叶片光合作用差异, 进而影响树木生长和植物群落的演替过程^[2]. 森林的结构特征还影响风速、空气温湿度、土壤蒸发量、土壤热储量、土壤温度等林内小气候特征, 并影响林冠和外界大气环境之间的能量交换^[2]. 从全球尺度来看, 森林结

构特征影响着地球表层的能量、水分和物质交换过程, 进而影响全球气候变化.

森林的垂直分层很自然地也导致森林关键结构参数在三维时空上的异质性, 同时极大增加了森林物质能量交换过程和遥感辐射传输建模的复杂性. 为了深入分析森林生态系统的内在结构和功能, 完善地表能量水分交换过程模型, 掌握并分析森林变化对全球变化的影响, 必须对森林的垂直结构参数进行定量研究.

森林冠层结构参数, 如冠层孔隙率(gap fraction)、冠层郁闭度(canopy closure, CC)、叶面积指数(leaf area

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index, LAI)和聚集指数(clumping index, CI)等是描述森林结构的关键参数. 森林孔隙率描述森林冠层对光的投射能力, 在森林各个方向孔隙大小都会不同. 冠层郁闭度与冠层孔隙率相对应, 指的是林地一点向上仰视树冠遮挡天空半球的比例. 植被LAI指的是单位地表上的植被叶片面积, 单位为 m^2/m^2 . 与LAI对应的是叶面积密度(leaf area density, LAD)分布, 指垂直方向上不同高度的叶面积分布密度, 单位为 m^2/m^3 . CI描述叶片在空间上的分布特征, 比如是随机分布、有规律的分布还是聚集分布. 对植被冠层来说, 叶片在空间的分布通常不是随机的, 而是呈聚集状, 这就是植被的聚集效应.

上述几个参数通过Beer-Lambert定律相关联^[3]:

$$P(\theta) = e^{-G(\theta)\text{LAI}_e(\theta)/\cos(\theta)} = e^{-G(\theta)\Omega(\theta)\text{LAI}/\cos(\theta)}, \quad (1)$$

其中, θ 为视场角, $P(\theta)$ 为冠层孔隙率或透射率, $\Omega(\theta)$ 为聚集指数, $G(\theta)$ 是投影函数. LAI_e 为植被的有效LAI, CI定义为 LAI_e 和LAI的比值^[4]:

$$\text{CI} = \text{LAI}_e / \text{LAI}. \quad (2)$$

在一个特定的地面点, 冠层郁闭度可以从冠层孔隙率计算得到:

$$\text{CC} = 1 - \int_0^{\pi/2} P(\theta) \sin\theta d\theta. \quad (3)$$

森林垂直结构参数通常通过地面测量或遥感估算方法获取. 本文首先总结了森林垂直结构参数地面测量与遥感估算的方法, 然后介绍了目前国内外现有的一些垂直结构参数产品. 文章分别以LAI和CI两个关键植被结构参数为例探讨了二者的垂直分布特征, 然后对森林垂直结构参数在陆面模型、冠层辐射和森林管理中的应用进行了分析. 最后总结了目前森林垂直结构参数研究的进展并对未来的发展方向进行了探讨.

1 地面测量方法

关于植被结构参数的测量方法已有诸多研究进行过详细的分析评述^[4,5], 但这些研究大多是针对植被结构参数总体特征的测量, 没有专门讨论垂直结构参数的测量. 本节主要介绍常用的森林垂直结构参数的直接测量方法、间接光学测量方法和测量平台, 同时分析了地面测量中应该注意的一些事项.

1.1 直接测量方法

地面测量方法中最直接的方法就是基于破坏砍伐

测量, 用这种方法直接将树木砍伐然后测量各层的结构参数^[6-8]. 比如, 朱春全等人^[9]对集约经营与粗放经营杨树人工林分的叶面积垂直分布及其季节动态变化进行了对比研究, 首先选择了研究区的样树并伐倒, 然后从树冠顶端开始每1 m分层切割, 接着测量各层内平均叶面积并计算总体LAI. 不过, 直接的破坏砍伐方法一般都比较费时费力, 对农作物的测量还相对方便^[10,11], 但对森林则难于开展大范围采样, 一般都选择研究区的标准木进行测量, 仅有个别研究借助森林抚育的机会进行大规模的砍伐. 比如, Iiames等人^[12]先测量了样地总体的LAI, 然后用机械方法和除草剂除去所有林下植被并再次测量林冠层LAI, 二者的差值则是林下植被的LAI.

1.2 光学测量方法

森林冠层结构参数的获取传统上都是通过森林地表实地测量得到, 比如通过冠幅测量方法测量郁闭度^[13]、通过收获法或叶面积仪获取LAI^[14]、通过数字半球相机(digital hemispherical photography, DHP)获取CI等^[15].

LAI-2200以及先前的LAI-2000叶面积仪由美国的LI-COR公司生产, 是多年来广泛使用的测量植被LAI的仪器^[16-18]. LAI-2200计算LAI的基本原理也是基于式(1). 它假设植被叶片是不透明的而且是在空间随机分布的一些点, 然后通过同时测量5个不同高度角冠层顶部和底部的漫射辐射计算透射率和孔隙率. 该仪器使用便捷, 在农田测量时可以方便地对不同高度冠层分层测量^[10], 对森林测量时可以用双杆同步测量, 即一个杆在林区外的空地测量入射辐射, 另一个在冠层中不同高度同步测量透射辐射^[19]. LAI-2200通常只用于测量LAI单个参数, 无法同时获取其他结构参数的测量. 实际使用时通常与其他测量方法如DHP等一起开展测量.

半球摄影(hemispherical photography, HP)技术从二十世纪六七十年代起就一直在植被结构参数测量中发挥着重要的作用^[20]. 早先的HP技术都是基于胶片摄影, 然后需要经过数字化后再用图像处理软件获取结构参数. 比如, Soudani等人^[21]利用HP相机分别放置在地表(0.15 m), 草本层之上(1.7 m)和灌木层之上(2.7 m)获取了法国松林不同层的LAI并分析了各层之间的关系. 二十世纪八九十年代, 一度流行同时使用HP和LAI-2000结合测量垂直叶面积分布特征^[22]. 进入21世纪, 由于数字技术的发展, DHP已经逐步取代了原先基于胶片的

HP方法. DHP方法简单易用, 而且可以同时获得多个冠层结构参数, 如孔隙率、郁闭度、LAI和CI等, 已经在植被结构参数测量中得到越来越广泛的应用, 目前也有相当多的商用和开源软件可供选择^[4].

许多仪器, 如Sunfleck Ceptometer和AccuPAR等, 通过测量森林对光合有效辐射(photosynthetically active radiation, PAR)的透射率来估算LAI, 其原理类同式(1)^[23,24]. 分层LAI则通过测量不同高度的PAR垂直剖面来推导^[25,26]. 比如Vose和Swank^[26]利用观测塔, 从地面1.4 m开始, 每隔2 m测量PAR透射率, 然后通过式(1)计算不同高度的LAI分布. 因为PAR测量是许多生态系统通量网站的标准测量数据, 该方法为获取全球代表性站点的森林垂直结构信息提供了极为重要的数据源.

TRAC冠层分析仪也常常用于同时测量LAI和CI^[27]. TRAC的一个特色是在获取冠层孔隙率的同时能获取冠层孔隙大小的分布并用于估算CI. TRAC可以方便地测量林冠层和总体LAI, 从而计算林下植被的LAI^[28]. 不过因为测量时需要手持仪器稳步移动, 该仪器无法用于测量更多层的垂直结构参数.

1.3 测量平台

森林垂直结构信息的测量实际上是传统地表测量方法在垂直方向的延伸^[29-31]. 森林垂直观测平台可以分为静止塔和移动平台两大类. 为了观测不同高度的结构特征, 许多研究人员就在样树旁搭建观测架子或利用观测塔进行分层测量. 借助观测塔的便利, 各种经典冠层结构的地面测量方法都可以使用, 比如利用收获法对叶面积进行测量^[32], 或广泛利用LAI-2000冠层分析仪^[17,19,33]和DHP^[21,34,35]进行测量. 例如, Song和Ryu^[16]利用一个4 m间距的5层观测塔测量温带落叶阔叶林的分层LAI. 不过, 基于观测塔的测量因为受塔址和塔本身的限制, 位于单个塔点的测量往往难以代表样区的状况.

为了克服固定观测塔的局限, 一些研究人员开始利用移动采样设备, 如利用载人液压升降机可以很方便地测量不同高度的叶面积^[18,22,36-38]. 在液压升降机上, 可以使用破坏采样或间接的光学测量方法测量叶面积等结构参数. 利用液压升降机, Wang等人^[22]在9个移动采样点同时利用LAI-2000和半球摄影获取了8个不同高度的垂直LAI分布数据. 不过移动式液压升降机属于大型装备, 自身重量往往比较大, 在野外操作和迁移转换存在诸多不便, 而且使用时受地形限制, 设备本

身也难免会对冠层造成一定影响.

在巴西热带雨林, Fauset等人^[39]尝试了使用绳索悬挂PAR传感器和DHP的方法测量不同高度的透射率. 该方法虽然成本很低, 简单易行, 但缺陷也很明显, 一方面得有高大的树木可用于下悬相机, 另一方面测量容易受树木本身的限制.

1.4 实测注意事项

虽然野外地面实测方法能够提供较为准确的森林垂直结构信息, 但野外测量一般比较费时费力, 而且通常只能获取有限样点上的数据, 应用范围受到了极大的限制. 地面破坏法测量大多是基于独立标准木的测量, 塔基和移动升降机测量的空间代表性往往有限. 受测量数据的限制, 目前对森林垂直结构参数的时空变化特征还缺乏深入的了解. 比如, 对LAI和CI在时空上的变化耦合关系、对CI在不同高度和角度上的变化特征等, 目前都还缺乏明确的认识.

对森林来说, 林冠层和林下植被对光能和降水截留的区分明显. 但目前的野外实测中二者经常被混淆. 如果用林冠层的LAI作为总体LAI会给LAI估算和产品验证以及陆面过程的应用带来很大的误差. 一种实用的方法是分别测量林冠层和总的LAI, 林下植被的LAI可以从总的LAI中减去林冠层的LAI得到^[28,40]. 分别利用上视和下视DHP则可以方便地获取林冠层和林下植被的结构参数^[34,41]. 对CI的测量和验证来说, 同样需要区分林冠层和林下植被. 因此, 正确区分林冠层和林下植被是进行森林垂直结构参数测量的前提.

另一个需要注意的是植被的木质部分(树干和树枝等)对LAI和CI测量的影响, 因为在光学测量中难以区分植被的叶片和木质组分^[42]. 对落叶林而言, 可以在落叶季节测量木质面积指数(woody area index, WAI), 并在植被面积指数(plant area index, PAI)中减去WAI得到单纯的LAI($LAI=PAI-WAI$). 对常绿林, 则只有通过破坏砍伐再进行叶面积测量^[43].

2 遥感估算方法

遥感技术的发展为冠层结构参数的获取提供了新的手段. 遥感技术主要通过被动光学、LiDAR和合成孔径雷达方法来估算森林垂直结构参数.

2.1 被动光学遥感估算方法

经典的利用光学遥感方法估算植被结构参数主要

通过经验统计关系或物理模型反演来进行估算,两种方法都可以通过向垂直方向拓展来估算垂直结构参数.用统计方法估算植被垂直结构参数首先通过建立植被结构参数与植被指数或其他参数之间的经验关系,再将经验关系用于估算不同层片的结构参数.估算植被结构参数使用最广泛的是归一化差值植被指数(NDVI).比如Liames等人^[12]利用NDVI经验统计方法从IKONOS数据估算林冠层和林下植被的LAI,但IKONOS估算得到的林下植被LAI低估了实测的LAI值. Pi-sek等人^[44]则利用一个改进的比值植被指数(SR),从多角度MISR数据分别估算了北美森林植被林冠层和林下植被的LAI. 基于三维冠层辐射传输模型模拟, Kobayashi等人^[45]从归一化水体指数(NDWI)估算了林冠层和林下植被的LAI并分析了不同层LAI的季节变化特征. 芬兰赫尔辛基大学的Heiskanen等人^[46]利用LAI与植被覆盖度(fractional vegetation cover, FVC)的对数关系,分别估算了芬兰北方森林站点林冠层和林下植被的LAI.

统计方法虽然比较简单易用,但该方法得到的经验关系不一定能用于不同区域的植被类型,可推广性有局限. 有少数学者尝试了利用冠层辐射传输模型来估算不同高度的结构参数. Wang和Li^[47]开发了一个多层的冠层辐射传输模型(MRTM),该模型考虑了植被垂直方向上不同的生物物理和生物化学参数,如LAI、叶绿素含量、水分和干物质含量等,取得了比单层模型更好的模拟效果. Huang等人^[48]利用高光谱Hyperion数据,从森林辐射传输模型FRT中反演了龙门河自然保护区林冠层和林下植被的LAI. 总体来说,受限于成像机理,利用被动光学方法估算森林垂直结构参数尚存在很大的局限性,虽然有少量学者在局地作了一些尝试但在实践中应用还很少.

2.2 LiDAR遥感估算方法

由于被动光学遥感方法的局限性,在实践中估算森林垂直结构参数大量使用的是LiDAR主动光学遥感技术^[29,49]. LiDAR系统首先发射一个激光束到探测物体,通过接收到的激光回波特性分析探测对象的基本特性. 根据搭载平台不同,有地基、机载(空基)和天基(卫星或国际空间站)等LiDAR系统^[49,50].

地基LiDAR光斑尺寸小、分辨率高,对植被冠层具有一定的穿透力,能够获得植被冠层内外详细的三维结构信息^[51,52]. 处理时一般先通过高精度LiDAR点

云构建冠层体元(voxel)模型,然后结合基于体元的冠层分析方法(voxel-based canopy profiling, VCP)估算LAI、LAD及其垂直分布情况^[51,53,54]. 使用机载LiDAR时,系统通常安装在固定翼机、直升机或无人机上^[40,55]. 机载LiDAR最常用的一个数据源是美国航空航天局(NASA)的机载全波形陆地植被和冰面传感器(LVIS)数据(<https://lvis.gsfc.nasa.gov/Home/index.html>),该数据一直被广泛用于反演冠层分层结构研究^[56,57]. 星载LiDAR提取森林垂直结构参数的研究相对少,目前只有冰卫星(ICESat)上的地球科学激光高度计系统(GLAS)在实践中得到了部分应用^[58]. 后续发射的第二颗冰卫星(ICESat-2)上搭载了高级地形激光高度计系统(ATLAS),具有一定的估算分层结构参数的潜力^[59,60]. 最近,国际空间站上搭载的全球生态系统调查仪(GEDI)发布了南北纬51.6°范围内5 m分层的冠层覆盖度、PAI和植被面积体密度(PAVD)等分层结构信息^[61],提供了首套全球尺度基于LiDAR的分层参数产品.

利用LiDAR反演森林结构参数的基本原理都是基于孔隙率和LAI以及CI三者之间的关系(式(1)),一般也可以分为基于经验统计的方法和基于物理模型的方法两种^[4]. 用统计方法估算森林垂直结构参数一般先计算激光穿透指数(LPI)或上下比率指数(ABRI),然后通过LAI与孔隙率的相关关系来估算LAI^[62,63]. 另外,也可以先通过LiDAR估算得到的林冠覆盖率、林冠高度或叶密度,然后通过异速生长方程(allometric equation)来估算LAI^[64,65].

基于物理模型的方法则首先模拟特定林分的LiDAR波形(waveform),然后通过模型反演的方法估算LAI等参数^[56,66,67]. 例如, Tang等人^[56]从机载LVIS反演得到了0.3 m高度间隔的LAI垂直分布曲线,而且与实测LAI的分布吻合较好($R^2=0.63$, RMSE=1.36). Tang等人^[58]进一步利用ICESat/GLAS数据估算了全美植被不同高度层的LAI分布图. Wang和Kumar^[68]则尝试利用地基全波形LiDAR计算了森林CI的垂直分布剖面,利用该CI数据可以对不同高度的有效LAI进行聚集效应修正^[52,69].

LiDAR技术的一个最大优势就是能够获得不同冠层高度的森林垂直结构特征^[55,58,67,70]. 但是地基LiDAR受观测点位的影响,不利于大范围高效采样测量. 实践中,常常利用机载和地基LiDAR的综合优势来联合反演森林结构参数^[71],也可以用地基数据来对机载Li-

DAR进行定标和检验^[72]。LiDAR数据同时包括了树冠木质部分和树叶部分的信息,可以基于不同物体的散射特性,通过图像处理技术剔除非光合作用部分^[52,54]。

当前利用LiDAR估算森林结构特征的研究在全世界方兴未艾,但是目前绝大多数关于森林垂直结构的研究都是基于地面和机载LiDAR。新的天基LiDAR技术的发展,如ICESat-2/ATLAS和国际空间站上的GEDI等,将大大推进全球尺度森林垂直结构信息的获取。相比LAI,植被CI的遥感反演研究开展较晚,现有通过LiDAR反演CI的研究还不够成熟,还没有现成产品能满足地面过程模型或遥感建模的需求。另外,LiDAR仪器操作和数据处理还是相对复杂,使得大范围应用受到一定限制。

2.3 合成孔径雷达估算方法

合成孔径雷达的优势在于能弥补普通光学遥感获取数据时受云和降水等影响导致的数据缺失问题。利用合成孔径雷达估算植被结构参数也可以分为经验方法、半经验方法或模型反演方法等^[73]。比如,一般通过建立LAI与雷达后向散射系数的经验关系来估算LAI^[74,75]。也有个别研究通过反演雷达物理模型来估算^[76]。但这些方法容易受观测条件、传感器设置、冠层结构以及下垫面等因素的影响,使用困难,不易推广,难以在实践中用于估算森林的垂直结构参数。未来通过融合光学与雷达数据或许有助于提高LAI等森林结构参数的估算^[77]。

近年发展的层析雷达(TomoSAR)技术扩展了传统二维雷达成像方法,可获取不同观测角的多个图像^[78]。利用TomoSAR可以反演森林冠层不同高度的散射强度,从而进行三维成像,这一新技术为获取森林垂直结构信息带来了新的启发^[79,80]。但由于计算过程比较复杂,对LAI的提取精度受限,验证也比较困难,在实践中并未得到广泛应用。目前的研究大多集中在基于TomoSAR的三维点云构建,距离实际反演冠层垂直结构参数还有一定距离。

3 遥感产品与验证

目前关于森林垂直结构参数的遥感产品还非常少,仅有少量研究生成了关于LAI分层的产品。比如,中国科学院地理科学与资源研究所从MODIS和MISR生产的林冠层和林下植被分层的全球LAI产品^[81],日本太空发展署(JAXA)基于GCOM-C卫星生产的分层LAI产品

(https://suzaku.eorc.jaxa.jp/GCOM_C/data/update/Algorithm_LAI_en.html),美国马里兰大学从GLAS得到的全美分层LAI^[58],以及最新从GEDI得到的中低纬分层PAI和PAVD等^[61]。利用星载LiDAR可以有效地估算全球森林垂直结构参数,但目前大部分工作集中在对全球树高的估算^[82,83],除了仅有的GEDI数据,尚缺乏对孔隙率、郁闭度、LAI和CI等分层参数的估算。由于星载LiDAR数据庞大处理复杂,目前的工作大多集中在局部小区域,相对缺乏业务化的全球分层产品生产能力。

与所有陆面参数产品的验证类似,大尺度垂直结构参数的验证可以通过不同产品之间的交叉对比或者通过与小尺度数据来进行对比验证。比如,Liu等人^[81]对比分析了GLOBMAP林冠层和林下植被的LAI与SPOT/VGT估算得到的分层产品,进一步的验证则需要通过与地面实测数据对比。与此类似,星载LiDAR的反演结果可以用机载LiDAR来进行验证^[84,85],而机载和地基LiDAR得到的结构参数则主要依赖于与其他传统的野外测量,比如LAI-2200、DHP或TRAC等的结果对比验证^[86,87]。依前文所述,关于森林垂直结构参数的地面实测数据极为缺乏,这大大限制了对遥感反演垂直结构参数的验证。比如,Liu等人^[81]的分层LAI产品仅在有限的北方森林站点进行了验证,而且林冠LAI的均方根误差(RMSE)达到1.36,而马里兰大学生产的全美植被分层LAI^[58]以及最新的GCOM-C和GEDI分层产品^[61]都有待充分验证。

总体来看,虽然目前已有一些研究通过遥感方法获取了少量森林垂直结构产品,但由于缺乏足够的地面实测垂直结构数据,遥感获取的垂直结构信息大多缺乏充分的地面验证,不同遥感方法获取的垂直结构数据之间也缺乏足够的对比分析。现有的验证工作只能基于有限的站点或观测塔数据来对部分遥感结构参数进行验证。由于站点和塔基观测往往缺乏空间代表性,这样的验证工作难以充分反映研究区的空间异质性特征。近年来新兴的无线传感器网络^[88,89]和无人机遥感^[90,91]为获取植被结构参数提供了新的有效手段,受到了越来越广泛的关注^[92,93]。未来有必要进一步研究使用便捷有效的观测方法来获取大量的植被分层结构信息,对遥感获取的垂直结构参数进行充分的验证。

国际上,对地观测卫星委员会(CEOS)下设的陆表关键参数验证计划(LPV)(<https://lpvs.gsfc.nasa.gov/>)专门负责组织和协调对卫星获取的各种地表参数产品进行验证。由于起步较晚,目前CEOS/LPV还没有专门设

置对LiDAR获取的地表参数进行验证的工作组。对森林垂直结构参数,除了个别研究人员的工作,还没有专门的联合验证计划,这极大限制了LiDAR结构参数的应用范围。一批新的卫星和传感器,如ICESat-2、GCOM-C、GEDI、BIOMASS、Tandem-L和我国的陆地碳卫星等都提出用新的技术对全球森林垂直结构异质性进行观测。很明显,亟须建立对森林的垂直结构遥感数据进行地面验证的网络和技术体系。

4 LAI和CI的垂直分布特征

4.1 LAI的垂直分布特征

本节聚焦LAI和CI两个关键植被结构参数,讨论森林垂直结构分布特征。不同的森林类型具有不同的垂直结构特征,简单的可分为上层林冠层和林下植被,稍复杂的如Baldocchi等人^[94]将温带森林分为5层植被外加1层土壤层。另外也有其他的分层方案,比如按照对光的截获率分层^[95]。森林的整体LAI是乔木层、灌木层和草本层的总和。相比较而言,针叶林的垂直结构比较简单,一般由上层乔木和下层草本构成,林下植被的LAI通常占总体的20%~40%^[19]。热带雨林的垂直结构比较复杂,其中还包括缠绕在树上的藤本植物的LAI^[32]。遥感获得的LAI通常是森林整体的LAI值。为此,在野外测量时,需要同时获取乔木、灌木和草本的LAI值来对遥感LAI进行验证。实践中,由于各植被层不易区分,也可以按一定间隔分层测量不同高度层的叶面积。按不同高度分层的叶面积分布数据也有利于验证LiDAR反演的结果^[4]。

LAI的垂直分布模式一直是植被结构研究的重要主题,而且该分布模式常常被用于模拟植被不同高度的降水截留、辐射传输和光合作用过程^[41,96]。早在1981年,Ross^[97]就提出用正态随机分布来表示不同高度的农作物叶面积分布,随着作物的生长,可以逐步用正态对数分布来表示。随后,Ross等人^[98]又尝试了用5次多项式拟合柳树在不同时期的叶密度分布函数。但对森林冠层而言,无论是正态分布还是多项式拟合目前都已经很少使用。对阔叶林来说,现有研究普遍采用韦伯分布(Weibull distribution)来表示LAI(或叶密度)的垂直分布^[6,18,99]。针叶林冠层形态则相对复杂,人们尝试过多种分布函数。比如,一些研究表明贝塔分布(beta distribution)^[100,101]和卡方分布(chi-square distribution)拟合针叶林冠层的效果比较好^[100]。Jerez等人^[102]则探索

了用约翰逊S-B分布(Johnson's S-B distribution)来拟合针叶林叶密度的垂直分布。但Weiskittel等人^[103]在美国缅因州的针叶林测量则发现韦伯分布比贝塔分布和约翰逊S-B分布的拟合效果都好。地面测量和遥感估算方法的发展将有助于增进人们对LAI垂直分布的理解。

4.2 CI的垂直分布特征

森林CI的值通常在0.3~1.0^[104]。在加拿大,落叶林的CI一般在0.7左右^[105]。Zhao等人^[106]基于LiDAR和DHP在美国加州测得的针叶林CI在0.46~0.97之间。Vincent等人^[107]获得的热带雨林CI平均为0.48。现有的基于观测塔的测量^[108]和三维模型模拟^[109]研究均表明CI随着森林冠层高度会发生明显的变化。由于森林冠层上部的孔隙一般比下部大,通常来讲,随着冠层高度的增加,聚集效应也随之增强(CI值减小)。Haverd等人^[110]提出不同高度的CI可以用一个随冠层密度和孔隙度变化而变化的解析式来表达。由于样本较少,目前还没有一个统一的分布模式来表达森林CI的垂直分布特征。

地面测量时,由于冠层上部的叶片受到下层的遮挡,近地表的CI测量可能会低估冠层的总体聚集效应^[111]。与此相反,对卫星遥感反演得到的CI来说,因为卫星遥感获取的森林光学和结构信息主要还是来自冠层顶部,而冠层顶部通常更为聚集,因此卫星反演得到的CI有可能高估冠层的总体聚集效应^[112,113]。森林冠层CI随高度的变化对辐射传输建模以及验证LiDAR反演的CI高度产品都有重要的影响。比如,Ni-Meister等人^[114]在冠层辐射传输建模时对林冠层和林下植被赋予不同的CI值。而在作遥感CI产品验证时,必须综合考虑林冠层和林下植被的CI分布特征。不过,也有个别研究认为森林冠层内部的辐射吸收对CI的垂直分布并不敏感,可以用一个常数来代表冠层整体的CI^[110]。

5 应用研究

5.1 森林碳氮水循环与陆面过程模型模拟

森林的垂直结构特征直接影响森林对太阳辐射和大气降水的截获能力以及植被的光合作用^[2]。森林垂直结构参数如冠层高度、植株密度、冠层分层特征和LAI等是精确理解森林碳氮水循环过程和陆面过程模型模拟的必备要素。森林对太阳辐射和降水的截留首先发生在林冠层。在我国福建三明森林生态站的研究表明,格式栲天然林林冠层的降水截获率高达38%以

上^[115]。森林林冠层和林下植被的碳储量有明显的区别。在冠层密度比较低的地区,林下植被可占森林总体生物量的40%^[19]。在芬兰北方森林地区,下垫面植被的光合作用碳吸收可达到生态系统碳吸收的一半以上^[116];而在阿拉斯加,下垫面植被的碳吸收量高达61%^[117]。

陆面过程模型模拟陆地表面与大气界面上的辐射、热量、水分和动量交换过程^[118]。三维陆面过程模型则通过植被叶片和枝干在三维空间的分布来计算每个空间体元对光能和降水的截获。相比用整体叶面积而忽视冠层的垂直分异,对冠层垂直结构作分层处理能更好地模拟地上净初级生产力(NPP)在空间的变化^[119]。这方面最具代表性的模型是法国Grenoble大学领衔开发的ORCHIDEE模型,该模型能计算不同垂直高度冠层对光能的透射、吸收和反射状况^[120]。在ORCHIDEE模型中,冠层可以细分为多达20层,每层都可以设置不同的参数值,其中各层的LAI分别由最大LAI估算得到。同时ORCHIDEE模型中还用一个分层CI参数来计算太阳光在特定冠层深度的透射率^[121]。与ORCHIDEE模型类似,英国气象局研发的JULES模型也允许用户对冠层进行分层(缺省为20层),每层用不同的LAI值来对直射和漫射光的辐射传输进行模拟^[122]。法国农业科学研究院开发的MuSICA模型则把植被冠层分为4层,每层的叶子都有不同的光学特性和叶龄,而且相关参数还可以随季节变化^[123]。与观测数据比较发现该模型能非常好地模拟冠层的显热通量^[123]。另外,韩国首尔大学开发的FvCB模型则把冠层分为8层,每层附不同的结构参数来模拟冠层光合作用。目前,三维陆面过程模型的发展方向在于发展高精度的多层模型,这对冠层结构参数的三维时空分布提出了更高的要求。

5.2 辐射传输建模与参数真实性检验

森林垂直结构信息为遥感辐射传输建模和参数真实性检验提供了基础条件。目前已有的主要植被冠层辐射传输模型包括单层混合介质模型、多层模型和三维模型等^[4]。单层混合介质模型是将整个植物冠层看成是同质的混沌介质,类似一层大叶,来模拟光在冠层中的辐射传输过程。这方面典型的模型如SAIL系列模型^[124]。后期改进的SAILH模型则可以模拟分层冠层并对不同层设置不同的参数值。多层模型则是将冠层分层并考虑植被结构的垂直差异,同时模拟光在经过不同叶层产生的光强衰减,比如经典的ACRM模型将植

被冠层分为两层进行模拟^[125]。三维模型则通过对冠层结构进行详细的三维刻画,由此来计算冠层内光的传输过程,如DART模型等^[126]。

不论是多层模型还是三维模型,都需要明确的关于冠层结构的垂直分布信息,来对模型进行模拟和参数反演验证。森林垂直结构参数的获取为多层模型和三维辐射传输模型提供了必要的参数化条件,而且有助于降低植被冠层反射率模拟的系统误差^[47]。目前由于缺乏具体的垂直分层信息,许多情况下在对多层模型模拟时不得不进行简化,最后还是以单层的方式进行模拟^[127]。这种对冠层结构的简化有时会给冠层反射率和能量交换的模拟带来很大的误差^[47,128]。

5.3 森林多样性监测与森林经营管理

森林垂直结构信息是森林多样性监测和高质量森林经营管理的重要依据。森林的生物多样性是地球生物多样性的主要组成部分,获取森林垂直结构信息不仅有利于深入了解森林生态系统的多样性,也有利于合理培育和经营森林群落。冠层郁闭度和LAI是国际对地观测组织(GEO)生物多样性观测网络(GEOBON)中研究生态系统结构的两个重要指标^[129]。森林生态系统的生物多样性监测应该是立体的和动态的。森林垂直结构信息有助于更好地掌握不同高度森林的动植物资源特征,为深入研究不同动植物的栖息空间和食物条件提供重要信息,为森林生态系统生物多样性研究提供科学保障。

森林经营管理包括更新造林、森林抚育、林分改造和伐区管理等,主要目的是获得林木产品或生态效益^[130]。森林郁闭度和叶面积的变化是检验森林经营好坏的重要指标。研究表明,森林三维结构的异质性有利于增进森林对各种扰动的抵抗能力^[131],同时也提高了森林的林木产量^[132]。LiDAR数据已经在森林管理中发挥巨大的作用,利用地基LiDAR获取的叶面积垂直剖面信息可以作为林木健康的指标,有助于管理人员作出合理的修剪、灌溉和施肥决策^[57,133]。由于受外部扰动(如大风、林火、洪水和滑坡等)和自然演替的影响,森林结构时常处于动态变化之中。掌握森林结构特征及其在时空上的变化,有利于科学规划森林经营管理方案,获得最大的经济和生态效益。

6 结语

森林垂直结构参数是直接影响森林对太阳辐射和

大气降水截获的关键参数。目前对森林垂直结构参数的获取主要基于地面测量和遥感估算方法。LiDAR反演森林垂直结构参数已展示了极大的潜力,产生了一些区域产品,同时具备了生产全球产品的能力。一些森林垂直结构参数已经在森林物质和能量交换过程和遥感辐射传输建模中得到了应用,提升了人们对森林垂直结构的认识。

目前,关于森林垂直结构野外测量的局限性还比

较大,各种地面测量方法之间还存在诸多差异,而且地面测量数据普遍缺乏。遥感反演森林垂直结构参数当前主要还是依赖LiDAR数据源,各种遥感手段获取的垂直结构数据也缺乏充分的定量分析和对比验证。未来的研究需要进一步探索新的地面测量和遥感反演方法,并充分利用各种新型LiDAR数据源生成高质量垂直结构产品,为遥感信息机理研究、陆面过程模型模拟和森林经营管理服务。

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Summary for “森林垂直结构参数实测与遥感研究进展：以叶面积指数和聚集指数为例”

Retrieval of forest vertical leaf area index and clumping index through field measurement and remote sensing techniques: A review

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Forest vertical stratification directly affects the transfer of solar radiation and water evapotranspiration in the canopy. Consequently, leaf photosynthesis varies in different parts of the canopy, affecting the growth of trees and the succession process of the plant community. The vertical distribution of forest structural parameters, such as the leaf area index (LAI) and clumping index (CI), is critical not only for understanding of the forest carbon, nitrogen, and water cycles and remote sensing radiative transfer processes, but also for forest monitoring and management practices.

Forest vertical LAI and CI can be obtained through field measurement and remote sensing inversion methods. For field measurements, LAI-2200, digital hemispherical photography, and photosynthetically active radiation sensors are frequently used instruments. Vertical structural measurements are usually carried out through destructive sampling, tower-base measurement, and mobile elevators. In general, field measurements are more accurate; however, they are time-consuming and laborious, making them unsuitable for large-scale applications.

Remote sensing technology uses the passive optical method, the light detection and ranging (LiDAR) technology, and synthetic aperture radar (SAR) methods to estimate forest vertical LAI and CI. The classical passive optical method is based on either the empirical vegetation index estimation method or physical model inversion method. The vegetation index method establishes an empirical relationship between vegetation structural parameters and vegetation indices. Subsequently, the relationship is used to estimate the structural parameters for different layers. The physical model inversion method is based on a physical radiative transfer model. In general, the application of both passive optical and SAR methods in forest vertical parameter retrieval is limited.

As an active remote sensing technology, the LiDAR technology has shown its unique advantages in the inversion of vertical structural parameters. Based on the platform used, LiDAR can be classified into three categories: Terrestrial laser scanning (TLS), airborne laser scanning (ALS), and spaceborne laser scanning. The basic rationale of the LiDAR technology is based on the Beer-Lambert Law, which estimates canopy LAI and CI from the canopy gap fraction; both empirical statistical and physical inversion methods are used during the process. The use of LiDAR to estimate LAI and CI is gaining popularity worldwide, but most of the research is based on TLS and ALS. The development of new space-based LiDAR technologies, such as the Global Ecosystem Dynamics Investigation on the International Space Station, will greatly advance the acquisition of forest vertical structural information on a global scale. However, the relatively complex operation and data processing requirements have limited its widespread application.

The vertical distribution of forest LAI can be represented by the normal, Weibull, beta, chi-square, and Johnson's S-B distributions. The CI values usually decrease with the increase in canopy height because the upper part of the canopy usually has larger gaps. However, mature global vertical LAI and CI products that can meet the application requirements are currently unavailable. Due to the limits of ground measurements, forest vertical LAI and CI retrieved from remote sensing lack sufficient ground validation. In field measurements, the LAI values of trees, shrubs, and herbs should be acquired simultaneously in order to validate the remote sensing LAI. The development of wireless sensor networks and unmanned aerial vehicles provides convenient and effective methods to obtain a large amount of vertical structural information useful for validation purposes.

Forest vertical LAI and CI have been applied in land surface and radiative transfer models and forest management studies. In future research, new field measurement and remote sensing inversion methods should be explored. Various LiDAR data sources can be used to generate high-quality vertical structural products, and these vertical products should be fully validated to better meet the requirements proposed by the research and management communities.

vertical structural parameters, leaf area index (LAI), clumping index, field measurement, remote sensing inversion, LiDAR

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