植物多样性遥感监测技术研究进展

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摘　要：生物多样性是提供生态系统服务与维持生态系统功能的基础，其中绿色植物是地球生物多样性的重要组成部分。传统的植物多样性调查可获取点尺度以及局部区域的多样性瞬时值，但很难反映大范围植物多样性的动态变化。随着新型遥感平台和高分辨率地面—近地面—机载—星载传感器的不断涌现，遥感技术在空间和时间角度极大拓展了对于不同生态系统植物多样性的定量监测能力。本文围绕物种、功能、基因三个生物多样性核心维度，分别聚焦于植物物种多样性的假说和算法，植物功能性状的提取与功能多样性建模，以及光谱特征与系统发育多样性的敏感性分析，结合实例系统综述了植物多样性遥感监测技术的研究进展。随后，针对森林、草地、湿地和农田生态系统分别探讨了植物多样性遥感监测方法的适用性。最后，总结并展望了遥感技术在植物多样性监测研究中的前沿与未来趋势。综合"天空地"各种观测技术手段的特点和优势，发展植物多样性遥感核心监测指标与数据产品，探讨多样性监测的时—空—谱尺度问题，构建适用于不同生态系统类型的植物多样性外推模型，实现大范围植物多样性的快速、准确监测是未来研究的重要方向。加强遥感学家与生物多样性研究者之间的沟通与合作，有助于将遥感技术与生物多样性研究更紧密地结合，推动生物多样性监测和保护的科学发展。

关键词：植物多样性，物种多样性，功能多样性，系统发育多样性，遥感，森林，草地，湿地，农田

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1 引　言

生物多样性是提供生态系统服务与维持生态系统功能的基础。近年来，受气候变化和人类活动等因素的共同影响，大量生物生境丧失，生态系统服务与功能损失日益加剧（Paquette和Messier，2011）。在《联合国生物多样性公约》第十五次缔约方大会上通过的《昆明宣言》和《2020后全球生物多样性框架》推动下，生物多样性保护已成为全球关注的热点问题，各国都在加强生物多样性监测工作，制定与更新生物多样性保护战略与行动计划，以确保生物多样性在2030年以前走上恢复之路（Cardinale等，2012；罗茂芳等，2022）。及时掌握生物多样性的现状、格局、变化趋势和面临的危机，是生物多样性保护政策和措施实施的前提。因此，需要利用最新的技术和地球大数据从生物多样性动态监测角度提出创新性的方法体系，以科学认知生物多样性变化的

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主导过程及影响机制。

生物多样性通常指特定时空内所有生命体的多样性和变异性，是时间和空间的函数（Isbell等，2017；马克平，1993）。一个地区的总体多样性（γ多样性）可以分成群落内的多样性（α多样性）和群落间的多样性（β多样性）（Whittaker，1960）。生物多样性也是生命系统的基本特征，包括多个组织层次暨生物尺度，从基因、器官、个体、种群到群落、生态系统、生物圈，每个生物尺度都存在丰富而多样的变化。生物多样性还是一个多维概念，包括但不限于物种多样性、功能多样性和基因多样性等关键维度。其中，物种多样性是指一定区域内物种的数量和物种分布的均匀程度，可反映生物种类的丰富性（Hill，1973）；功能多样性指影响生态系统功能的有机个体所具有的功能性状大小、范围及分布（Hooper等，2005），其综合考虑种内和种间变异及功能冗余，可探测生态系统功能及过程变化（Díaz等，2007）；基因多样性代表生物种群内和种群间的遗传结构变异，常用系统发育多样性（系统发育进化树上物种之间的分支长度）反映物种演化的历史和物种间的遗传距离（Swenson，2014）。

绿色植物是地球生物多样性的重要组成部分。传统的植物多样性监测主要依赖地面抽样调查，耗时耗力，获得的数据仅为点或局部区域的瞬时值，难以反映大范围植物多样性的动态变化。遥感可迅速监测大面积的植物多样性状况，而且是以连续的、无边界的、可重复的方式呈现，为生物多样性监测由点到面的尺度拓展提供了有力支持（吴炳方 等，2020）。早期的植物多样性遥感监测主要利用航空遥感数据和中低分辨率的多光谱卫星数据（≥30 m，<10个波段），如Landsat、MODIS等。随着遥感技术的快速发展，具有高时空和光谱分辨率的地球观测卫星，如Sentinel-2、Quickbird、IKONOS、Planet、Worldview-2/-3等，进一步提升了遥感监测植物多样性的能力（Ustin和Middleton，2021）。近年来新型传感器如高光谱成像光谱仪和激光雷达（LiDAR）的广泛应用，使得获取精细的植物光谱和结构特征成为可能，显著提高了对植物物种、功能和基因层次细微差异的探测能力（Féret和Asner，2013；Lefsky等，2002；张艺伟 等，2023）。此外，通过协同地面、近地面、航空和航天等不同观测尺度的多源遥感数据，构建生物多样性监测网络（Turner，2014），可实现从样地、局地、景观到区域、国家乃至全球的植物多样性监测与评估。

为获取周期性、可对比的标准生物多样性监测数据，GEO BON（地球观测组织—生物多样性观测网络）提出了生物多样性核心监测指标EBVs（Essential Biodiversity Variables）（Pereira 等，2013）及10种生物多样性遥感监测指标，并对现有生物多样性遥感监测产品进行了优先级排序（Skidmore等，2015，2021；任涫 等，2022）。然而，在不同生态系统植物多样性遥感监测的实际应用中发现，遥感监测产品与EBVs评价指标之间仍缺乏一致性。例如光谱混合问题（森林冠层阴影、草地土壤背景、湿地水面干扰）影响了植物多样性的监测精度；光谱特征可分性（同物异谱与同谱异物）及空间分辨率限制了草地和湿地生态系统较小个体植株的物种识别能力；时间重访率影响了农田生态系统作物多样性的监测能力等。因此，如何基于有效的遥感观测尺度利用最佳的技术方法在不同生态系统中开展多层次生物尺度的多样性精准监测，有待详细的梳理、归纳、分析与思考。

本文首先结合实例综合分析了基于天空地多源遥感数据与不同遥感技术在物种、功能、基因3个多样性维度中的监测方法，分别聚焦于植物物种多样性的假说和算法，植物功能性状的提取与功能多样性建模，以及光谱特征与系统发育多样性的敏感性分析。随后，针对森林、草地、湿地和农田生态系统分别探讨了植物多样性遥感监测方法的适用性。最后，总结并展望遥感技术在植物多样性监测研究中的发展方向和未来趋势（图1）。

2 不同维度的多样性遥感监测方法

2.1 物种多样性

物种多样性遥感监测可大体分为全球—区域尺度和景观—局地尺度，两个尺度分别依据不同的理论基础（图2）。在全球—区域尺度，主要是水分—能量假说（Water-energy hypothesis）、生产力假说（Productivity hypothesis）和生态位理论（Ecological niche）。其中，水分—能量假说认为物种丰富度或多样性分布与宏观地形和气候因子（温

度、降水和蒸散等）存在一定的关系（Hawkins等，2003；Kreft和Jetz，2007）；生产力假说指出环境资源和能量所决定的初级生产力调控着生态系统中的物种多样性（Allen等，2007；Grime，1973）；生态位理论则是将物种的生态位投射到地理空间以估测物种的分布、生境适宜度和物种丰富度（Soberón，2007）。在景观—局地尺度，主要包括栖息地异质性假说（Habitat heterogeneity hypothesis）、种—面积关系假说SAR（Species-Area Relationship）、物种分类方法和光谱变异假说SVH（Spectral variation hypothesis）。其中，栖息地异质性假说认为多样化的生态系统包含多类型的栖息地，因而拥有更加丰富的生物物种（Kerr和Ostrovsky，2003）；种—面积关系是生态学中的经典法则，描述物种数量随生境面积变化的幂函数关系（Drakare等，2006）；物种分类方法通常利用高分辨率遥感数据直接识别植物物种或群落类型及其分布；光谱变异假说则认为不同物种具有不同光谱特征，光谱的时空异质性可以估测植物物种多样性（Palmer等，2002），是近年来在不同生态系统开展植物物种多样性监测最常用的理论基础。

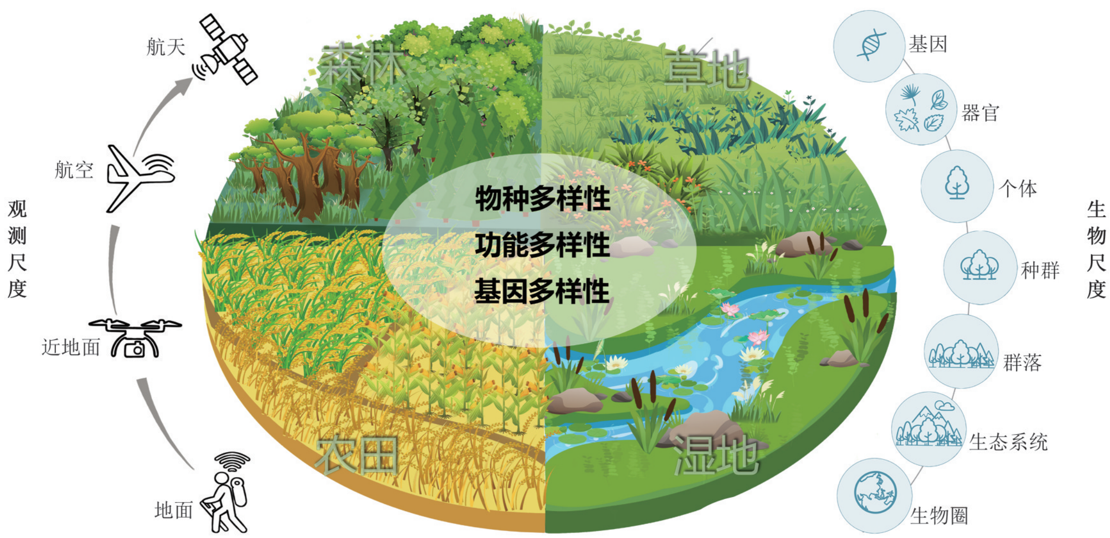

图1　植物多样性遥感监测概念图

Fig.1　Conceptual diagram of remote sensing monitoring of plant diversity

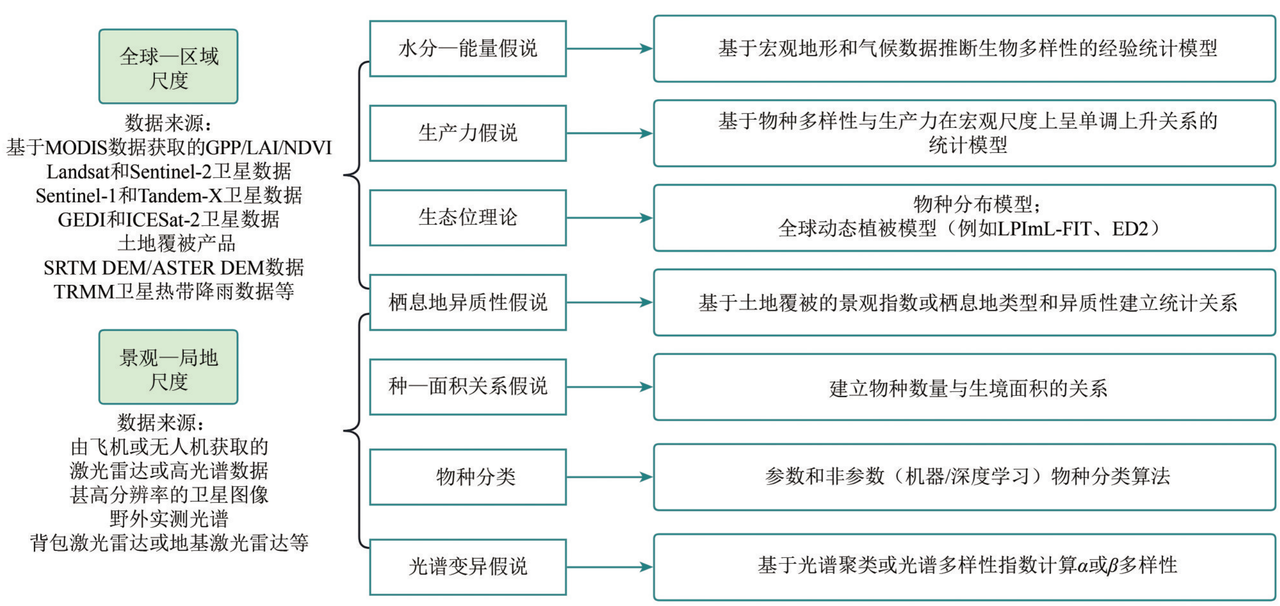

图2　不同尺度植物物种多样性遥感监测的理论基础与方法

Fig.2　Theory and methods for remote sensing monitoring of plant species diversity

2.1.1 全球—区域尺度监测方法

全球—区域尺度的植物物种多样性监测，主要利用光谱参数、植被指数或环境变量结合地面观测数据，构建统计模型来间接估算植物物种多样性。如Kreft和Jetz（2007）通过整合气候、水热指数和生物地理区划数据，获取了全球植物物种多样性的空间格局；Brun等（2019）使用植被指数（NDVI和EVI）和土地覆被数据估算北半球温带地区的植物物种多样性，验证了生产力与植物物种丰富度的正相关关系；Sabatini等（2022）利用历史气候变化、生境异质性和生产力指标评估了欧洲植物多样性的分布格局，揭示了多环境变量耦合对物种多样性预测的重要性。近年来，数据驱动的机器学习模型也广泛应用于区域/全球尺度的植物物种多样性监测（Cai等，2023；Keil和Chase，2019；Yang等，2022；Zhao等，2024；周楷玲 等，2022）。然而，由于地域复杂性、传感器差异、环境变量分辨率低以及与地面调查数据的时空匹配性等因素，加之混合像元和冠层结构对植物光谱的影响，基于统计模型估算植物物种多样性仍存在不确定性。如有研究表明NDVI标准差可以解释区域内30%—87%的物种多样性变化（Cayuela等，2006；Fairbanks和McGwire，2004），也有研究认为NDVI标准差与物种多样性关系甚微（Rocchini等，2004）。

此外，生态位模型可利用物种已知分布点位数据以及环境因子数据来估算物种在特定时空条件下的地理分布，遥感数据及其衍生产品可提供更为丰富且精确的环境信息及物种分布信息，因此生态位模型与遥感数据相结合，将成为大尺度植物物种多样性监测的另一手段。如Malavasi等（2019）将代表繁殖压力、非生物驱动因素和生物环境的遥感变量集成到生态位模型，估算了沿海沙丘生态系统中的植物丰富度；Bradley和Fleishman（2008）利用遥感技术扩充了大斑块及景观尺度的物种分布数据作为生态位模型的输入参数；Estes等（2010）引入基于遥感的结构复杂性指数表征微生境变异，提高了物种分布模型的准确性。具有生态意义的遥感产品，如蒸散、叶面积指数、物候等数据，以及遥感气候再分析数据，也能够在一定程度上提高生态位模型的精度（Cord等，2011；Randin等，2020）。然而，现有的生态位模型少有结合物种自身生理特征参数进行物种生态位模拟，而且从点到面的尺度外推也给模型预测结果带来了不确定性。如何有效地结合生态学过程、地理学背景、遥感大数据以及统计学机理，优化生态位模型在全球—区域尺度植物物种多样性监测中的应用仍有待突破。

2.1.2 景观—局地尺度监测方法

景观尺度的植物物种多样性监测早期主要利用栖息地异质性指数以及种—面积关系进行评估。如Stoms和Estes（1993）开展了土地覆被制图并利用提取的栖息地异质性信息估算了物种丰富度指数。Tomaselli等（2013）在土地覆被数据基础上生成了栖息地类型图，实现了景观尺度植物物种多样性变化的定期监测。Heidrich等（2020）发现栖息地异质性与物种多样性主要呈正相关关系，栖息地面积是影响两者关系的重要因素，而且高破碎化的生境并不一定具有高物种丰富度（魏彦昌 等，2008）。因此，可将栖息地异质性与种—面积关系相结合估算植物物种多样性。如Westman等（1989）基于遥感提取的栖息地破碎度指数和种—面积模型，预测了典型热带森林因栖息地面积丧失而受威胁的物种数量。然而，栖息地异质性方法通常忽略了生境或群落内部的差异，物种多样性估算的准确性在很大程度上受栖息地类型精细程度的影响。

在景观—局地尺度上还有一种最直接的物种多样性监测方法，就是在个体尺度上对物种进行分类。如Clark等（2005）及Féret和Asner（2013）分别利用机载高光谱数据，基于参数与非参数分类方法，在热带雨林对树种进行了分类，最优模型精度均超过90%；刘丽娟等（2011）和Li等（2023b）同样基于高光谱数据，分别应用支持向量机和光谱角匹配方法，实现了中国北方和亚热带典型森林的树种分类和多样性监测。融合激光雷达、高光谱或高分辨率多光谱数据，还可进一步提高森林冠层优势物种分类及多样性评估的精度（Torabzadeh等，2019；Liang等，2025；Liu等，2017）。然而，分类方法依赖于大量样本以及米级/亚米级数据，而且仅能实现优势主导物种的分类。植物个体形态各异，不同生长阶段和物候期往往具有不同的生理特性与冠层结构特征。目前，个体尺度的物种分类研究主要集中在森林，

对于草地、湿地等较小的物种个体，直接利用物种分类估算物种多样性几乎很难实现。

近年来在景观—局地尺度应用最广泛的植物物种多样性监测方法是基于光谱变异假说的光谱多样性指数方法（Torresani等，2024；田佳玉 等，2022）。光谱多样性指数反映了植物光谱反射率在植物物种之间或同种个体之间的变异程度，可以综合表征植物的生化组分和形态特征差异，无需进行具体的物种识别，而是通过变异性估算不同物种的数量和多样性信息，可快速高效地揭示植物物种多样性的空间分布格局及其变化。

2.1.3 基于光谱多样性指数的监测方法

常用的光谱多样性指数算法可大致分为基于植被指数、基于信息理论和基于光谱聚类3种方法（Wang和Gamon，2019），利用多源遥感数据计算的光谱多样性指数已在不同生态系统的植物物种多样性监测中有众多研究（表1）。

表1 基于光谱多样性指数的物种多样性监测研究案例

Table 1 Case studies for estimating species diversity based on spectral diversity

类别	遥感数据	生态系统	指数/方法	参考文献
植被指数	UAV多光谱/星载GF-1	湿地	平均NDVI	Zhu等（2022）
	星载MODIS	森林	EVI	Waring等（2006）
	星载MODIS	草地	EVI/ NDSVI/ LSWI	John等（2008）
	UAV多光谱	湿地	MTCI/ NDREI	Fu等（2024）
	星载Landsat	草地	MSAVI	Chitale等（2019）
	星载Landsat	农田	平均NDVI	Duro等（2014）
信息理论	机载高光谱	草地	光谱变异系数	Lucas和Carter（2008）
	UAV多光谱	湿地	光谱变异系数	Tan等（2022）
	轨道式近地/机载高光谱	草地	光谱凸包面积/体积	Gholizadeh等（2018）
	机载高光谱	森林	光谱方差分解	Laliberté等（2020）
	机载高光谱	森林	光谱方差分解	Badourdine等（2023）
	星载Landsat/ Quickbird	湿地	光谱质心距离	Rocchini等（2007）
	机载高光谱	农田	光谱凸包体积	Dahlin等（2016）
光谱聚类	轨道式近地高光谱	草地	监督分类/PLS-DA	Wang等（2018b）
	机载高光谱	森林	聚类算法/K-mean	Féret和Asner（2014）
	UAV高光谱	湿地	聚类算法/FCM	Villa等（2025）
	地面高光谱	草地	聚类算法/K-mean	Hayden等（2024）
	机载高光谱	森林	聚类算法/FCM	Zhao等（2018）

归一化植被指数（NDVI）、增强植被指数（EVI）、红外指数（IRI）、中红外指数（MIRI）、大气阻力植被指数（ARVI）和修正的土壤调节植被指数（MSAVI）常作为光谱多样性指数用于物种多样性监测（Cabacinha和de Castro，2009；Nagendra等，2010；Wang等，2016）。光谱反射率及其导数等衍生指数也可作为光谱多样性指数，如Peng等（2018）直接利用高光谱指数评估了草地物种多样性。此外，基于反射率提取的光学特征值（OTIs）与植物物种多样性及物种组成均有显著的相关性，估算物种多样性的精度往往优于原始的冠层光谱（Feilhauer等，2017）。研究还发现，不同植被类型的多样性监测需要选择适用的植被指数，如NDVI对于竹林和干燥落叶林的物种丰富度具有较高的解释力，而MSAVI对高山草地的估算精度较高（Chitale等，2019）。

基于信息理论的方法是将多个波段同时纳入光谱多样性指数的计算中，最大程度的避免了某些波段因反射率相近无法体现光谱差异而影响物种多样性估算的精度。其中，光谱变异系数CV（Coefficient of Variation）是较为通用的光谱多样性指数。例如Lucas和Carter（2008）基于高光谱数

据多波段的CV预测了草地的物种丰富度；Tan等（2022）利用无人机多光谱数据计算NDVI的CV实现了湿地植物的物种多样性监测。另外，光谱多样性指数还包括光谱角（Cho等，2010）、光谱信息散度（Chang，2000）、光谱凸包体积或面积（Gholizadeh等，2018）、光谱方差分解（Laliberté等，2020）、光谱质心距离（Rocchini，2007）等。这些指标的内涵都是通过计算局部区域光谱的多样性或者异质性来反映不同物种的种间差异，光谱差异越大，表明该区域的物种差异越大。但是基于信息理论的方法反映的多是像元间的差异，容易受土壤、凋落物、水面等背景因素的干扰，还会受到群落结构复杂性的影响，因而光谱多样性指数所表现出的异质性不完全来自于植物物种的多样性。此外，光谱多样性指数与物种多样性的关系并不稳定，甚至在有些研究中出现负相关，主要与观测仪器、植被类型、物候期、数据分辨率、样方大小等有关（Perrone等，2023；Schmidtlein和Fassnacht，2017）。因此，在计算光谱多样性指数时，将物种构成、土壤比例、生物量、植物开花/死亡等因素考虑在内，可进一步提高基于光谱—物种多样性关系的监测能力（Perrone等，2024；Rossi等，2022；Xu等，2022）。

基于光谱聚类的方法是对植物的光谱特征进行非监督分类或聚类，得到特定空间范围内具有相似光谱特征的光谱信息团聚体，将不同团聚体认为是植物物种的替代指标，从而计算植被群落的α多样性（Féret和Asner，2014；Schäfer等，2016）以及更大范围的β多样性（Bongalov等，2019；Féret和Boissieu，2020）。在物种—生化—光谱和物种—结构—点云关系基础上，聚类因子可以选择光谱特征、生化组分（水分、叶绿素、类胡萝卜素、比叶面积、氮、磷、纤维素、木质素等）和结构参数（冠层高度、密度、叶面积指数等），采用不同聚类算法（自适应模糊C均值聚类、均值漂移聚类和密度聚类DBSCAN等），结合移动窗口方法实现物种多样性的区域成图（Asner和Martin，2009；董文雪 等，2018；衣海燕 等，2020）。

然而，聚类因子的分辨率影响着聚类模型的精度，因为像元大小与观测个体之间的比例决定了光谱混合的程度（Cavender-Bares等，2017）。如有研究发现森林聚类因子的最优分辨率可参考平均冠幅的大小（Liu等，2024），草地的最优分辨率建议从1 mm到10 cm范围根据植被类型进行先验分析（Wang等，2018a）。另外，聚类模型还存在饱和问题，遥感可预测的物种数量会随着聚类因子的增加而达到饱和，所以在应用聚类算法之前需要利用模拟方法如蒙特卡洛模型明确聚类因子对物种多样性的解释能力，针对不同植被类型，选择最优聚类因子，以提高聚类算法的物种识别能力与适用性（Zhao等，2016，2021a）。

聚类的尺度主要包括聚类单元和移动窗口范围两方面。研究表明，与像元尺度的聚类相比，基于单木的聚类更接近于野外个体采样方法，减少了非植被的信号混淆，可进一步提高森林的物种多样性估算精度（Zhao等，2018）。但对于个体矮小且交错重叠的草地、湿地等植被类型，单个植株分离较为困难。另外，移动窗口大小设置通常与实测样方大小一致，便于进行精度验证。然而，理想的窗口范围应综合考虑聚类因子所能预测的最大物种数，结合样方实测物种多样性和种-面积关系，选择不同的聚类窗口进行模型构建，通过多尺度对比确定最佳移动窗口范围，以实现空间连续的物种多样性制图。

2.2 功能多样性

随着功能生物地理学的兴起，基于功能性状的功能多样性在植物生态学中引起特别关注（Díaz等，2013；Violle等，2014）。功能多样性的遥感监测方法主要有功能组分类方法、基于方差或距离的单维和多维性状空间方法等（Asner等，2017；Laliberté和Legendre，2010；Tagliabue等，2020；Villéger等，2008）。选择遥感可估算的且与生长速率、光合作用、生产力等功能相关的植物生理和形态性状，是有效监测植物功能多样性的前提（Díaz等，2016；Homolová等，2013；严正兵 等，2022）。由于目前很难提出一个全面涵盖所有功能性状信息的单一功能多样性指数（Mason等，2005），因此功能多样性通常采用能够表征功能性状分布不同特征的互补指数来综合评价，如功能丰富度FRic（Functional Richness）、功能均匀度FEve（Functional Evenness）、功能离散度FDiv（Functional Divergence）等（Ahmed等，2019；Schneider等，2017）。植物生理与形态性状以及功能多样性的遥感监测案例如表2所示。

表2 植物生理与形态性状以及功能多样性的遥感监测案例

Table 2 Case studies for monitoring plant functional traits and functional diversity by remote sensing

类型	功能性状/多样性	观测平台	生态系统	监测方法	参考文献
生理性状	叶绿素	无人机/星载	草地	PLSR/植被指数	Li等(2018a);Zhao等(2021b)
	类胡萝卜素	航空	草地	PLSR/GPR/植被指数	Wang等(2019)
	比叶面积	航空/星载	森林	PLSR/植被指数	Zheng等(2021,2023)
	木质素/纤维素	地面/航空	森林	PLSR	Zhao等(2016,2018)
	相对叶绿素	地面	湿地	PLSR	Dou等(2018)
	碳/氮/磷	无人机	湿地	PLSR/机器学习	Li等(2020,2023b);Cui等(2020)
	含水量	航空/星载	森林	植被指数/ 辐射传输模型	Helfenstein等(2022); Zhu等(2019)
	比叶重	地面	湿地	PLSR/辐射传输模型	Villa等(2021,2024)
	氮含量	地面	农田	辐射传输模型	Li等(2018b)
	籽粒营养元素	星载	农田	PLSR/植被指数	Belgiu等(2023)
	碳含量	地面/航空	森林/草地等	PLSR	Wang等(2020)
形态性状	冠层平均高度	无人机	草地	冠层高度模型	Zhang等(2018a)
	盖度/叶面积指数	航空	湿地	植被指数	Villa等(2017)
	植被覆盖度	无人机	草地	冠层高度模型	Zhang等(2021b)
	盖度/冠层最大高度	地基/无人机	草地	植被点云比例/最高	Zhao等(2022)
	叶面积密度	地基	农田	基于体素的叶面积剖面	Su等(2018)
	冠层平均高度	航空	森林	95%分位高度	Coops等(2016)
	郁闭度	星载	森林	几何光学模型	Zeng等(2008a,b)
	冠幅面积	航空	森林	单木分割	Zhao等(2014)
	叶高度多样性	星载	森林	分层叶盖度变异	Kacic等(2021)
	冠层熵	无人机	森林	熵计算	Liu等(2022)
	冠层结构密度	星载	森林	多形态指标归一化加权和	Li等(2023a)
功能多样性	功能丰富度/均匀度/离散度	航空/星载	森林	基于像元的多维性状空间/ 性状概率密度	Schneider等(2017,2020)
	功能丰富度/均匀度/离散度	航空	森林	基于单木的多维性状空间	Zheng等(2021)
	功能丰富度/均匀度/离散度	地面/无人机	湿地	核密度超体积/GAM/RF	Villa等(2025)
	功能分散指数	地面/星载	森林	PLSR	Ma等(2022)
	Rao's Q	星载	草地	基于性状的Rao's Q	Hauser等(2021)
	功能丰富度/均匀度/离散度/冗余度	地面	农田	性状概率密度	Carmona等(2020)
	策略模型	地面/航空	草地	竞争/承受/生存力策略型	Schweiger等(2017)

2.2.1 植物功能性状的监测方法

植物生理性状的监测方法主要分为物理模型、统计模型及两者混合方法（Wang等，2019）。常用的物理模型包括叶片尺度的PROSPECT和冠层尺度的SAIL、INFORM等辐射传输模型（Darvishzadeh等，2011；Schlerf和Atzberger，2006）。物理模型具有一定的稳健性和可移植性，但是模型参数化较为复杂（Darvishzadeh等，2008；Malenovský等，2013），通常应用于特定的生理性状反演，如叶绿素、水、氮、纤维素、木质素等（Jacquemoud等，1996）。多项研究表明，物理模型对于生理性状的估算精度往往低于统计模型（Jurdao等，2013；Verrelst等，2012，2015）。其中，逐步多元线性回归（SMLR）、偏最小二乘回归（PLSR）、高斯过程回归（GPR）、广义加性模型（GAM）和随机森林回归（RF）是最常用的统计模型。

早期的植物形态性状监测主要基于光学数据结合统计或物理模型反演（Zeng等，2008a，2008b），在激光点云数据快速发展的背景下，形

态性状可在垂直高度（如平均高度、百分位高度等）、水平密度（如冠幅面积、郁闭度、叶面积指数等）和冠层内部复杂度（如高度标准差、叶高度多样性等）3个维度进行精细估算，尤其是在森林形态性状的监测中精度可达80%以上（Asner等，2015；Coops等，2016；Schneider等，2020；胡天宇 等，2025）。此外，也有研究整合冠层结构在水平与垂直等多个维度上的分布异质性，提出综合性形态性状指标，如冠层熵、冠层结构密度等（Li等，2023b；Liu等，2022）。

2.2.2 植物功能多样性的监测方法

植物功能多样性监测现阶段最常用的方法是通过相关分析、主成分分析等选择相对独立的最优生理与形态性状构建多维性状空间，也有研究利用前3个主成分或植被指数构建三维性状空间。计算的原理是每个像元或植物个体代表生理或形态性状空间中的一个点，利用代表一定地理范围的移动窗口，根据功能性状空间中点之间的距离，基于凸包体积计算功能丰富度，基于各点与重心的平均加权距离计算功能离散度，基于最小生成树分支长度的均匀性计算功能均匀度，并进行区域成图（Durán等，2019；Helfenstein等，2022；Schneider等，2017；Zheng等，2021，2022）。近年来，植物功能多样性指数的构建还处在不断发展和完善中，其中功能分散性指数FDis（Functional Dispersion）和Rao二次熵指数Rao's Q（Rao's quadratic entropy index）被认为具有较高的应用潜力（Botta-Dukát，2005；Laliberté 和 Legendre，2010；韩涛涛 等，2021），特别是融合空间与时间异质性成为新型功能多样性指数构建的方向。

除了基于多维性状空间的方法，直接利用地面实测样方的功能多样性，与遥感数据建立统计模型也可估算功能多样性指数。如Ma等（2019）利用Sentinel-2数据与偏最小二乘回归方法估算了欧洲6个区域的森林功能分散性指数。Villa等（2025）基于无人机高光谱数据，利用广义加性和机器学习模型估算了意大利5个湿地的功能丰富度、均匀度和离散度指数。此外，Grime（1974）提出的三策略模型（竞争力、承受力和生存力）与功能性状存在很强的相关性，也被应用于植物功能多样性监测。如Schweiger等（2017）和Schmidtlein等（2012）分别基于地面/航空高光谱数据估算了植物群落的策略类型，揭示了草地功能多样性的空间生态格局。

然而，功能多样性指数的计算容易受性状精度及异常值的影响，且不同观测尺度的功能多样性结果很难进行直接对比。近年来提出的性状概率密度（Trait probability density）算法和核密度超体积（Hypervolumes）算法（Carmona等，2019；Mammola和Cardoso等，2020），综合考虑了性状的概率分布，结合可推广的归一化方法（Pacheco-Labrador等，2023），有望实现多尺度可拓展的植物功能多样性估算。

2.3 系统发育多样性

系统发育多样性可代表生物多样性的基因维度，通过构建系统发育树，利用Faith's系统发育多样性指数PD（Phylogenetic Diversity）、平均系统发育距离指数MPD（Mean Phylogenetic Diversity）、最近亲缘关系指数NTI（Nearest Taxon Index）、系统发育物种变异性指数PSV（Phylogenetic Species Variability）等来度量（Faith，1992；Helmus等，2007；Webb，2000；Webb等，2008）。

目前植物系统发育多样性的遥感监测方法可归纳为3大类：光谱回归、性状聚类和谱系分类。如Schweiger等（2018）在叶片尺度构建了光谱、功能和系统发育相异性矩阵，发现物种间的系统发育距离越大，光谱差异与功能差异越大。Cavender-Bares等（2016）和Zhao等（2021a）的研究表明，相较于功能性状聚类，直接基于叶片光谱进行聚类与植物系统发育史的相似程度更高。Meireles等（2020）和D'Odorico等（2023）利用偏最小二乘判别分析（PLS-DA）评估叶片光谱和生理性状对于植物谱系分类的能力，实现了主要植物类群的目、科及亚种分类。Li等（2023a）分析了不同实验条件下遗传和非遗传因素对光谱变异的响应，发现基因变异对叶片光谱变异的影响远大于环境等其他因素。以上研究证明了植物叶片光谱能够体现物种种属内的遗传变异，因此利用遥感数据可以直接或间接监测系统发育多样性。

然而，基于光谱特征进行植物系统发育多样性的监测主要集中在叶片尺度上，如何上升到冠层尺度以获取大范围的系统发育多样性，目前还仅停留在对某个单一优势种的种内多样性研究

（Madritch等，2014；Czyż等，2020）。另外，高通量基因测序的发展使得直接获取植物的基因数据更为便捷，但解析基因功能以及定位基因区域需要大量的表型数据。整合多源遥感数据获取光谱与结构的高通量表型数据，全方位探测植物系统发育多样性的空间变异，可为解决区域尺度的基因多样性监测提供可能。

3 植物多样性遥感监测方法在不同生态系统的适用性

3.1 森林生态系统

森林生态系统具有群落结构复杂、生长周期长、海拔梯度明显等特点。森林植物多样性的监测研究可以追溯到20世纪90年代（Davis等，1990；Warner和Shank，1997），早期遥感数据由于分辨率的限制，难以获取丰富的光谱与结构信息，近年来融合高光谱与激光雷达数据的树种分类、物种多样性估算、功能性状反演等研究日益增长（郭庆华 等，2020）。虽然快速发展的遥感技术已可提取单木水平的功能性状和物种信息，但是由于山区地形导致的阴坡/阳坡光影变化、冠层内部的阴影以及复杂结构，影响了单木分割及多样性监测的精度（Féret和Asner，2013）。此外，宏观气候和林内微气候也对树种分布和生长模式有显著影响，不同森林类型的物种组成与层次结构差异较大，如热带森林的林冠呈梯状郁闭，现阶段只考虑森林顶层的多样性，很难捕捉到垂直分层的信息及其内部的多样性分布。

在生物多样性极其丰富的热带及亚热带森林地区，多云雨天气降低了光学数据的可用性（吴立新 等，2022），需要引入微波等多源遥感数据，确定最佳的观测物候期和监测尺度，以便采用适配性最高的数据与方法实现森林植物多样性的有效监测。另外，森林植物多样性在大区域尺度的监测也取得了一定进展，如Sabatini等（2022）利用sPlot数据库和增强回归树方法，实现了全球森林物种多样性成图；Aguirre-Gutiérrez等（2025）利用TRY等性状数据库与机器学习算法，估算了全球热带森林的功能性状与功能多样性。然而，地面与遥感数据直接建模的监测精度受野外采样策略差异及遥感数据时空尺度不匹配的影响。通过地面—近地面—机载—星载逐级上推的方式构建尺度外延模型，可为大范围植物多样性监测提供另一种思路。如Becker等（2023）利用机载激光雷达数据作为训练样本，结合Sentinel数据和深度学习算法，实现了挪威国家尺度10 m分辨率的5个森林形态性状估算。因此，适用于大范围不同森林类型的多样性监测方法仍有待进一步研究。

3.2 草地生态系统

草地植物群落物种组成的季节和年际动态变化明显，易受气候变化和草地退化的影响。直接利用遥感数据对草地个体进行物种分类很难实现，而像元尺度的草地物种分类也主要局限于分布较为均匀或草种类型较少、群落结构相对简单的区域，如荒漠化草原（Yang和Du，2021）。对于草种分布混杂度较高的草地类型，如草甸草原等，光谱混合现象对植物多样性的监测影响很大。因此，融合光谱、纹理、物候特征（如开花、结实、黄枯期）与亚像元信息的草地植物多样性监测是重要的研究方向（Rossi和Gholizadeh，2023）。

无人机或地面的高光谱数据能够捕捉草地物种间的生理特征差异，但是无人机激光雷达数据获取草地结构特征仍不理想（Zhao等，2022），草地冠层高度往往存在低估问题（Xu等，2023）。选择适用的生理和结构参数，识别其对草地物种的可分性并提高估算精度，是草地植物多样性遥感监测的基础。此外，已有的多样性研究多集中于叶片尺度或人工控制实验平台上具有一定物种梯度的草地研究区，相同的方法在自然条件下的复杂草地研究区很难获得较高精度。不同类型草地的生长环境、优势物种、群落结构、物候动态等差异明显，需要综合考虑草地的光谱—生化—结构，特别是时相变化特征，提出新型的草地多样性指数，以实现草地物种与功能多样性的精准监测。

3.3 湿地生态系统

湿地生态系统植物多样性遥感监测在全球尚处于起步阶段。湿地的面积相对占比小，破碎化程度高，已有的研究主要集中在特定水生植物群落的分类制图，如红树林、互花米草、芦苇等（Jia等，2023；Piaser和Villa，2023；Sun等，2024；Villa等，2015）。也有部分研究利用遥感数据基于栖息地异质性与光谱多样性指数方法监测湿地物

种多样性，但模型的精度普遍不高（Heumann等，2015；Rocchini，2007；Taddeo等，2019，2021；Tan等，2022）。

针对湿地植物的功能性状估算，由于水生植物的叶片及冠层光学特性与生理性状之间的关系和陆地植被有明显不同，基于陆地数据建立的统计或物理模型在湿地植物性状估算中的适用性不佳，例如受到水汽的影响，湿地植物氮含量的遥感估算精度较低（Villa等，2024）。Zhou等（2015，2018）建立了模拟水生植被冠层的辐射传输模型，并进行了模型参数的敏感性分析，但该模型仍然难以准确反演水生植物冠层的生理性状。此外，漂浮/浮叶植物与挺水植物处于大气—水体的交互界面，沉水植物位于水面以下，使得水生植物的冠层高度、密度及复杂性等结构特征较难衡量。因此，利用遥感技术估算湿地植物功能性状，现阶段仅涉及叶绿素、类胡萝卜素、含水量、比叶面积等几个特定性状，适用于功能多样性监测的多维度最优生理与形态性状还不明确。另外，基于遥感的湿地植物功能多样性和基因多样性研究相对较少，所以湿地植物多样性监测仍然是目前多样性监测领域的难点和前沿。

3.4 农田生态系统

农田生态系统是耦合自然和人类活动的复杂系统，相对于自然植被而言，作物的主要特点是以地块为种植单元。作物物种多样性主要包括作物类型和品种的多样性。其中，基于遥感的作物类型识别方法相对成熟，特别是综合考虑了作物全周期的光谱及纹理特征，主要作物的分类精度通常超过90%（Mehedi等，2024；Piiroinen等，2015；Yao等，2022；Zhang等，2018b）。利用作物类型直接计算物种多样性指数可在大范围农田中进行应用，估算的准确性取决于作物类型的数量与分类精度。但是作物品种的遥感监测技术仍是难点，因为不同品种的细微光谱差异很难获取，目前仅针对水稻等少数作物有尝试性研究（Rauf等，2022）。此外，作物类型与品种在时间和空间上的多样性主要体现在种植强度和模式方面，如轮作、间作等（Qiu等，2022，2024；Yan等，2019；Zhang等，2021a），监测方法分别依赖于高时间分辨率数据获取作物类型的季节性变化，以及高空间分辨率甚至三维数据获取具有空间遮挡问题的间作作物。

作物的功能多样性监测，一方面是利用高光谱数据获取叶片、冠层或籽粒中的叶绿素、氮、水分、蛋白质、微量营养元素等生理性状（Belgiu等，2023；Li等，2018b；2022；Sun等，2022；Yu等，2024），另一方面是利用机载或地基激光雷达数据估算作物的形态性状，如株高、叶面积指数、叶倾角等（Su等，2018；刘婷 等，2016；Zang等，2023），来开展干旱胁迫、生产能力、营养品质等功能预测。基于高光谱遥感的作物基因多样性监测在表型组学大数据分析和作物育种方面也取得了一定的进展（Tao等，2022）。目前，已有研究尝试基于遥感数据分析作物多样性对产量及其稳定性的影响（Gu等，2024；Meng等，2024），而作物多样性对于生产、环境、营养、健康的互作机制及级联效应，仍有待跨文化、跨气候区、跨学科的综合对比研究。

4 结　语

在生态遥感大数据背景下，深度学习等人工智能技术的应用为植物多样性监测开辟了新的视角（Gillespie等，2024）。集成地面数据、多源遥感数据、生态学理论和人工智能方法，构建适用于不同生态系统的全方位、立体化、多维度、跨尺度植物多样性监测技术体系，研发一套面向国家乃至全球范围的植物多样性遥感核心监测指标及其数据产品，是生物多样性监测发展的共同目标，也是支撑昆蒙框架实施进展评估的迫切需求。

无论是遥感技术本身还是在植物多样性监测中的应用都离不开尺度问题。空间分辨率决定着遥感获取观测对象异质性的能力，越精细的空间分辨率并非对应于越准确的多样性监测，而地面采样尺度与空间分辨率的比例才是更为重要的影响因素。在时间尺度上，需要进一步考虑如何引入年内不同植被物候期的差异以提高多样性的辨识度，发展年际间的植物多样性动态监测方法还可以实现历史追溯与未来预警。在光谱尺度上，不同波段对植物多样性估算的贡献度各异，敏感波段的选择至关重要，尤其是热红外波段和叶绿素荧光成像技术在解析植物功能性状、群落组成及其环境适应机制中的潜力尚待深入挖掘。

随着遥感平台及传感器技术的快速发展，无人机逐渐成为精细尺度生态学及生物多样性研究

中的重要观测平台，融合星—机—地多源数据的时空互补性，将小范围高精度的植物多样性数据外推至区域尺度，成为大范围植物多样性监测的有效方法（Cavender-Bares等，2022；Pinto-Ledezma等，2025）。此外，新型高光谱激光雷达一体化传感器提供的三维光谱信息为植物多样性监测拓展了新的途径（龚威 等，2022）。未来即将发射的具备全球覆盖能力的高光谱卫星，如NASA的 SBG 及 ESA 的 CHIME（Lee等，2022；Celesti等，2022），可为大区域尺度的植物多样性快速精准监测提供可能。

由于生态和遥感学科之间的差异，目前利用遥感估算的生物多样性评价指标和监测结果与用于解决生态学问题的数据需求仍存在不一致性。因此，亟需推动生态与遥感的进一步融合，深入分析生态系统深层次的过程与隐性表现，充分挖掘遥感数据的时—空—谱特征，摆脱生态遥感当前“数据丰富而信息贫乏”的困境，构建具有生态学指示性意义的新型遥感指数，发挥人工智能技术在物种识别中的潜能，突破生物多样性监测方法的创新，并在全球变化背景下，为生态系统研究和生物多样性保护提供科学有效的决策支持。

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Monitoring plant diversity by remote sensing techniques: Progress and perspective

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Abstract: Biodiversity is the foundation for providing ecosystem services and maintaining ecosystem functions, with plants playing a key role of biodiversity on Earth. Traditional plant diversity surveys provide localized point-scale snapshots of diversity, but are limited in capturing dynamic changes in plant diversity over large areas. With the development of new-generation platforms and high-resolution sensors, remote sensing technologies have significantly expanded the capacity to quantitatively monitor plant biodiversity across broader spatiotemporal scales. This review focuses on the three core dimensions of biodiversity—species, functional, and genetic diversity—exploring recent advancements in remote sensing technologies for plant diversity monitoring. Specifically, it addresses developments in plant species diversity hypotheses and algorithms, functional traits and functional diversity modeling, and the sensitivity of spectral characteristics to phylogenetic diversity. We further discuss the applicability of remote sensing methods for monitoring plant diversity across different ecosystems, including forest, grassland, wetland, and cropland. Finally, we summarize the current trends and future directions of remote sensing technology in plant biodiversity monitoring. Rapid and accurate monitoring of large-scale plant diversity is identified as a key challenge in plant diversity research. The future of this field lies in integrating multi-source remote sensing technologies across field, aerial, and space scales, developing Remotely-Sensed Essential Biodiversity Variables and constructing plant diversity upscaling models applicable to various ecosystems. Strengthening communication and collaboration between remote sensing experts and biodiversity researchers will further facilitate the integration of remote sensing technology with biodiversity issues, advancing scientific research in biodiversity monitoring and conservation across space and time.

Key words: plant biodiversity, species diversity, functional diversity, phylogenetic diversity, remote sensing, forest, grassland, wetland, cropland

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