湖泊碳循环研究中遥感技术的机遇与挑战

黄昌春[1]，姚凌[2,3]，李俊生[4]，周成虎[2,3]，郭宇龙[5]，李云梅[1]

1. 南京师范大学 地理科学学院, 南京 210023;
2. 中国科学院地理科学与资源研究所, 北京 100101;
3. 南方海洋科学与工程广东省实验室（广州）, 广州 511458;
4. 中国科学院空天信息创新研究院, 北京 100094;
5. 河南农业大学 资源与环境学院, 郑州 450002

摘　要：湖泊碳循环是全球碳循环过程中的重要环节，随着全球碳循环研究的不断深入，湖泊碳循环对全球碳循环的影响，以及其对全球气候变化的调节作用越来越受到关注。然而，由于湖泊分布的破碎性（大于0.002 km^2的湖泊约有1.17×10^8个，并零星地分布在全球）和多样性（流域生态多样性，湖泊类型多样性，分布的气候带多样性等），使得全面监测和研究全球湖泊碳循环具有较大的挑战性。具有大面积同步连续观测优势的遥感技术可以克服传统观测方法的局限，可为全球湖泊碳循环研究提供大面积同步观测数据的支撑。同时，由于光谱在物质识别和探测方面的优势，使得遥感技术在有机质类型反演方面与地球化学方法存在结合的可能。本文回顾了目前水环境遥感研究中与湖泊碳循环相关的湖泊不同类型碳浓度、水体理化参数等遥感反演算法及其应用的现状，结合湖泊碳循环中有机碳迁移转化的生物地球化学过程，以及湖泊碳循环研究、遥感大数据和人工智能的发展，探讨了湖泊碳循环研究中遥感技术应用的机遇和挑战。

关键词：湖泊碳循环，遥感，生物地球化学，大数据与人工智能，水环境，温室气体

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1　引　言

随着湖泊碳循环在全球碳循环中作用和地位的日益突出（Cole等，2007；Tranvik等，2009；Tranvik，2018），其相关研究得到了越来越多的关注，并已成为全球碳循环研究的热点和前沿。已有研究表明，陆地输入到湖泊和河流中的有机碳大约为5.7 PgC/a（Le Quéré等，2015），湖泊水生植物通过光合作用大约可以固定大气中的二氧化碳1 PgC/a（Lewis，2011），其中大约有68%有机碳（3.88 PgC/a）被转化为CO_2和CH_4排放到大气中（Raymond等，2013），16%（0.95 PgC/a）或更高将被输入到海洋中（Tranvik等，2009；Raymond等，2013；Le Quéré等，2015），剩余的约16%（0.95 PgC/a）有机碳将被埋藏在沉积物中。内陆水体通过传输、矿化和埋藏大量的有机碳，进而调节全球碳循环和气候变化。尽管2020年全球碳收支平衡报告（Friedlingstein等，2020）已基本完成了全球大气、海洋、陆地的碳库以及相互传输量的估算，但是目前仍有-0.1 Pg碳的不平衡。同时，由于模式空间分辨率的不足，以及排放清单上内陆水体碳排放量的不完善，无论是通过大气模式自上而下、还是通过排放清单自下而上的估算，内陆水体（包括河流、湖泊、水库）在全球碳循环中的作用仍然具有较大的不确定性。因此，作为湖泊碳循环中较为活跃的成分，有机碳的迁移、存储和转

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第一作者简介：黄昌春，1982年生，男，教授，研究方向为湖泊生态环境遥感与碳循环。E-mail：huangchangchun@njnu.edu.cn

化过程的研究将有利于更加全面和系统地认识湖泊碳循环及其在全球碳循环中作用，进而制定更加完善的气候变化调节策略。

全球湖泊总面积约为 5×10^6 km^2，其中大于 0.002 km^2 的湖泊约有 1.17×10^8 个（Verpoorter 等，2014）。相对于海洋而言，湖泊不仅面积较小（海洋面积约 3.61×10^8 km^2，湖泊约占海洋面积的 1.38%），而且分布极为破碎。湖泊镶嵌在陆地生态系统中，生态环境负荷较小，使得湖泊碳循环体系对流域内输入的营养盐、有机碳、无机碳等的变化较为敏感。随着全球人类活动、水土侵蚀的加剧，大量的有机碳、无机碳和营养盐通过地表径流输入到湖泊中（Galy 等，2015），不仅直接增加了湖泊碳库中的外源碳输入，过量的营养盐也加剧了湖泊富营养化及其引起的藻类“水华”，即增加了内源碳的生成（Schindler 等，2008）。同时，由于湖泊自身生态环境（营养盐、光照、温度等）、浮游植物种群结构等差异，使得湖泊初级生产力、有机碳的矿化、温室气体的排放（微生物的作用、光化学降解等）以及食物链的群落结构具有较大的复杂性和时空差异性（Gudasz 等，2010；Kosten 等，2010；Yvon-Durocher 等，2011，2014；Williamson 等，2014；Marsay 等，2015）。湖泊的破碎性、流域和湖泊自身生态环境的多样性使得湖泊碳循环过程及其影响因素具有较大的时空差异。传统的样点观测，如利用原位顶空法（或静态箱法）测量水体中温室气体的浓度或通量（Qi 等，2020）、野外采集水样测量不同形态碳含量（颗粒有/无机碳、溶解有/无机碳等）（Duan 等，2014；Jiang 等，2015）、通过沉积柱中有机碳的沉积速率估算湖泊碳埋藏量（Huang 等，2018a）等，不仅费时费力，而且难以获取大面积同步观测结果。因此，迫切需要具有大面积同步连续观测优势的遥感技术对湖泊碳循环中关键要素进行观测。

目前，遥感技术已经被广泛地应用于湖泊生态环境的监测，在湖泊水质、水体面积、水体光学特性、颗粒有机碳、溶解有机碳等方面都开展了大量的相关工作（Duan 等，2014；Jiang 等，2015；张杰 等，2015；Huang 等，2015，2017a，2017b），本文将从碳循环角度阐述遥感技术在湖泊碳循环研究中的作用及其遇到的机遇和挑战。

2 湖泊碳“管道”模式

早期，湖泊（以及水库、河流等内陆水体）仅仅是作为全球碳循环体系中连接内陆与海洋碳库之间传输通道；然而，大气、陆地和海洋 3 个碳库之间的不平衡，使得越来越多的研究将内陆湖泊水体作为独立单元纳入到全球碳循环研究中（Schlesinger 和 Melack，1981；Degens 等，1991）。Cole 等（2007）在综述前人研究成果基础之上，认为陆地输入到内陆水体的碳量几乎与陆地的净初级生产力相当，远大于河流输入到海洋中的碳量，并提出内陆水体碳平衡模式“Active Pipe”模型（图 1）。该平衡模式可以简化为陆地输入到内陆水体的碳总量（I=1.9 Pg）为内陆水体碳排放量（G=0.75 Pg）、沉积埋藏量（S=0.23 Pg）以及输出到海洋的输出量（E=0.9 Pg）之和。相关研究对内陆水体碳循环进行了详细的论述 https://aslopubs.onlinelibrary.wiley.com/toc/23782242/20181313［2021-04-16］，指出内陆水体碳循环从最初的独立体系已经逐步成为全球碳循环中重要的碳汇（沉积 S）和碳源（排放 G），并提出湖泊碳循环研究地理学框架，即应该从湖泊流域属性和特征出发对其进行综合研究。

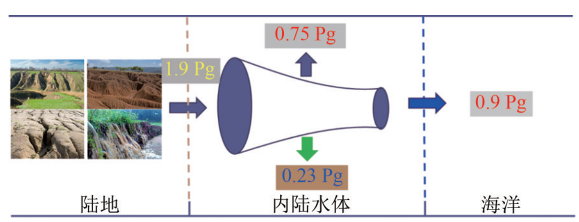


图 1 内陆水体在全球碳循环中作用示意图
（改绘于 Cole 等，2007）

Fig. 1 Schematic diagram for the role of inland water bodies in global carbon cycle（Redrawn from Cole et al., 2007）

陆地向湖泊水体输送的碳量受到湖泊流域内包括地形、降雨、土壤属性等自然条件和土地利用、种植方式等人为因素的影响。同时，大量的营养盐随着碳一同被输入到湖泊中，促进了水体中的生产力，进而增大了水体中的碳库。遥感技术在湖泊碳循环研究中的应用主要包含了以下 3 个方面：（1）直接定量估算水体中各个碳库的大小；（2）定量估算影响湖泊碳库及其转化的水体理化性质；（3）定量估算流域内影响碳迁移的流域景观特征（图 2）。GHG，温室气体；DIC，溶解无机碳；TSM，总悬浮颗粒物；CDOM，有色溶解有

机质，POC，颗粒有机碳；PBC，颗粒黑炭；DOC，溶解有机碳；DBC，溶解黑炭；Chl-a，叶绿素；POC_{Allo}，外源颗粒有机碳；POC_{Auto}，内源颗粒有机碳；POC_{Phy}，浮游植物有机碳；N\P，氮磷营养盐；K_d，漫衰减系数；PAR，光合有效辐射；T，温度。

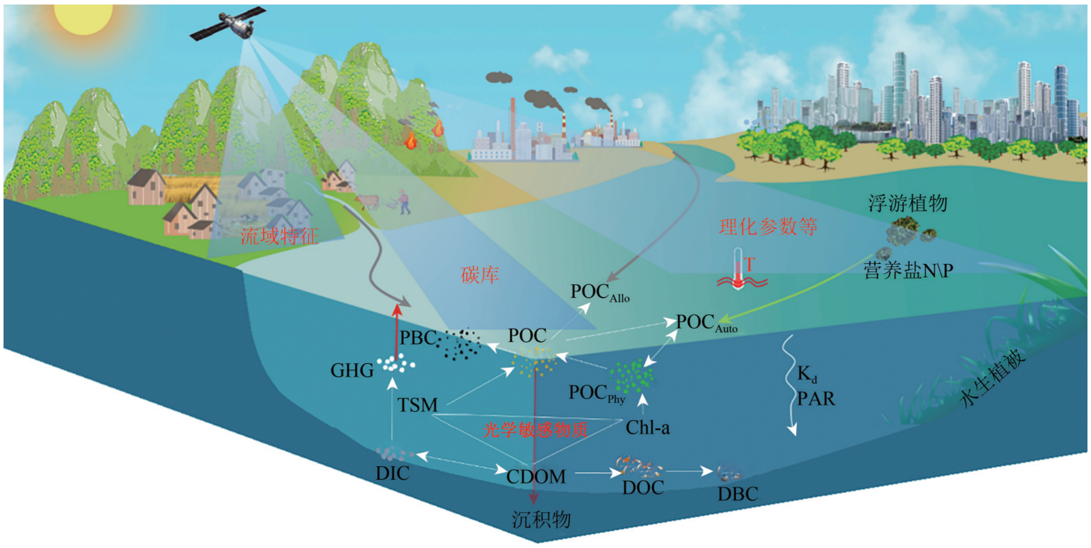


图2 湖泊碳循环中湖泊流域特征、水体碳库和理化性质等遥感监测示意图

Fig. 2 Schematic diagram of remote sensing monitoring of lake basin characteristics, water body carbon pool and physical and chemical properties in lake carbon cycle

（1）定量估算水体中各个碳库的大小。由于水体中不同类型和形态的碳存在较大的生物地球化学特性差异，通常根据碳的形态、来源和属性差异对湖泊碳库进行一定的区分。根据可溶性，水体中的碳库主要包括颗粒态（PC）和溶解态（DC）两种形式，这两种形式里面又分别可以划分为有机碳（POC，DOC）和无机碳（PIC，DIC）两种类型。根据来源，有机碳可以分为外源和内源有机碳，其中外源有机碳主要是通过地表侵蚀输入的陆源有机碳（POC_{Allo}），内源有机碳（POC_{Auto}）主要是与湖泊浮游植物初级生产相关的浮游植物、水生植被等有机碳（POC_{Phy}）和光合细菌等。目前，由于不完全燃烧产生（化石燃料、森林火灾等）的黑炭具有高稳定性、高芳香性等特性，其生物地球化学特性与有机碳以及无机碳存在显著差异，黑炭（包括颗粒态和溶解态：PBC和DBC）在全球碳循环中越来越受到关注。目前，通过遥感可以直接估算水体中POC、DOC、DIC（二氧化碳、甲烷）、内源和外源有机碳的浓度和初级生产力等（Duan等，2014；Jiang等，2015；张杰 等，2015；Huang 等，2017a，2017b；Qi 等，2020；Engram等，2020）（图2）。在获取湖泊水体不同类型碳浓度后，结合浓度垂直分布模式、水体深度和水域面积，可以计算湖泊水体不同类型碳库的大小。然而，准确估算内陆浑浊水体的水深以及不同类型碳垂直分布模式仍存在一定的挑战。目前，水质和有机碳垂直分布模式主要通过垂直分布经验模型（Bi等，2019；Lei等，2020）或者水动力模型（黄昌春，2011）来进行分类模拟表达，难以做到逐像元准确计算其垂直分布。

（2）定量估算影响湖泊碳库及其转化的水体生态环境性质。湖泊水体中各个碳库之间的迁移转化较为复杂，如颗粒有机碳和溶解有机碳之间的转化、有机碳的矿化降解等，难以利用遥感技术监测各个碳库之间的转换通量；但是，遥感技术可以监测对湖泊水体碳库之间迁移转化产生重要影响的湖泊理化参数，如：水体面积、水生植被分布、水体温度、光线强度、营养盐等。通过遥感监测的具有大面积同步观测的水体理化性质数据，支撑湖泊水体碳循环模型，进而估算水体不同有机碳库的大小及其迁移转化。

（3）定量估算流域内影响碳迁移的流域景观特征。由于湖泊的破碎性、流域和湖泊自身生态环境的多样性，使得湖泊碳循环具有较大的时空差异性。充分认识到湖泊碳循环的多样性，需要结合流域内的陆地植被初级生产力、植被类型、

地形地貌、土壤属性、人口密度等自然和人为景观特征，利用地理学生态空间和景观格局的自相关性、差异性和相似性（朱阿兴 等，2020），明确湖泊碳循环时空异同的内在驱动，建立湖泊碳循环地理学框架体系（Seekell 等，2018；Klaus 等 2019）。利用遥感技术获取的流域内长时间陆地植被初级生产力、植被类型、土壤有机碳等湖泊流域景观数据，结合流域水文和碳循环模型，实现地理学框架下湖泊碳循环模拟，对湖泊碳循环进行综合性研究。

3 文献计量特征

通过Web of science科学引文库，利用关键词湖泊（Lake）、遥感（Remote sensing）和碳（Carbon）分别组合“Lake” & “Remote sensing”和“Carbon” & “Remote sensing”进行检索（2000-01—2020-12）发现遥感技术在湖泊和全球碳循环两个方面的研究文献分别达到了9261和12461篇并呈现快速增长的趋势（图3），表明遥感技术已经在湖泊和碳循环研究中得到了广泛应用。利用关键词“Lake” & “Remote sensing” & “Carbon”组合结果搜索遥感技术在湖泊碳循环中应用的文献仅525篇，其中2000年—2009年总计仅71篇（年均7篇），2013年以后年发文量年均超过了40篇，2020年达到了63篇。与遥感技术应用在碳循环和湖泊环境监测两个方面的发文量相比，遥感技术在湖泊碳循环方面的应用相对较低，但是引用频次从2002年的6次升高到2020年的2460次，可见遥感技术在湖泊碳循环中的应用得到了越来越多的关注。

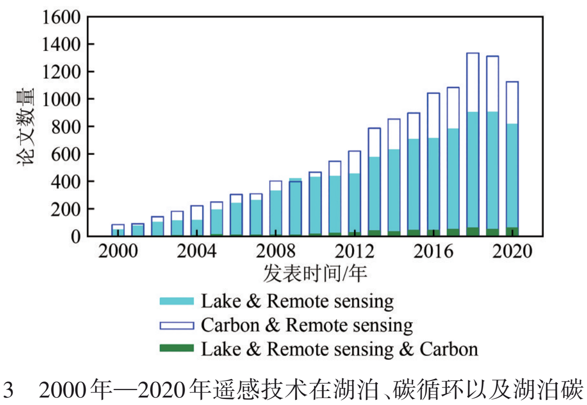


图3 2000年—2020年遥感技术在湖泊、碳循环以及湖泊碳循环中应用的发文量

Fig. 3 Distribution of published papers for the remote sensing application in lake and carbon cycle during 2000 to 2020

表1统计了国内在湖泊遥感方面发文量前10名的单位，贡献了全球17.7%的发文量，表明中国在湖泊碳循环遥感方面的研究在国际上占有重要的地位。前10名中主要是中国科学院和高校，排在前4名分别是中国科学院南京地理与湖泊研究所、南京师范大学、武汉大学和中国科学院东北地理与农业生态研究所，占比都超过了1%；剩下的7个单位发文量分别占到了0.76%和0.57%。

表1 国内湖泊遥感研究相关论文贡献前20名单位

Table 1 Top 20 domestic organizations for the contributions to related papers in lake remote sensing research

序号	单位	数量	贡献/%
1	中国科学院南京地理与湖泊研究所	42	8.00
2	南京师范大学	11	2.10
3	武汉大学	7	1.33
4	中国科学院东北地理与农业生态研究所	6	1.14
5	中国科学院遥感与数字地球研究所	5	0.95
6	中国科学院地理科学与资源研究所	4	0.76
7	中国科学院寒区旱区环境与工程研究所	4	0.76
8	江西师范大学	4	0.76
9	新疆大学	4	0.76
10	兰州大学和西北师范大学	各3	1.14

4 遥感在湖泊碳循环中相关应用现状

4.1 湖泊水体不同类型碳遥感反演

水体中3大光学活性物质（悬浮颗粒物（TSM）、叶绿素（Chl-a）和有色溶解有机质（CDOM））是水体中碳的主要载体，也是遥感反演碳的重要物质依据（图2）。其中，CDOM是反演DOC以及DBC的物质基础（Song等，2017a）；TSM和Chl-a是反演POC和POC_{phy}的物质基础（Duan等，2014；Jiang等，2015；Huang等，2019）。湖泊水体悬浮颗粒物和叶绿素浓度算法相对较为成熟，已经应用到包括Landsat、MODIS、MERIS、Sentinel、GOCI等国际卫星数据和环境卫星（HJ）、高分卫星（GF）等国产卫星数据。

4.1.1 湖泊颗粒有机碳与溶解有机碳遥感反演

针对湖泊，基于POC与悬浮颗粒物和叶绿素之间的物质关联，常用于湖泊水体TSM和Chl-a反演算法的红和近红外波段遥感反射率，被用来建立POC反演模型，并成功应用于POC的空间分布

特征监测（Duan等，2014；Jiang等，2015；张杰等，2015；Kutser等，2015；Huang等，2015，2017a）。由于湖泊水体光学复杂性，基于有机质和总悬浮颗粒物光学特性分类的POC半分析算法被尝试用在MERIS卫星数据上反演内陆浑浊湖泊水体中POC含量（Lyu等，2017），以期获得普适性较强的湖泊水体POC遥感反演模型；然而，其普适性在不同光学特性水体中仍受到一定的限制（Lin等，2018）。由于湖泊水体DOC来源的复杂性，使得DOC经验算法在内陆湖泊的普适性和精度难以得到较大提升；相应的利用DOC与CDOM之间关系，进行DOC反演也同样遇到了DOC与CDOM之间关系不稳定的瓶颈（Li等，2017a；Huang等，2017b；吴铭 等，2021）。无论是通过经验算法还是基于CDOM的半分析算法在湖泊中应用仍存在一定的限制，因此，仍然需要开展大量的基础性工作，来提高湖泊CDOM或DOC遥感反演算法的精确性和普适性（Song等，2017a；Huang等，2017b），如DOC的来源、不同类型湖泊CDOM与DOC的关系等。水体中颗粒态黑炭（PBC）和溶解态黑炭（DBC）是POC和DOC的重要组成部分，随着全球黑炭排放量的快速增加，准确估算湖泊中的PBC和DBC有助于细化湖泊碳循环机理研究（吴沁淳 等，2016）。已有研究表明DBC和DOC以及PBC和POC具有较好的相关性（Stubbins等，2015），有望通过DOC和POC来实现对PBC和DBC的遥感反演，但是其反演算法和光学机理需要进一步深入研究。

4.1.2 湖泊温室气体遥感反演

湖泊不仅通过初级生产力固定了大量CO_2，同时，在微生物、光化学降解、呼吸和矿化等作用下，水体释放了大量的温室气体（CO_2、CH_4）（Raymond等，2013）。静态箱、顶空法或者涡度相关等测量方法可以较为方便准确地获取水体离散样点和时间连续的温室气体排放特征和排放量，但由于湖泊生物化学和物理过程较为复杂，基于离散样点水体温室气体排放估算仍存在较大的不确定性（Bauer等，2013；Chen等，2013）。水体的CO_2含量（或与大气之间的差异，CO_2分压，pCO_2）与水体的温度、pH、叶绿素、混合层深度等理化参数具有较强的相关性（Stephens等，1995；Rangama等，2005；Ono等，2004；Sarma等，2006）。因此，基于水体温度、叶绿素浓度、光照条件等遥感经验算法被广泛应用于水体CO_2浓度或其分压（pCO_2）的估算（Lohrenz和Cai，2006；Chierici等，2012；Zhu等，2009；Chen等，2016；Lohrenz等，2018）。由于水体CO_2产生较为复杂，各影响因子并非简单的线性叠加，神经网络、自组织神经网络等机器学习方法被用来解决算法中的非线性问题以提高模型的反演精度（Lefèvre等，2002；Telszewski等，2009；Hales等，2012）。针对CO_2产生的生物化学和物理过程和遥感经验算法的不稳定性，具有生物地球化学过程机理特征的pCO_2半分析模型被开发并应用于美国路易斯安那和中国东海沿岸水体的pCO_2估算（Bai等，2015；Le等，2019）。内陆湖泊水体CO_2（pCO_2）遥感反演算法研究相对较少，Qi等（2020）根据太湖实测水体溶解CO_2浓度与叶绿素、水温、PAR和K_d（PAR）等因子之间的相关性，建立太湖水体CO_2浓度多元回归遥感反演模型，遥感反演CO_2结果与太湖野外实测CO_2数据具有较好的一致性，将该模型应用于MODIS遥感影像，获取了2003年—2018年太湖水体CO_2浓度长时间序列结果。相对于CO_2，CH_4主要是由水体和沉积物中甲烷菌分解有机质产生，与水体光学活性物质等水体性质关联性较弱，难以用遥感技术针对CH_4进行单一准确估算，结合遥感数据和流域属性，通过地统计方法被推荐用来估算CH_4排放量（Hondula等，2021）。水体CH_4排放主要分为冒泡和扩散两种形式，目前遥感（合成孔径雷达）被尝试应用于北方冰冻湖泊冒泡CH_4的监测（Engram等，2020）。但是，湖泊温室气体的遥感监测仍具有较大的挑战性。

4.1.3 湖泊生物有机碳遥感反演

作为无机碳转化为有机碳的重要途径，水体的初级生产力和浮游植物有机碳一直是全球碳循环研究的热点，也是遥感估算的重要目标。由于湖泊面积相对较小，湖泊初级生产力的研究相对较为迟缓。目前，通过重新率定海洋初级生产力模型参数，VGPM（Vertically Generalized Productivity Model）模型在湖泊水体中得到了一定的应用（Bergamino等，2010；Kauer等，2015；Deng等，2017；Soomets等，2020）。但是，基于碳生物量和固有光学特性的初级生产力模型在湖泊中应用较少。这主要是由于湖泊水体浮游植物有机碳（POC_{ph}）遥感反演模型

发展较慢。Huang等（2019）基于大量叶绿素和颗粒有机碳数据，利用实测遥感反射率建立了湖泊水体遥感反射率—叶绿素—POC_{ph}浓度反演算法，并在太湖进行了应用，利用MODIS卫星数据获取了太湖POC_{ph}长时间序列的分布特征及其驱动因素。Lyu等（2020）从浮游植物中藻类的种类、数量及其与浮游植物有机碳之间的关系出发，建立了太湖水体浮游植物有机碳遥感反演模型，并成功应用于Sentinel-3 OLCI影像。该算法结果与Huang等（2019）算法结果，结合同位素地球化学方法的遥感反演结果（3种独立算法）具有好的一致性（图4）。目前，浮游植物有机碳和湖泊初级生产力在全球尺度上并没有得到充分的应用，全球湖泊初级生产力的获取仍然存在一定的困难。

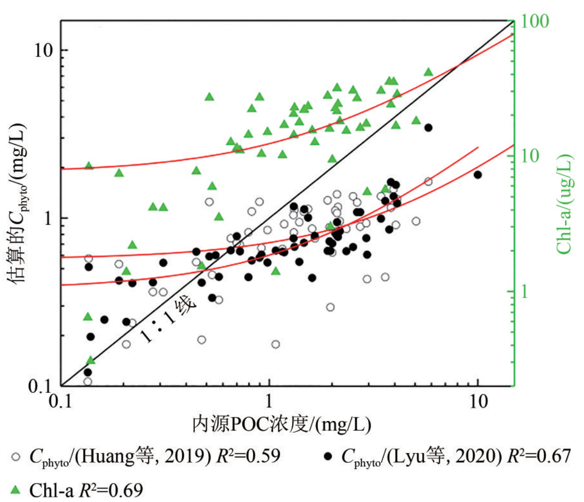


图4 基于叶绿素—浮游植物有机碳，藻类物理特征—浮游植物有机碳和同位素—内源有机碳估算结果对比，内源POC为同位素估算结果，估算浮游植物POC为遥感反演结果（Zhao等，2021）

Fig. 4 Comparison of the endogenous POC and estimated phytioplankton POC from remote sensing results by Zhao et al. (2021)

内陆湖泊水体水生植被不仅是重要的碳汇之一，同时也调节了水体的温室气体排放，因此，水生植被信息的提取将有利于进一步准确估算湖泊水生植被生物量和温室气体排放（郭佳 等，2020）。目前水生植被主要是通过经验、半分析分类模型，光谱分解模型，波段比值等方法来进行识别和提取（Oppelt等，2012；Villa等，2013；Giardino等，2015）。光谱指数和分类树（classification tree）被成功应用于太湖水生植被的提取，并且获得较好的效果（Luo等，2014，2016）。为了减小水深影响，进一步提高识别和提取精度，利用深度不变指数（depth-invariant indices）对水生植被进行提取的同时还识别出了其他入侵物种（Roessler等，2013；Brooks等，2015）。由于湖泊水体光学特性的复杂性，水生植被生物量测量、水生植被冠层结构等相关研究仍然较弱。一方面，陆地生物量传统调查方法在水生植被调查中实施的困难性较高；另一方面，受水体及其组分影响，水生植被高度、覆盖度、冠幅等与生物量相关的参数难以通过遥感准确获取，因此导致目前遥感技术在湖泊水生植被生物量估算方面的研究受到较大限制，需要被进一步关注。

4.2 湖泊碳循环影响因素遥感反演

湖泊水体理化性质（湖泊温度、深度、水域面积、光照、营养盐等）对各个碳库的大小、相互之间的转化具有强烈的调节作用（Tranvik等，2009；Behrenfeld等，2005；Stramska和Cieszyńska，2015；Williamson等，2014；Marsay等，2015）。如：水体温度显著影响了有机碳的矿化、温室气体的排放、浮游植物的初级生产力等；水体深度显著影响溶解氧和温度的垂直分布；水体的面积是估算水体温室气体排放的基本物理量，其变化也显著影响了水陆交错带的温室气体排放等。因此，水体理化性质数据的有效获取将极大支撑湖泊碳循环的定量研究。

光线在水体中的穿透深度（漫衰减系数K_d、真光层深度）是影响水体光和热的重要物理量，也是影响水生植物光合作用的重要生态因子。漫衰减系数是有水体固有光学量和水下光场结构决定的，目前漫衰减系数包含经验算法和基于水体吸收系数和后向散射系数的分析反演算法（Shi等，2014；Lee等，2005a，2005b，2013，2014）。该类型反演算法在内陆湖泊水体中也得到了充分使用，基于分析算法获取的遥感影像长时间序列数据有效支撑了湖泊理化性质、初级生产力和碳循环的研究（Kauer等，2015；Huang等，2017d；Song等，2017b；Qi等，2020）。水温遥感监测主要是基于遥感热红外数据，相关算法（波段比值经验算法、Split-window algorithm，Mono-window Algorithm）较为成熟（Alcântara等，2010；Chao Rodríguez等，2014；Simon等，2014），已经具有成熟的产品；其中相关算法在湖泊和水库中也得

到了广泛的使用（Schneider和Hook，2010；Politi等，2012；Wan等，2018；Liu等，2019；Yu等，2020），并应用于MODIS、AVHRR、AATSR、Landsat等遥感影像，获取了包括小时、月和年尺度在内的长时间序列结果。

水体的光学信号与陆地等其他地物具有显著的差异，因此通过水体光谱指数（Normalized Difference Water Index；Modified Normalized Difference Water Index）相对较为容易地将水体从影像提取出来。从低分辨率遥感影像（例如MODIS，覆盖范围广、重返周期短）提取和反演内陆湖泊水体水面积、水深和库容量较为方便（Carroll等，2009），但是从高分辨率影像（例如Landsat，SPOT，Sentinel-2，覆盖范围小、重返周期长）获取精度更高细节更全的内陆湖泊水体信息需要花费大量的人力物力（Fisher等，2016；Feng等，2016；Du等，2016；Yang等，2017）。在遥感数据处理能力大幅提升和全球科研人员的协作下，具有更高分辨率和细节的全球内陆水体（包括河流）及其长时间序列变化数据集被成功完成（Pekel等，2016；Allen和Pavelsky，2018；Grill等，2019）。利用遥感光学传感器对水体面积的监测和提取，Huang等（2018b）从传感器、算法等角度进行了较为全面的综述。全球水系的演变极大地促进和支撑了湖泊和水系沿岸干—湿交替对温室气体排放影响的研究（Arce等，2019；Keller等，2020）。水深的光学反演主要集中在较为清洁的水体，浑浊水体的水体信号难以传输到水体表面，因此较难以准确反演，但通过合成孔径雷达（SAR）卫星数据可以较好地弥补光学遥感的不足（Hong等，2010；Mason等，2012；Kim等，2014）。结合水深和水域面积，水体容量（Water storage volume）能够较方便的被计算出来（Busker等，2019）。利用多源卫星数据，分别反演地形和水域面积同样能够达到估算水体容量的目标（Song等，2013；Crétaux等，2016；Wang等，2018a），也有通过水域面积与水体容量之间的经验关系，通过提取的水域面积来估算水体容量（Cai等，2016）。尽管目前影响湖泊碳循环的水体理化参数遥感反演算法较多，并且部分成熟的参数遥感反演算法已经用于相关产品生产，但是湖泊理化性质遥感反演结果与湖泊碳循环之间应用和研究相对较少，如何通过湖泊水域面积、温度、富营养化等全球大面积同步观测结果研究其对内陆湖泊水体温室气体排放影响等需要进一步深入挖掘和研究。

4.3 湖泊碳循环地理学框架下流域景观特征遥感监测

湖泊流域不仅直接向湖泊输入陆源碳，同时还向湖泊水体输入泥沙、营养盐等，进而影响湖泊水体的透明度、光热传输和初级生产力。如，由于人类活动、水土侵蚀的加剧，全球近63%的湖库，欧洲约55%的湖泊，亚太地区60%的湖泊，非洲30%的湖泊，北美50%的湖泊和南美40%的湖泊都遭遇到了不同程度的富营养化问题（Wang等，2018b），促进了浮游藻类等内源有机碳的增加。内源和外源碳输入的增加显著改变了湖泊水体有机碳库以及湖泊原有碳循环体系（Tranvik，2018；Seekell等，2018），并且由于流域以及流域内人类活动的差异，不同流域内的碳库体系及其迁移转化具有较大的时空差异性。因此，需要从流域尺度上进行湖泊碳循环研究。已有研究表明，土壤侵蚀直接决定了陆地向水体输入的碳量、营养盐等（Raymond等，2008；Quinton等，2010；Regnier等，2013；Galy等，2015）。目前，针对土壤侵蚀相关研究已经从统计分析进入到定量模式，在对土壤侵蚀机理认识的基础之上已经开发了包括EPIC模型、WEPP模型、LISEM模型、EUROSEM模型、GUEST模型在内的土壤侵蚀物理模型，其中SWAT模型具有较强的代表性，并被广泛应用于流域土壤侵蚀、营养盐流失、有机碳输出模拟（Kiniry等，2000；沈胤胤，2018；Batista等，2019）。流域输入参数的准确、全面和精细化表达是模型准确模拟、深入解析流域过程机理的重要保证。

流域内的陆地植被初级生产力、植被类型、地形地貌、土壤属性、气候条件、人口密度等自然和人为景观特征的获取和高精度的定量表征将大大提高流域土壤侵蚀、湖泊水体营养盐和碳输入的估算精度（周涛 等，2007；Li等，2017b；Mzobe等，2020；Fabre等，2020；Edwards等，2021）。流域中陆地初级生产力、植被类型等是影响湖泊流域碳输出的重要影响因素，其不仅影响了流域内有机碳的产量，同时还影响了流域内土壤侵蚀强度。陆地植被及其初级生产力的遥感监测技术已经较为完善，发展了大量与陆地植被相关的遥感产品（NDVI、LAI、GPP、NPP等），这

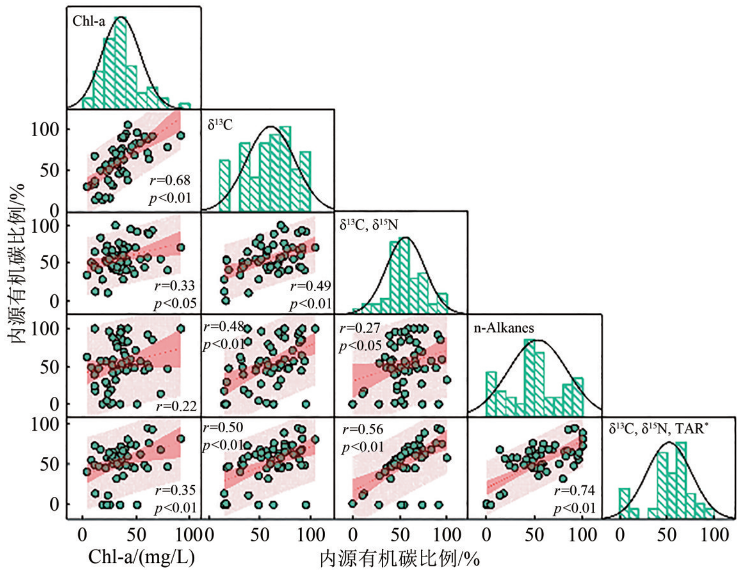
些产品也被广泛应用于陆地碳循环和生态系统研究中（Spruce等，2011；Verma等，2014；Fang等，2019；穆西晗 等，2021）；新的研究表明，利用激光雷达数据获取的植被冠层等信息，进一步将传统的光学传感器获取的植被二维特征推向了三维，更加准确地获取植被的生物量（Armston等，2013）。土地利用覆盖、土壤、地形和气象等条件是影响土壤侵蚀的重要因子。通过遥感技术可以准确地获取流域内土地利用、植被覆盖度等情况；同时，地形数据、降雨、土壤属性等影响土壤侵蚀过程的流域属性数据，遥感技术也取得较为丰硕的成果。然而，湖泊流域内的生态景观、人类活动等影响因素与陆地输入到湖泊中碳含量之间的内在驱动机制研究仍较为缺乏。但针对土壤侵蚀及其内在驱动机制的相关研究值得借鉴。相关机制机理研究是落实湖泊碳循环地理学框架的重要基础。在湖泊碳循环地理学框架体系下，一方面，利用流域遥感数据反演结果，推动流域要素与湖泊碳循环之间的内在关联机制研究，促进湖泊有机碳沉积、矿化量的估算；另一方面，利用遥感数据的宏观性和同步观测优势，可以将湖泊碳循环研究从局域尺度推广到更大的尺度；同时，多传感器（光学传感器、微波、激光雷达等）的交叉融合，以及高分辨率和高光谱数据的重访周期和全球覆盖能力的提高，将使得遥感技术在流域属性参数反演等方面发挥更大的作用。

5 机遇与挑战

5.1 遥感与地球化学技术的协同反演

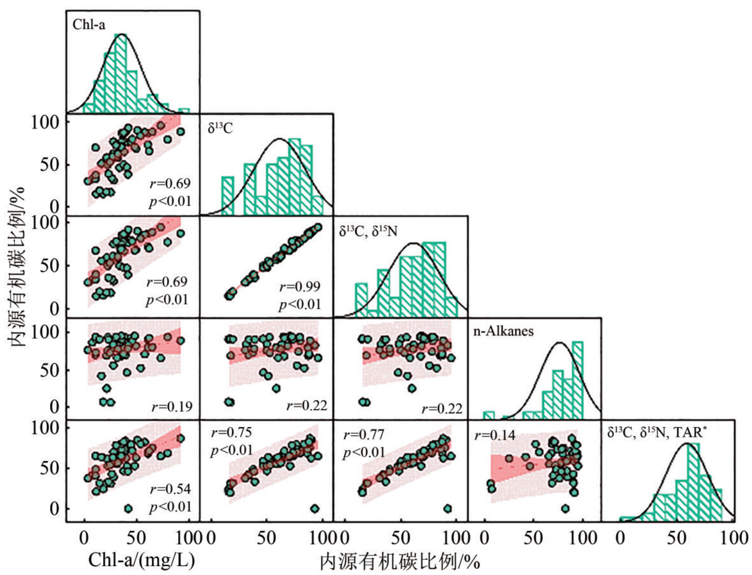
湖泊碳库中较年轻的陆源有机碳和内源有机碳将通过异养作用在相对较短时间内被矿化成CO_2、CH_4和N_2O等（Wilkinson等，2013；Galy等，2015），较老的陆源有机碳将优先被埋藏到沉积物中，进入长周期的碳循环体系（Battin等，2008；Guillemette等，2017）。然而，由于受到活性有机碳的作用（称为“激发效应”），较老的陆源有机碳在沉降和沉积过程中仍会被降解（Kuzyakov等，2000；Kuzyakov 和 Bol，2006；Kuzyakov，2010；Guenet等，2010，2012；Bianchi，2011）。已有研究表明，“激发效应”可能可以导致土壤系统中CO_2排放量增加400%到1100%（Bianchi，2011），水体系统中CO_2排放量增加10%—500%（Guenet等，2010）。有机碳库的组成变化显著改变了湖泊水体温室气体排放和有机碳的埋藏量。此外，水体有机碳（POC和DOC）遥感反演算法中，由于有机碳来源的差异性，使得基于遥感反射率的经验反演模型或基于有机碳与水体组分（TSM和Chl-a）之间组分关系的半分析模型的应用受到一定的限制。因此，湖泊水体有机碳来源的确定不仅可以有助于深入揭示湖泊水体温室气体排放和有机碳埋藏特征和机理，同时，也将有助于提高有机碳遥感反演模型的精度和普适性。

有机碳组成较为复杂，但不同来源的有机碳在分子结构、同位素分馏等方面存在较大的差异性，这为区分有机碳来源提供了物质基础。有机氮主要存在于有机体的蛋白质和核酸中，而有机碳大量的存在有机体的木质素和纤维素，因此有机质中碳氮比值可以有效地区分富含木质素和纤维素的高等植物（高有机碳氮比值，一般大于30）和低等植物（低有机碳氮比值，一般小于10）（Müller和Mathesius，1999；Lund-Hansen等，2004；Kendall等，2001；Yu等，2010；Meisel和Struck，2011）。植物在生长过程中对碳、氮同位素分馏作用使得植物有机体内的碳氮同位素自然丰度具有一定的差异（一般陆源高等植物碳同位较低，水生藻类碳同位素较高），通过碳氮同位素可以有效地区分高等和低等植物（Machiwa，2010）。随着分子技术的发展，分子标识物（不饱和脂肪烃、烷烃等）成为一种新的有机质来源示踪方法。正构烷烃是一种广泛存在于植物和藻类中的脂类分子，其碳链分布可以有效地区分有机质的来源，其中短链部分（$n-C_{14}-n-C_{20}$）主要来源于藻类、细菌和真菌类，中链部分（$n-C_{20}-n-C_{25}$）主要来源于沉水和挺水的大型植物，而长链部分（$n-C_{27}-n-C_{33}$）主要来源于陆生高等植物（Meyers，2003；Sojinu等，2010；Rao等，2014；Ortiz等，2016）。结合正构烷烃单体碳同位素，可以对C3和C4来源的有机质进一步区分（Alewell等，2016）。新的超高分辨率傅立叶变换离子回旋共振质谱技术（FT-ICR-MS）可以精确测量有机质中碳氮氧硫磷元素的组成，通过有机质的元素组成对有机质的来源进行分析示踪（Hertkorn等，2012）。但是，由于不同示踪因子和示踪模型具有一定的局限性，利用不同示踪因子和模型估算有机碳来源的结果具有一定差异（图5）。同时，地球化学方法不仅耗时（前处理复杂和测量周期长）花费大（测量成本极高），而且难以获取大范围空间连续观测数据。



（a）多源混合模型

（a）Multi-source mixing model



（b）贝叶斯混合模型

（b）Bayesian mixing model

图5　利用多源混合模型和贝叶斯混合模型结合不同示踪因子估算的湖泊内源有机碳结果对比图（Meng等，2021）

Fig. 5　comparison the estimation results of endogenous POC from Multi-source mixing and Bayesian mixing models with different trance factors（Meng et al., 2021）

随着湖泊碳循环问题的日益突出、机理的日益明确和技术的日益成熟，湖泊碳循环对湖泊水体碳库、来源组成及其时空动态分布的遥感观测需求日益迫切。将具有大面积同步连续观测优势的遥感技术与地球化学方法相结合，不仅可以缩短测量时间节省测量成本，还可以大范围空间连续观测有机碳的来源组成。遥感技术与同位素联合示踪估算方法已经在POC来源和含量反演中得到了应用（Xu等，2020，2021），主要是利用碳氮同位素端元法计算有机碳来源组成比例，再利用各组成和来源与水体固有光学量或叶绿素之间的内在关联，建立遥感反射率—固有光学量（叶绿素）—有机碳来源组成定量遥感反演模型。利用遥感技术获取的不同来源有机碳量及其空间分布将极大的促进不同类型有机碳库之间相互作用机制研究及其对碳循环的影响（Zhao等，2021）。然而通过单一指标方法难以准确定量识别有机碳的来源，需要进一步利用有机质端源的分子标识物、

碳氮氧硫磷元素组成以及碳氮同位素等多源指标，结合复合指纹、质量守恒优化模型等数学方法可以定量评估有机质来源（Huang等，2017c，2017e；Meng等，2021）。同时需要对有机碳端元的结构和组成特征进行深入研究，进一步明确有机碳来源与水体组分和生物光学特性的内在机理。针对不同来源有机碳的衍生物和标识物（黑炭、烷烃类等），由于其在水体中浓度含量较低，以及其对应的响应波段与传统水质存在一定的差异，因此，对遥感数据的光谱分辨率和辐射分辨率提出了新的要求。具有更高辐射分辨率的高光谱遥感数据，以及具有相位信息的合成孔径雷达数据具有较大的优势，值得关注和应用。

5.2 遥感大数据和人工智能

湖泊零星地分布在陆地上，相对较为分散，面积范围跨度较大（0.1—100000 km^2），存在较大的空间尺度差异。因此全面监测全球湖泊水体及其碳循环需要更高空间分辨率的遥感数据。针对内陆湖泊水体碳循环的动态变化特征，特别是温室气体的排放，对于遥感数据的时间分辨率提出了较高要求；同时，要定量获取湖泊水体理化性质、定量反演水体物质含量和不同类型碳含量，在光谱分辨率和辐射分辨率上需要满足更高条件（图6）。然而，高空间分辨率遥感数据（如Landsat、Sentinel等）通常覆盖范围较小，重访周期较长，覆盖全球湖泊的长时间遥感数据需要大量的遥感影像，这将会对数据存储、处理和计算提出新的要求。在全球遥感大数据平台，如Google Earth Engine（Gorelick等，2017；Parente等，2019；Tamiminia等，2020；Wang等，2020a）等支持下（Landsat、Sentinel、MODIS等），大尺度湖泊水域面积提取、理化性质反演等获得了较快的发展（Busker等，2019；Gong等，2019；Yin等，2021；Paul等，2021）。人工智能（深度学习、随机森林等）算法的快速发展进一步遥感大数据在湖泊相关研究中的应用（Teluguntla等，2017；Luo等，2019；Zhou等，2019；Yao等，2019；Mahdianpari等，2019；Wang等，2020b）。尽管目前遥感大数据和人工智能针对湖泊碳循环遥感研究相对较少，但是，借助遥感大数据平台和人工智能技术，可以更加快速推进全球湖泊碳循环的相关研究。此外，遥感大数据和人工智能技术可以进一步推动遥感数据融合等遥感影像处理技术，在一定程度上弥补了单一遥感数据在湖泊碳循环应用时的光谱、空间和时间分辨率不足等缺陷（Guo等，2020）。

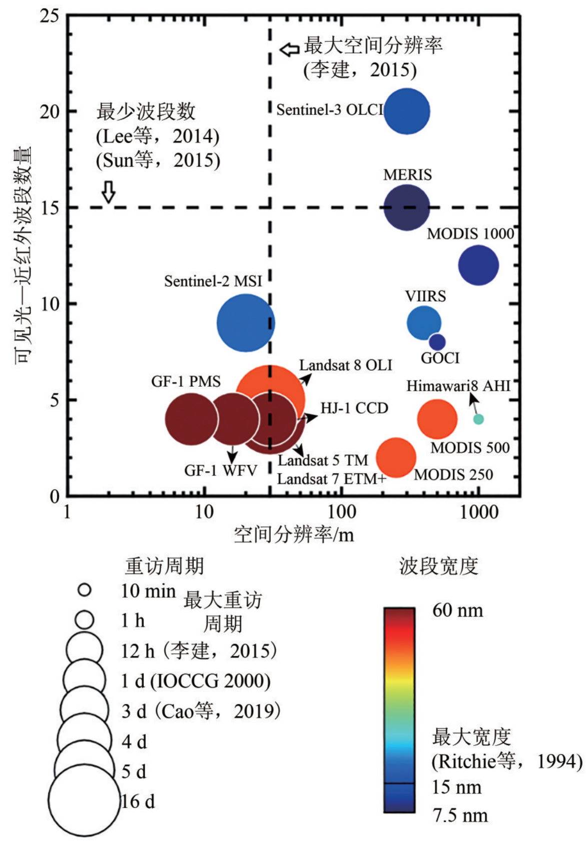


图6 目前卫星传感器时间、空间、光谱分辨率分布图

Fig. 6 Distributions of satellite sensors with different temporal, spatial and spectral resolutions

6 结语

目前，针对湖泊水体碳库的遥感反演算法在反演精度、普适性等方面存在较大不确定性，湖泊水体有机碳的遥感算法精度和普适性有待进一步提高，无机碳（CO_2，CH_4）等遥感反演算法需要进一步完善，而新类型碳（黑炭等）遥感反演算法的研究需要被重视。湖泊不同类型有机碳的组成和来源对湖泊碳循环以及遥感反演精度的影响较大，对于有机碳的来源估算，需要结合生物地球化学技术，进一步深入研究；同时，不同类型有机碳之间的相互作用机制也需要进一步明确。湖泊分布广泛，类型丰富，湖泊碳循环研究属于湖泊流域综合性研究，开展湖泊碳循环研究需要大量的野外实测数据、遥感卫星数据等，获取完整和丰富的数据是一个系统性工程，有必要建立全国性的湖泊数据共享平台和研究联盟，合理推进湖泊碳循环和遥感研究。

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Remote sensing technology in the study of lake carbon cycle: Opportunities and challenges

HUANG Changchun[1], YAO Ling[2,3], LI Junsheng[4], ZHOU Chenghu[2,3], GUO Yulong[5], LI Yunmei[1]

1. School of Geography, Nanjing Normal University, Nanjing 210023, China;
2. Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China;
3. Southern Marine Science and Engineering Guangdong Laboratory, Guangzhou 511458, China;
4. Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing 100094, China;
5. Henan Agricultural University, College of Resources and Environmental Sciences, Zhengzhou 450002, China

Abstract: lake carbon cycle is an important segment in the global carbon cycle. Growing attention has been received to lake carbon cycle for its virtual effect on the global carbon cycle and climate change. However, comprehensive monitoring and assessment of the global lake carbon cycle is still challenging due to the fragmentary distribution and diversity in ecology, type and climatic zone of lake. Remote sensing technology with advantages of large area continuously synchronous observation could conquer the limitations of conventional observation method, supporting the research of global lake carbon cycle with huge of observation data. Meanwhile, the estimation of organic carbon source and composition via the remote sensing technology could be combined with biogeochemical technology for the advantage of spectral detection by remote sensing. In this paper, recent studies about the remote sensing application and research on lake basin and water were reviewed based on the active demand of remote sensing in the lake carbon cycle. The application of remote sensing in a geography of lake carbon cycling was proposed due to the highly variable among lakes within basin characteristics. Much more precision and higher spatial resolution results of land use, vegetation canopy, primary productivity, soil properties, population density and other watershed attribute data from remote sensing should be considered in geography of lake carbon cycling to improve the estimation of carbon input in lake. The remote sensing retrieval of particulate and dissolved organic carbon concentration in the lake water have been widely used, yet the carbon pool estimation is flimsy for the difficulty in the acquirement of carbon vertical distribution. Meanwhile, the sources of organic carbon significantly affect the turnover time of organic carbon, presenting the short turnover time of endogenous organic carbon and relative long turnover time of terrestrial organic carbon. The remote sensing should be cooperatively estimated endogenous and terrestrial organic carbon with isotopic geochemistry technology, which can distinguish the source of organic carbon effectively. The retrieval algorithms of inorganic carbon, such as $\mathrm{CO_2}$ and $\mathrm{CH_4}$, are being developed by the active and passive remote sensing. The black carbon from incomplete combustion of fossil fuel and biomass is a higher aromatic content and different from other types of organic carbon (such as: terrestrial, endogenous organic carbon) should be taken as a new inversion parameter from remote sensing. The estimation of physicochemical characteristics of lake water, which significantly affected the lake carbon cycle, should be concerned and combined in the research of lake carbon cycle. The virtual sensors with high temporal, spectral and spatial resolution should be established due to the limitation of current remote sensing satellite data. Multi-source remote sensing data fusion is a recommendable method to overcome the limitation application of remote sensing in lake carbon cycle due to the exclusive highly temporal, spectral or spatial resolution. The opportunities and challenges of remote sensing application in the lake carbon cycle were discussed according to biogeochemical processes of carbon in the lake and the recent advances of big data and artificial intelligence in remote sensing technology, as well as the development of lake carbon cycle studies.

Key words: lake carbon cycle, remote sensing, biogeochemistry, big data and artificial intelligence, water environment, greenhouse gase

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