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内陆水体浮游藻类遥感监测与预警技术

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摘 要: 内陆水体富营养化引发的浮游藻类水华频发已成为全球性的水环境挑战,遥感技术凭借宏观、快速的优势,为藻华爆发的精准防控提供了时空连续的观测手段。本文综述了内陆水体浮游藻类遥感监测与预警的研究进展,梳理了从藻华提取、色素浓度反演、种群识别到藻华一维时序及时空分布预测的技术体系,并重点探讨了基于数据驱动的人工智能模型在上述领域的应用优势,以及多源数据、多平台的协同监测模式。结果表明:人工智能方法与多源协同观测显著提升了复杂光学环境下的监测与预警精度,在一定程度上能弥补单一传感器时空分辨率不足及易受云层遮挡的短板;长时序遥感观测与数据驱动方法的深度耦合推动了一维时序预测和时空分布预测的发展。然而,现有模型仍面临小样本过拟合风险高及物理可解释性较弱等挑战。未来研究应深化多源数据协同以及探索数据增强等技术突破样本依赖瓶颈,并发展融合藻华演变机制的过程-数据双驱动模型,以提高鲁棒性与可解释性。

关键词: 富营养化;叶绿素 a;机器学习;种群识别;早期预警

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Remote sensing monitoring and early warning technologies for phytoplankton in inland waters

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Abstract: Eutrophication-induced frequent phytoplankton blooms in inland waters have become a global water environment challenge. Relying on macroscopic and rapid advantages, remote sensing technology provides spatiotemporally continuous observation methods for the precise prevention and control of algal bloom outbreaks. This paper reviewed the research progress of remote sensing monitoring and early warning for phytoplankton in inland waters, systematically summarized the technical systems ranging from algal bloom extraction, pigment concentration retrieval, and taxonomic identification to one-dimensional time series prediction and spatiotemporal distribution prediction of algal blooms, and focused on discussing the application advantages of data-driven artificial intelligence models in the above fields, as well as the collaborative monitoring models of multi-source data and multiple platforms. The results show that artificial intelligence methods and multi-source collaborative observations significantly improve the monitoring and early warning accuracy in complex optical environments and to a certain extent compensate for the shortcomings of single sensors, such as insufficient spatiotemporal resolution and susceptibility to cloud occlusion; the deep coupling of long-term remote sensing observations and data-driven methods promotes the development of one-dimensional time series prediction and spatiotemporal distribution prediction. However, existing models still face challenges such as high risks of overfitting with small samples and weak physical interpretability. Future research should further deepen multi-source data synergy, explore technologies such as data augmentation to break through the sample dependence bottleneck, and develop a process-data dual-driven model integrating algal bloom evolution mechanisms to improve robustness and interpretability.

Keywords: eutrophication; chlorophyll a; machine learning; taxonomic identification; early warning

内陆水体是人类赖以生存的重要淡水资源,承载着供水、灌溉及生态调节等关键功能[1-2]。但在全球气候变化与人类活动的双重驱动下,内陆水体富营养化问题日益严峻,频繁爆发的浮游藻类水华已经成为全球性的水环境问题[3-4]。其中蓝藻水华在中国太湖[5-6]、美国伊利湖[7]和英国内伊湖[8]等

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地区频发,严重威胁了附近居民的饮用水安全。硅藻水华则会对自来水厂的混凝沉淀、过滤等工艺造成堵塞等不良影响[9-10],甲藻水华也在内陆湖泊水库中频频出现[11-12]。

藻类的直接检测技术主要包括显微镜镜检、分子生物学与流式细胞术等,虽然在藻类识别和定量分析上具有很高的精度优势,但是存在实验流程复杂、成本高和适用范围窄等问题[13-14]。另一方面,水质自动监测系统可以依靠在线荧光传感器实时测定叶绿素a(Chlorophyll-a, Chl-a)、藻蓝蛋白(Phycocyanin,PC)等参数[15-16],解决了成本和时间连续性的问题,但孤立的监测点位也无法反映藻华在水域中的空间分布[17]。相比之下,遥感技术因其范围广和周期性监测的特点,为大尺度、长时序地认知水体状况及其变化提供了不可或缺的技术手段,并已经在海洋、内陆水体等监测任务中得到了检验[18-19]。

浮游藻类含有的关键色素会对不同波长光表现出反射率特征[20-22],遥感技术能基于此实现从藻华范围识别到参数定量反演的多维度监测。随着对地观测和计算机技术的更新迭代,该领域正呈现出新的发展趋势。在数据源上,向着多源异构数据融合的范式转变:一方面,构建了多源协同观测体系,利用时空融合、无人机等方式弥补光学卫星在时空分辨率及云层干扰下的短板[23-24];另一方面,引入了气象、水文等环境因子与遥感光谱进行耦合,以提升复杂环境下的模型精度[25-26]。在方法与任务上,人工智能技术的深度介入推动了从传统模型向数据驱动的转变[27-28],应用目标也正从现状监测向解决藻华何时发生的早期预警跨越[29]。

近年来,关于内陆水体浮游藻类遥感监测的综述不断出现。较早期的研究[30]梳理了基于遥感监测体系的发展趋势,但在人工智能应用方面探讨较少。近期研究[31-32]虽然丰富了机器学习的相关应用,然而关注点还集中于现状监测方面。随着技术发展,相关研究[33]开始探讨藻华预测的相关模型,内容上更侧重对不同算法的讨论。鉴于此,本文旨在突破现有综述局限,系统梳理藻华范围提取、色素定量反演、种群精细化识别以及早期预警的完整技术体系,并将早期预警技术重构为一维时序预测与时空分布预测两类应用维度,重点探讨监测手段从单一到协同、反演方法从经验到智能的演变规律,以期为内陆水体富营养化的精准治理与应急决策提供科学依据。

1 内陆水体浮游藻类遥感监测关键技术

1.1 藻华爆发识别与提取

可见光和红外范围的光谱差异是识别遥感图像中藻华区域的关键,早期的识别方法主要基于光谱特征来构建阈值指数。归一化植被指数(normalized difference vegetation index, NDVI)[34]和浮游藻类指数(floating algae index, FAI)[35]是区分藻华和水体最为普遍的方法,因其计算简捷方便而被广泛使用。研究者也提出了适用性更强的光谱指数,如基于短波红外波段优化的调整浮游藻类指数(adjusted floating algae index, AFAI)[36]以及针对高浊水体开发的抗浑浊藻华指数(anti-turbid algal bloom index, ATBI)[37]等。但在面对较为复杂的内陆水体环境时,仅凭线性指数难以稳定区分藻华与背景干扰。机器学习因其较强的非线性拟合能力已被证明是藻华识别的有效工具,如随机森林(random forest, RF)[38-39]、支持向量机(support vector machine, SVM)[40]以及极限梯度提升算法(extreme gradient boosting, XGBoost)[41]等模型能够利用光谱数据中的非线性关系,在不同水体中表现出良好的适用性。然而,上述方法完全基于像元光谱数据进行识别,忽视了图像的空间信息。以U-Net等为代表的深度学习技术则能够实现光谱和空间特征的联合提取[42],如Zhu等[27]根据巢湖藻类的季节性光谱差异构建了双U-Net模型,在实现了90%以上识别精度的同时也很好地捕捉和保留藻华的轮廓。此外,为了改善深度学习的计算负担,轻量化模型的构建成为新的研究方向,能够显著减少模型参数数量和训练时间[43]。

在数据源方面,卫星的时空分辨率限制是藻华动态监测面临的一个难题。MODIS、GOCI(及GOCI-II)等高频次传感器适合捕捉藻华的短期变化[44-46],Landsat-8 OLI、Sentinel-2 MSI等高分辨率传感器则提供了更精细的空间细节[47-48]。但是单一卫星平台无法兼得高时空分辨率[49],且图像质量易受云层覆盖影响。为突破这一瓶颈,基于多源卫星的时空数据融合技术成为研究热点,该技术利用多源图像中时空信息的互补性生成高时空分辨率数据集[50]。例如,Zhao等[23]基于时空加权回归方法融合了MODIS与Landsat图像,重构了30 m分辨率的日尺度藻华监测数据,但此类方法还是依赖于线性假设。近年来,基于深度学习的时空融合可以捕捉异构数据间的非线性关联,进而优化融合图像的空间细节与光谱精度[51],为高时空分辨率的藻华监

测提供了可参考的技术路径。

尽管多源卫星在一定程度上缓解了时空分辨率矛盾,但云雨天气和卫星固定运行周期仍然会造成不可避免的观测盲区,近地遥感与主动遥感技术则提供了重要补充。近年来,无人机遥感带来空间分辨率的巨大提升,而且其按需获取影像的优势也有效填补了卫星过境的空窗期[52-53]。在此基础上,有关研究[24,54]通过捕捉精细的图像纹理信息实现了对小尺度藻华的精准识别,并发现无人机遥感能有效修正卫星反演存在的面积高估。另一方面,合成孔径雷达(synthetic aperture radar,SAR)作为一种主动遥感技术,为光学卫星遥感的云层覆盖问题提供了解决路径。SAR 系统能够穿透云层,无论天气状况如何都能提供图像,其在藻华聚集区域会因为后向散射受到抑制而出现暗区,从而实现进一步的识别提取。但低风速下的水面平滑效应也会产生类似暗区从而造成混淆[55]。相关研究中,SVM 能基于暗区的纹理、形状等多维特征,将藻华与低风速区域区分开来[56-57]。Phetanan 等[58]则使用了深度学习方法,将 Sentinel-1 影像数据输入 Faster R-CNN 模型,以自动识别和提取藻华。上述藻华识别方法的原理、研究区域及数据源等情况列于表 1。

表 1　基于遥感的藻华识别提取算法

Tab. 1　Remote sensing-based algorithms for algal bloom identification and extraction

算法	计算公式/核心架构	研究区域	数据源	文献
NDVI	$I_{NDVI}=(R_{NIR}-R_{RED})/(R_{NIR}+R_{RED})$	中国太湖	CBERS-02	[34]
FAI	$I_{FAI}=R_{rc,NIR}-R'_{rc,NIR}$ $R'_{rc,NIR}=R_{rc,RED}+(R_{rc,SWIR}-R_{rc,RED})\times(\lambda_{NIR}-\lambda_{RED})/(\lambda_{SWIR}-\lambda_{RED})$	中国太湖	MODIS	[35]
		中国星云湖	Sentinel-2、Landsat 8	[47]
AFAI	$I_{AFAI}=R_{rc,NIR}-R_{rc,RED}+(R_{rc,SWIR}-R_{rc,RED})\times 0.5$	中国东北地区 9 个湖泊及水库	Landsat	[36]
ATBI	$I_{ATBI}=I_{FAI}+R'_{RED}-R_{RED}$	中国巢湖、太湖、呼伦湖	MODIS	[37]
BWAI	$I_{BWAI}=H_{GREEN,NIR}\times\begin{cases}F_C & \ln(F_S)\leqslant T\\ F_C^{-1} & \ln(F_S)>T\end{cases}$	北美伊利湖	Landsat 7/8、MODIS	[23]
熵阈值分割	灰度共生矩阵结合 KL 散度		公开无人机影像	[54]
SVM	核映射与间隔最大化	中国太湖、北美伊利湖	Landsat 8 OLI、MODIS	[40]
		中国太湖、巢湖、丹江口水库	Sentinel-1	[56]
		中国太湖	ERS-2、ENVISAT	[57]
RF	基于 Bagging 与特征随机采样的决策树集成	中国云南高原湖泊群	Landsat 8, Sentinel-2, GF-1/6, HJ-1A/B	[38]
		中国太湖、巢湖、滇池	Sentinel-2	[39]
XGBoost	高效正则化梯度提升树	美国俄亥俄河	Landsat 7/8	[41]
Faster R-CNN	结合区域生成网络的端到端目标检测网络	韩国锦江流域	Sentinel-1、Sentinel-2	[58]
DeepLab V3 +	结合 ASPP 与编解码结构的分割网络	中国青海湖	实测无人机影像	[24]
U-Net	编码器-解码器结构与跳跃连接	中国巢湖	Sentinel-2	[27]
		中国太湖、滇池和美国奥基乔比湖	Sentinel-2	[43]

1.2　色素浓度定量反演

Chl-a 和 PC 是监测内陆水体浮游藻类生物量及群落结构的两个关键指标[59-60]。其中,Chl-a 广泛存在于所有真核藻类和水生植被中,是衡量浮游植物总生物量的通用代理。PC 则是蓝藻的标志性色素,有助于蓝藻即便在浑浊的水体中也能高效捕获光能用于光合作用[61]。从光学机理来看,Chl-a 在 440 nm 和 670 nm 附近存在吸收峰,浓度增加时也会在 700 nm 附近有一个显著的反射峰,PC 在 620 nm 附近有明显的吸收峰,为色素浓度的反演奠定了物理基础。传统的反演方法包括经验法、半经验法/半分析法和分析法,其中常用的有双波段比[62-63]、三波段[64-65]、四波段模型[66-67]和生物光学模型[68]等。经验法与半经验法/半分析法虽然相对简单且

应用广泛,但面对内陆水体复杂的光学性质难以保持稳定的反演精度。

随着人工智能技术的发展,研究者们逐步将机器学习模型应用到色素反演当中[28],以卷积神经网络(convolutional neural network,CNN)为代表的深度学习模型逐渐崭露头角。与依赖人工特征构建的常规机器学习方法不同,CNN 是一类可以使用卷积运算来从原始数据中提取特征的模型[69],在遥感领域也被广泛运用于分类和回归问题。根据输入数据的维度特性与特征提取方式的不同,常见的 CNN 定量反演模型可以分为 1D-CNN 与 2D-CNN 两类架构,图 1 展示了两种类型的对比。1D-CNN 专为序列数据设计[70],同样适用于挖掘连续光谱曲线中的精细特征。基于实测高光谱数据,Hong 等[71]提出了一种结合注意力机制的 1D-CNN 模型来实现 Chl-a 和 PC 的反演,相比生物光学模型取得了更高的整体精度。而针对非连续的多光谱数据,常规的卷积池化操作可能导致短序列中关键信息的丢失。为此,相关研究在构建基于 Sentinel-2 多光谱数据的 1D-CNN 模型时,均采用了无池化层的架构,有利于保留更完整的特征信息[48,72]。另一方面,2D-CNN 架构侧重于利用空间邻域信息来辅助反演。例如,Pyo 等[73]提出了一种点中心回归 CNN,其输入是以目标点为中心的图像窗口。在此基础上,注意力机制作为一种特征自适应加权方法,是筛选关键空间区域与波段的有效工具,能进一步提高 2D-CNN 在复杂水体环境下的反演精度[74]。

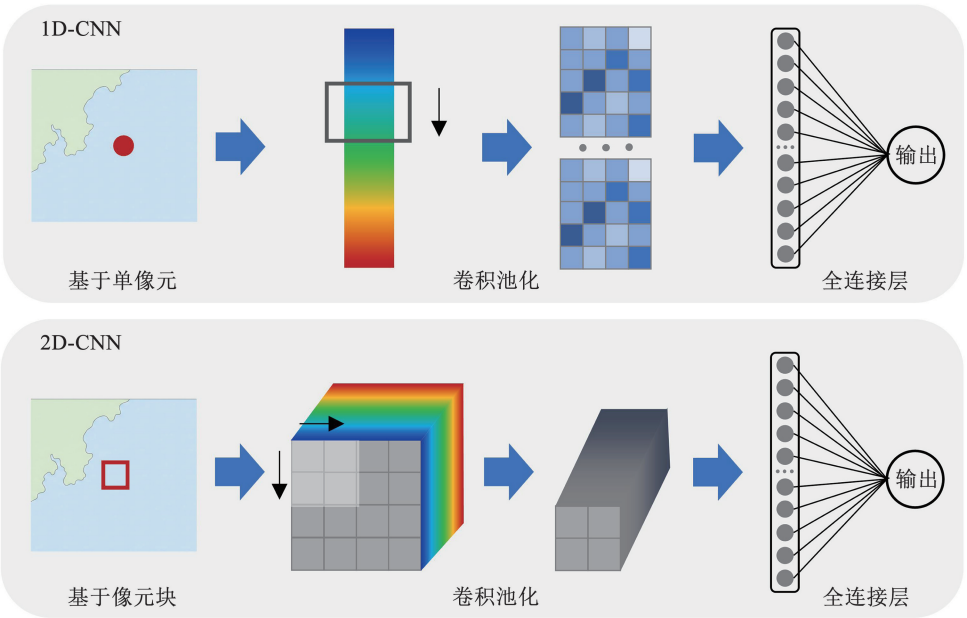


图 1 不同维度的 CNN 模型藻类色素反演流程

Fig. 1 Workflow of algal pigment retrieval based on CNN models with different dimensions

尽管人工智能手段可以显著提升反演精度,但其“黑箱”性质在面对内陆水体的时空异质性时存在明显局限。仅依赖数据驱动去拟合水质参数和光谱反射率难以解释由复杂环境导致的动态变化,导致模型在跨区域、跨季节应用时面临泛化性问题[75-76]。从原理上看,光照、温度等环境因素对浮游藻类的生长存在重要影响[4,77],是浮游藻类监测过程中的重要变量。因此,将环境数据引入反演体系成为新的突破方向。针对不同数据源的 Chl-a 反演研究表明,包含气象数据的模型取得了最优的性能指标,充分证实了环境因素的关键作用[78]。另外,Zhang 等[26]在呼伦湖的研究表明,将气象因子(如温度、降水、日照等)作为辅助变量输入机器学习模型,能有效弥补单一光谱数据的不足。Wang 等[79]针对岱海的研究同样发现,将现场测量的盐度因子与遥感波段共同作为输入特征,随机森林模型的决定系数 R^2 从 0.64 跃升至 0.92。这些结果表明,引入区域相关的环境因素能有助于模型更准确地学习遥感光谱与色素浓度之间的非线性关系。相关色素反演方法及其应用情况见表 2。

表 2　基于遥感的藻类色素定量反演算法

Tab. 2　Remote sensing-based algorithms for quantitative retrieval of algal pigments

算法	计算公式/核心架构	研究区域	数据源	浓度范围/($\mu g \cdot L^{-1}$)	评价指标	文献
双波段比值法	$C_{Chl-a}=0.016\times\exp[7.144\times(R_{709}/R_{665})]$	中国太湖	MERIS	叶绿素 a:2.9 ~ 26.9	$R^2=0.73$	[62]
	$C_{PC}=\exp[2.615\ 1\times(R_{740}/R_{665})-3.636\ 9]$	西班牙阿尔布费拉泻湖	Sentinel-2	藻蓝蛋白:10.0 ~ 1 287.9	$R^2=0.77$	[63]
三波段法	$C_{Chl-a}=331.01\times(R_{684}^{-1}-R_{690}^{-1})\times R_{718}+14.609$	中国珠江口	实测高光谱	叶绿素 a:4.8 ~ 92.6	$R^2=0.95$	[64]
	$C_{PC}=266\times(R_{615}^{-1}-R_{600}^{-1})\times R_{725}-4.96$	英国埃斯韦特湖、利文湖	机载高光谱	藻蓝蛋白:0 ~ 93.7	$R^2=0.92$	[65]
四波段法	$C_{Chl-a}=0.004\times(R_{662}^{-1}-R_{693}^{-1})\times(R_{740}^{-1}-R_{705}^{-1})^{-1}-0.044\ 9$	中国太湖	实测高光谱	叶绿素 a:4.0 ~ 158.0	$R^2=0.89$	[66]
	$C_{PC}=462.5\times[(R_{620}^{-1}-0.4\times R_{560}^{-1}-0.6\times R_{709}^{-1})\times R_{754}]+22.598$	中国、美国及荷兰多个湖泊	实测高光谱	藻蓝蛋白:0.3 ~ 317.7	$R^2=0.69$	[67]
生物光学模型	辐射传输方程	意大利加尔达湖	Hyperion	叶绿素 a:1.3 ~ 2.2	$R^2=0.59$	[68]
RF	基于 Bagging 与特征随机采样的决策树集成	中国呼伦湖	Sentinel-2	叶绿素 a:0 ~ 35.0	$R^2=0.76$	[26]
		中国岱海	实测高光谱	叶绿素 a:2.1 ~ 2.7	$R^2=0.92$	[79]
CNN	1D-CNN,一维卷积提取序列特征	韩国主要河流	实测/机载高光谱	叶绿素 a:0 ~ 55.5 藻蓝蛋白:0 ~ 537.3	$R^2=0.87$(叶绿素 a) $R^2=0.88$(藻蓝蛋白)	[71]
		中国鄱阳湖	Sentinel-2	叶绿素 a:0 ~ 57.0	$R^2=0.97$	[48]
		日本及越南多个水体	Sentinel-2	叶绿素 a:0 ~ 148.3	平均绝对误差:10.00 $\mu g \cdot L^{-1}$	[72]
	2D-CNN,二维卷积提取空间特征	韩国百济堰	机载高光谱	叶绿素 a:8.4 ~ 111.4 藻蓝蛋白:0.2 ~ 150.9	$R^2=0.73$(叶绿素 a) $R^2=0.86$(藻蓝蛋白)	[73]
		中国深圳河道	无人机高光谱	叶绿素 a:2.0 ~ 25.4	$R^2=0.92$	[74]

1.3　浮游藻类种群识别

针对浮游藻类种群的遥感监测研究,在大洋等一类水体中已有较为广泛的应用,然而针对内陆水体的相关研究却相对缺乏[80-82]。在机理层面,不同藻种的光学吸收及散射特征差异导致的反射率光谱可分性是建立遥感识别算法的前提。图 2 展示了蓝藻(铜绿微囊藻 *Microcystis aeruginosa*、灰假鱼腥藻 *Pseudanabaena cinerea*)、绿藻(小球藻 *Chlorella* sp.)及硅藻(小环藻 *Cyclotella meneghiniana*)在反射率光谱上的差别。相关研究中,Hunter 等[83]基于受控实验测试了 4 类浮游植物种群基于遥感光谱上的分类能力,但也指出基于主成分分析方法的精度随着光谱分辨率的降低而逐渐下降。此外,当 Chl-a 浓度较低时,水体背景噪声会严重干扰特征提取,体现了基于反射率的方法在低生物量条件下的局限[84]。Zhu 等[85]则尝试实现实验到应用的转变,基于实验室培养藻液和实测反射率构建了差异指数分类模型,将其应用于 Sentinel-3 OLCI 影像获取了太湖优势藻种的空间分布格局,但分类精度发生明显下降,表明仅依靠受控实验建立的模型难以迁移到真实水体。

而在基于实际水体环境的研究中,浮游植物群落结构与遥感反射率之间呈现高度非线性关系[86]。基于数据驱动的机器学习技术凭借其强大的非线性拟合能力,能够从混合光谱中捕捉不同藻类种群的信号。Yan 等[87]基于实测数据构建机器学习模型,利用 Sentinel-3 OLCI 数据在呼伦湖实现了三大优势藻群生物量丰度的定量回归。而针对藻类种群训练样本难以获取的难题,将原位高光谱传感器与荧光探针监测相结合能够快速构建包含不同类群色素浓度的丰富数据集[16]。然而,无论是传统的实地采样与形态学鉴定还是原位荧光监测手段都难以兼顾高

分类精度与大样本量的需求。为此,跨学科的数据协同成为新的突破口。Liu 等[88]利用环境 DNA 宏条形码技术高效获取了浮游植物类群的相对丰度信息,并结合 Sentinel-2 数据及多种水质参数,构建了基于梯度提升树的机器学习模型,成功识别出鄱阳湖中驱动水华的关键类群。这种基于多源数据协同的监测体系,也为富营养化湖泊浮游植物群落结构的精细化监测奠定了基础。

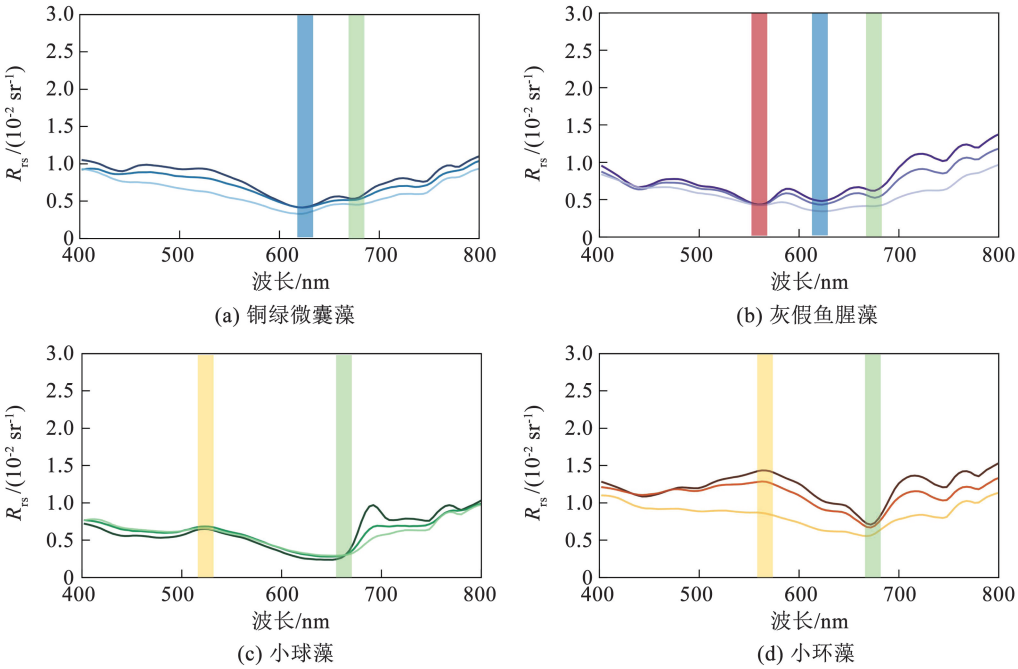


图 2 不同浮游植物藻种的遥感反射率光谱对比

Fig. 2 Comparison of remote sensing reflectance spectra among different phytoplankton species

2 内陆水体藻华爆发预警技术

在实现了对藻华的现状监测后,构建具有前瞻性的早期预警能力,对于降低生态灾害风险以及减少经济损失具有重要意义[29,89]。藻华预测模型可以分为过程驱动和数据驱动两种。过程驱动主要基于藻华爆发理论和数值模拟技术进行分析[90-91],但也面临藻华生长机制不明确和水动力过程复杂的挑战。相比之下,遥感技术的进步与人工智能的飞速发展为数据驱动模型带来了重大机遇。该类方法不依赖于物理或生物方程,而是通过从海量数据中挖掘演变规律来实现预测。在具体应用层面,基于遥感的数据驱动模型主要包括一维时序预测和时空分布预测两种,如图 3 所示。前者侧重于预报全湖或特定站点的藻华强度指标随时间的演变趋势,后者则是推演藻华在像素尺度上的空间连续分布。

2.1 一维时序预测

这类研究旨在回答“何时发生”以及“强度如何”的问题,其模型输出通常为一维时间序列数值。相关方法并不依赖卫星图像的空间信息,而是先通过反演算法将遥感数据转化为 Chl-a 浓度、蓝藻指数或水华总面积等定量指标,构建出长时序的数据集。随后,这些衍生的时序数据被作为输入特征或预测目标,输入到模型中以挖掘其随时间的演变规律。这种方式一定程度弥补了传统实地采样在时间连续性和空间代表性上的不足,为数据驱动模型提供了高频、长时序的训练样本。

基于遥感数据可以实现针对全湖尺度的宏观指标预测,简单统计模型或传统机器学习模型都表现出了较好的适用性。其中,基于移动平均的统计模型能对高风险藻华实现短期的有效预警,但无法捕捉由突发状况导致的剧烈波动,也在更长周期的推演中精度显著下降[92]。而针对次月尺度下的藻华复杂变化,融合气象与水文等多源变量的机器学习算法能实现更为精准的预测[25,93]。进一步地,为了充分挖掘藻华演变过程中存在的复杂非线性动态及长时序依赖特征,深度学习技术成为主流趋势。相比传统机器学习模型,长短时记忆网络(long short-term memory,LSTM)凭借其记忆单元结构,在利用时间序列数据挖掘演变特征上展现出独特的优势[94]。而针对单一模型在多源数据特征提取上的局限,CNN-LSTM 这类复合架构能利用 CNN 提取气象数据与历史时序中的高维特征,再驱动 LSTM 进行时序推演,有效提升了模型对复杂动态变化的捕捉能力[95]。

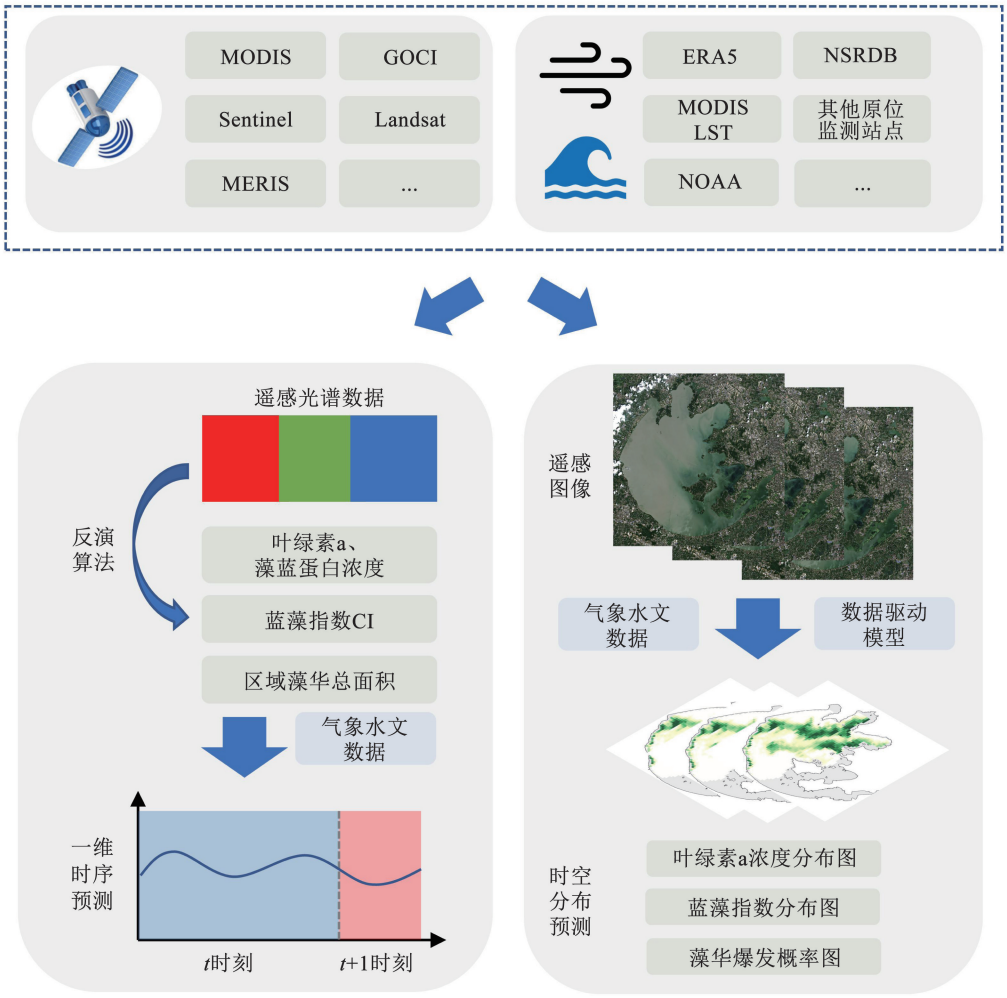


图 3　基于遥感数据的藻华预测与早期预警技术路线

Fig. 3　Technical route of algal bloom prediction and early warning based on remote sensing data

2.2　时空分布预测

时空分布预测主要是针对藻华在二维水域上的动态变化过程,其本质是利用历史时刻的遥感数据及环境因子,预测未来时刻在像素尺度上的发生概率或覆盖情况。将长序列遥感数据与贝叶斯理论的概率框架相结合,是实现时空分布预测的有效途径。贝叶斯方法的核心在于利用遥感影像中像素级的历史分布规律构建先验概率,从而实现对未来藻华时空分布的推演[96-97],但也因此缺乏对突发事件的应对能力。不同于侧重静态概率计算的统计方法,Zhao 等[98]构建了一种由遥感数据驱动的元胞自动机框架,利用氮磷浓度的空间分布特征实现对藻华从爆发中心向周边动态扩散的模拟。然而,该模型建立在无风、无流的理想化假设之上,且模拟过程中未能实现营养盐浓度的动态更新。基于人工智能的方法能够从海量高维数据中挖掘规律[44,99],但其训练精度也受限于高质量数据集。在小样本情况下,参数庞大的深度学习模型容易对训练数据产生过拟合,导致其泛化能力显著降低。考虑到模型训练对大规模标注样本的依赖,Ananias 等[100-101]开发了基于光谱指数的无监督标签自动生成框架,为缺乏实测数据的区域提供了低成本的工程化解决方案。针对云层遮挡导致的数据缺失,Tang 等[102]利用物理模型模拟的连续数据填补了遥感观测的空白,构建出较完备的数据集以驱动 ConvLSTM 模型,实现了对未来 14 d 藻华分布的预测。但数据驱动模型大多是基于“端到端”的架构,未考虑中间步骤,只通过输入遥感和气象水文等数据得到预测结果,也限制了预测精度的进一步提升。

在全球变暖等气候变化的背景下,藻华的表面漂移速度会显著加快[103],即使是日尺度预测也难以捕捉其快速的生消演变,这对藻华高频时空观测提出了更高的要求。相关研究中,基于 GOCI 的高频数据提供了解决方案,其小时级重访优势可以构建高时间分辨率的预测模型,成功实现了对藻华短时间内快速变化过程的精细化捕捉[44-45]。此外,

Himawari-8 卫星也被用于更短时间尺度(10 min)的太湖藻华预测,但相关研究仅尝试了未来 10 min 的预测,应用价值有待提升[99]。表 3 归纳了上述藻华预警方法在数据源、预测形式等方面的差异。

表 3 基于遥感的藻华爆发预警算法

Tab. 3 Remote sensing-based algorithms for early warning of algal bloom outbreaks

算法	核心架构	研究区域	数据源	预测形式	评价指标	文献
移动平均模型	滑动窗口平滑	全球 15 个湖泊、水库	Sentinel-3	一维:全湖平均 Chl-a 浓度	均方根误差:(16.9 ~ 22.7) μg·L^{-1}	[92]
贝叶斯模型	基于先验的概率预测	中国太湖、巢湖、呼伦湖	MODIS	时空:藻华发生概率	总体精度:83%	[96]
		滇池	MODIS	时空:藻华发生概率	AUC 为 0.8 ~ 1.0 的像元占比:83% ~ 91%	[97]
元胞自动机	局部交互与状态演化	中国太湖	MODIS、Landsat 8	时空:Chl-a 浓度分布	R^2 = 0.31 ~ 0.69	[98]
RF	基于 Bagging 与特征随机采样的决策树集成	北美伊利湖	MERIS、Sentinel-3	一维:全湖蓝藻指数总量	R^2 = 0.57 ~ 0.64	[25]
		北美伊利湖、中国太湖、印度奇利卡湖	MODIS	时空:藻华爆发分类	Kappa 系数:0.51	[101]
LightGBM	基于直方图的梯度提升树	中国太湖	GOCI	时空:藻华面积覆盖度	均方根误差:0.10	[45]
LSTM	门控记忆机制	美国奥基乔比湖	MODIS	一维:Chl-a 浓度预测、藻华爆发分类	R^2 = 0.43 F1 分数:0.67	[94]
混合级联模型	LSTM-RF	北美伊利湖	NCCOS 平台	一维:Chl-a 指数及分级	R^2 = 0.69 Kappa 系数:0.43 ~ 0.73	[93]
	Attention-LSTM-RF	中国太湖	GOCI、Sentinel-2	时空:藻华发生概率	F1 分数:0.72	[44]
	CNN-LSTM	中国太湖	MODIS	一维:全湖藻华总面积	R^2 = 0.91	[95]
ConvLSTM	卷积嵌入循环单元	美国奥基乔比湖	Sentinel-3	时空:蓝藻指数分布	均方根误差:0.007 9 ~ 0.009 7	[102]
		中国太湖	Himawari-8	时空:Chl-a 浓度分布	R^2 = 0.71 ~ 0.94	[99]

3 结 论

本文系统梳理了内陆水体浮游藻类遥感监测与早期预警技术的最新研究进展,通过对关键技术与应用模式的综合分析,得出以下主要结论:

1)基于数据驱动的人工智能方法在藻类监测预警全链条中发挥了重要作用,特别是在内陆水体复杂光学性质下能有效捕捉非线性关系与特征。但机器学习或深度学习模型均依赖于数据集的质量与规模,这在一定程度上限制了模型的泛化性能。为突破这一局限,未来研究一方面可尝试深度耦合气象、水文等环境驱动因子,以物理变量弥补单纯光谱数据集的不足;另一方面,可进一步探索利用深度学习或物理模拟的数据增强技术,或通过积极引入具备通用特征提取能力的遥感基础模型降低标注成本,以突破对数据集的依赖。

2)非光学及近地遥感手段是常规光学卫星受限时的重要补充,能够有效实现复杂天气条件及小范围区域下的浮游植物精准监测。未来可以进一步寻求不同平台间的联动机制,建立多源数据重构算法与协同观测网络,从而实现优势互补的立体化监测。另一方面,也可以重点依托新兴的卫星星座(如“吉林一号”、“珠海一号”等),构建高频高分协同观测网,以精准捕捉浮游植物的短期动态演变。

3)浮游植物种群精细化识别是水环境治理的重要方向,目前人工智能手段在内陆水体藻类种群生物量反演中已取得了较好的效果。但传统的实地采样手段难以高效获取大量的真值标签,导致用于驱动模型训练的精细化数据集严重匮乏。未来应探索跨学科的数据高效获取新范式,例如拓展环境 DNA 技术或原位传感设备与高光谱遥感的交叉融合,以更高效、自动化的方式丰富种群特征数据库,以驱动高精度的种群识别训练。

4)浮游植物的预测预警是实现精准防控的关键,但现有的一维时序预测无法体现藻华的空间分布特征,而大多数时空分布预测模型仅采用了“端到端”的数据驱动架构,忽视了藻华生长和水动力过程的影响。下一代高精度模型应致力于结合水动力输送、藻类生物群落迁移等关键物理与生态机制,作为先验知识或物理约束融入深度学习框架。同时

可进一步关注物理信息神经网络或可微分建模等前沿交叉架构,实现过程驱动与数据驱动的优势互补。

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