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深度学习驱动的土壤信息感知技术: 进展、挑战与展望

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摘要 农田土壤信息的快速感知是智慧农业的重要支撑, 为厘清土壤信息感知技术发展中存在的问题, 对深度学习驱动下土壤信息感知的研究现状进行系统梳理与分析。重点聚焦不同感知尺度和感知方法下, 各类深度学习模型在破解传统土壤信息反演难题中的创新实践, 深入分析各类方法与思路的优势与局限性。结果表明: 1) 对于近端感知系统, 深度学习通过构建各类深度神经网络模型, 有效解决了传统电性能传感器校准中环境因素耦合困难、适应性差的问题, 提升了土壤水分、盐分及养分原位检测的精度与鲁棒性; 同时, 深度学习方法在解决可见-近红外光谱预测有机质、全氮含量时面临的水分干扰、跨时空泛化性差等关键问题上展现出显著优势。2) 各类深度学习模型与方法广泛应用于处理星载和机载遥感数据, 构建了更精准的土壤有机碳、水分、盐分等参数的大范围反演模型, 显著提升了遥感数据的重建、校正与降尺度能力。3) 深度学习驱动的多模态、多尺度与多时相信息融合模型方法得到广泛应用; 各类轻量级网络、混合模型以及注意力机制的应用, 实现了各类异构数据的有效交互与融合, 显著增强了土壤有机质、水分、全氮等多参数同步预测的精度和实时性。4) 从各项研究趋势中发现, 发展适应复杂农田环境、具备强泛化能力的反演模型, 以及构建基于群智感知与协同感知的近端-机载-星载多尺度土壤信息感知网络是重要趋势; 同时, 结合土壤连续体模型理论, 未来需深入探索土壤微生物菌群动态与有机质周转过程的原位监测方法与定量关联模型, 以实现从单一理化参数监测向土壤生态系统健康评估的跨越。

关键词 土壤养分; 深度学习; 传感器; 智慧农业

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Deep learning-driven soil information sensing: Advances, challenges, and prospects

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Abstract The rapid sensing of farmland soil information is as a important support for smart agriculture. To clarify the existing issues in the development of soil information sensing technologies, a systematic review and analysis are conducted on the current research status of soil information sensing driven by deep learning. This study focuses is placed on the innovative practices of various deep learning models in addressing traditional challenges associated with soil information inversion under different sensing scales and methods, along with an in-depth

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examination of the strengths and limitations of these methods and approaches. The findings indicate: 1) For proximal sensing systems, deep learning has effectively addressed the coupling complexity of environmental factors and poor adaptability in traditional electrical sensor calibration by constructing various deep neural network models, thereby enhancing the accuracy and robustness of in-situ detection for soil moisture, salinity, and nutrients. Meanwhile, deep learning methods demonstrate significant advantages in overcoming key challenges such as moisture interference and poor cross-temporal/spatial generalization in Vis-NIR spectroscopy-based prediction of soil organic matter/total nitrogen content. 2) A wide range of deep learning models and methods have been applied to process spaceborne and airborne remote sensing data, enabling the development of more accurate large-scale inversion models for soil organic carbon, moisture, salinity, and other parameters. These approaches have substantially improved the reconstruction, calibration, and downscaling capabilities of remote sensing data. 3) Deep learning-driven multimodal, multi-scale, and multi-temporal information fusion models have gained widespread adoption. The integration of lightweight networks, hybrid models, and attention mechanisms has facilitated effective interaction and fusion of heterogeneous data, significantly enhancing the accuracy and real-time performance of synchronous multi-parameter prediction. 4) Emerging research trends highlight the importance of developing inversion models with strong generalization capabilities for complex agricultural environments and constructing multi-scale (proximal-airborne-spaceborne) soil information sensing networks based on swarm intelligence and collaborative sensing. Furthermore, integrating soil continuum model theory, future efforts should prioritize the exploration of *in-situ* monitoring methods and quantitative correlation models for soil microbial dynamics and organic matter turnover processes, aiming to transition from single physicochemical parameter monitoring to comprehensive soil ecosystem health assessment.

Keywords soil nutrients; deep learning; sensors; smart agriculture

土壤是农业生产的核心载体,其功能价值贯穿于作物生长的全生命周期。作为农业生产体系的物质基石,土壤不仅为植物根系构建了三维支撑框架,更通过复杂的理化过程持续供给作物生长所需的水分、矿质营养及微量元素。在田间管理实践中,土壤含水率、电导率、土壤有机质(Soil organic matter, SOM)与土壤全氮(Soil total nitrogen, STN)等构成评估土壤质量的关键指标体系^[1-2],其中,SOM通过胶结作用促进团粒结构形成,显著改善土壤孔隙度与通气性,其分解产物可持续释放氮、磷、钾等营养元素及中微量元素,形成动态平衡的养分供应库。自然生态系统中土壤全氮含量与有机质储量存在显著正相关关系^[3-5]。但现代农业体系下,土壤养分与土壤水盐参数拥有复杂的耦合关系,同时受包括如轮作、连作模式的种植制度差异、灌溉策略、有机肥施用强度等多重人为干预因素影响^[6]。快速、精确地获取与反演土壤信息对农业生产的发展具有重要的意义。

传统土壤分析多采用化学分析方法。土壤有机质的实验室检测方法主要包括以灼烧法为代表的损失法和以 Walkley-Black 氧化法为代表的化学测定方法^[7],如干燃法^[8]和重铬酸钾氧化-分光

光度法^[9];土壤全氮检测主要采用凯氏定氮法和杜马斯燃烧法^[10-11],或是使用元素分析质谱仪^[12];土壤水分、盐分的测定则通常分别依赖于烘干法和浸提液电导率测量。这些检测方法精度高、可靠性强,但涉及复杂的样本处理流程,需要较高时间、人力及耗材成本,无法快速高效地获取土壤信息,难以满足精细农业和智慧农业的效率要求。随着光学、电化学传感技术的发展,快速、无损的土壤信息感测方法及技术在过去 25 年内取得了快速发展。如在砂土和壤土中,土壤电导率值随着含水量的增大而线性增大,基于介电常数或电导率传感器可以较好地关联土壤水盐信息^[13-14];土壤水分、有机质与全氮中的羟基(-OH)、硝基(-NO₂)、碳碳双键(C=C)、氨基(-NH₂)等官能团在红外光谱中具有特定的伸缩振动吸收峰,通过光学透射、漫反射信息对其分频、泛频波段的吸收系数进行观测,可以进一步实现土壤有机质、全氮含量的反演。然而,土壤传感、遥感方案还同时面临着许多挑战,如传感器测得土壤的 EC 值不仅与土壤中的有机质、K 含量高度相关^[13],同时受到温度、土壤孔隙、植物根系等环境因素的影响;基于漫反射遥感光学传感器存在多种物质的光谱信息存在解混困难,抗扰能力

差等问题^[15],这些难题在大范围的田间实践中仍具有较大挑战。传统方法的高成本低效率与现有传感技术的环境敏感性双重瓶颈,严重限制了传统土壤信息感知与反演方法的鲁棒性与泛化能力。

21 世纪 10 年代后,以卷积神经网络(Convolutional neural network, CNN)、Transformer 为代表的深度学习模型与方法开启了人工智能连接主义(Artificial intelligence connectionism)的新阶段^[16]。连接主义认为智能行为源于大量简单单元(如神经元、卷积模块)通过动态连接关系实现的集体行为,而非预设的符号规则,如人工神经网络(Artificial neural network, ANN)、CNN,通过梯度下降调整连接权重实现知识表示和学习^[17-18]。连接主义的人工智能兴起对传统基于人工推导、测试、预设、调制的土壤感测设计、研究方法 with 模型构建形成了冲击,为解决土壤原位信息变异性强、环境复杂难题提供了新视角。如深度学习极大地拓宽了反演模型的信息容量,单一模型可以构建多种土壤的信息反演模型为田间泛化提供了执行基础^[19-20];此外基于深度学习特征对齐、特征融合等前沿方法为波谱、电化学等多源异构数据融合提供了新理论^[21-23];更多的,深度学习强化了土壤科学、光谱学等领域间交叉协同,进一步促进了土壤信息感知技术的发展。本研究拟从土壤养分感知系统与土壤信息反演模型 2 个角度,梳理分析人工智能及其相关技术驱动下土壤感知技术的研究进展,展望未来发展趋势,以期构建更高效、精准的土壤信息感知体系提供理论参考和技术指导。

1 土壤信息近端感知系统

目前,基于遥感、传感技术的土壤感知方法及技术形成了较为成熟的研究方法和技术手段,根据信息采集平台的工作尺度,可主要分为星载遥感、机载遥感、传感与近端遥感。其中,传感与近端遥感手段是精细获取土壤参数的关键,根据采集信息不同可主要分为电性能、力学、气体及波谱手段。本研究基于文献收集,分析整理得到不同土壤反演参数和应用场景下近端土壤感知的相关技术手段见图 1。

1.1 深度学习与土壤水分感知

针对土壤含水率(Soil moisture content, SMC)的传感器可主要分为体积含水率传感器和土壤基质势(Soil matric potential)传感器^[24-25],前者主要通

过间接方法关联土壤体积含水率,如以时域反射计(Time domain reflectometer, TDR)、电容探针为代表的介电技术,后者则主要通过测量从土壤中提取水分所需的力,利用土壤水分特征曲线反推土壤的体积含水率,如土壤张力计^[26]。基于电磁技术的传感器因其成本优势,在田间测试的可重复性、及其在校正、应用中的便利性和高效性而广受欢迎^[27],然而土壤的电磁特性同时受到多种因素的耦合(表 1),传统的线性校准方法和模型,难以同时满足不同时空场景下土壤水分的最佳反演效果^[28-29],进一步导致目前不同研究之间的校准方法缺乏标准化和一致性。

针对传统线性与非线性校准方法的适应性差,外部环境参数耦合难度高,需现场校准频繁等问题,越来越多的研究开始应用深度学习对电性能传感器的校准方法与反演模型进行优化^[49-50]。如 Palta 等^[51]基于 5 层深度的深度神经网络(图 2),结合 0.2~14 GHz 频段的电磁信息与包含土壤质地、含水率与温度的多变量试验数据,解决了土壤介电行为与频率、温度、含水量及质地的非线性耦合难题,该模型实现了对介电常数实部和虚部超高精度测量,平方根误差 RMSE(Root mean squared error)分别低至 0.025 8 和 0.033 6,决定系数 R^2 达 0.999 8,显著优于响应面法等传统方法。

石玉娇等^[52]通过构建 BP 神经网络模型,揭示了尿素质量与土壤水分传感器输出值的周期性振荡关系,解决了施肥干扰导致的测量误差问题,实现了误差峰值仅 2.07%、平均绝对误差为 0.64% 的精准预测。Jafaryahy 等^[53]利用前馈神经网络整合土壤多频段电导率与介电特性,解决了同时精准预测土壤钾含量(误差<0.05 g/kg)和水分(误差<0.4%)的技术难题。Aranda Britez 等^[54]基于土壤饱和点和田间持水量 2 个特征点结合深度学习方法,提出了一种土壤水分传感器自校准方法,解决了传统校准方法成本高、不实用的问题,实现了在无需大量地面参考数据的情况下,快速、准确地校准土壤湿度传感器,显著提高了土壤湿度测量的准确性。相较于传统人为标定与校准体积含水率传感器方法,深度学习的校准方法通过学习多种环境参数与土壤含水率之间的复杂关系,动态地影响测量值或反演值的输出,让体积含水率传感器在多区域场景下拥有更好的反演效果。

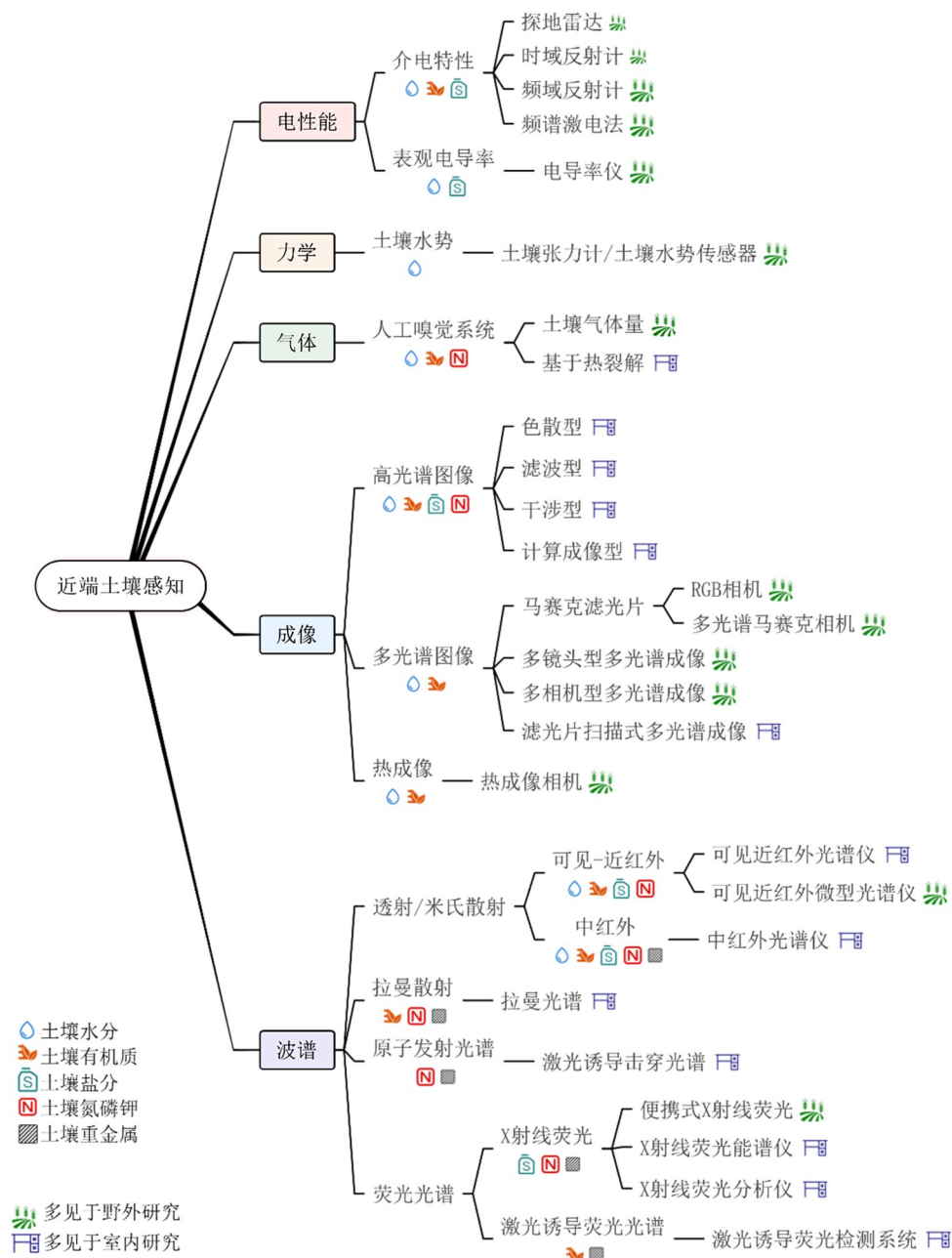


图1 近端土壤感知的相关技术手段

Fig. 1 Technological means related to proximal soil sensing

1.2 深度学习与SOM、STN感知

对于土壤有机质(SOM)和土壤全氮(STN)含量等更具有反演难度的土壤参数,除了使用介电参数和土壤表观电导率,其他感测技术也得到进一步研究和应用,如可见-近红外光谱、拉曼光谱、人工嗅觉、便携式X射线诱导荧光(Portable X-ray fluorescence)和激光诱导击穿光谱(Laser-induced breakdown spectroscopy, LIBS)等^[55-56]。经典的

SOM预测模型构建方法常利用优化算法筛选关键波段进一步结合机器学习算法实现某一时空场景下精确预测。但不同区域、土壤类型背景下筛选的SOM关键波段存在差异(表2),受制于成土母质与土壤环境的高变异性,这类建模无法形成统一的标准,在跨时空迁移学习中具有较大的挑战。其中,土壤湿度、土壤颗粒等因素还与SOM、STN等参数之间的光谱信息存在复杂的非线性耦合,这类实验

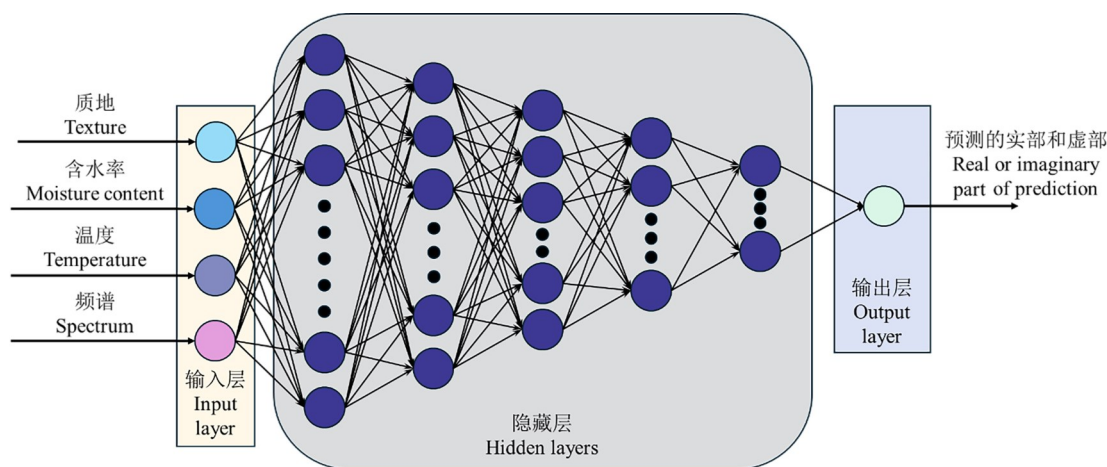
表 1 土壤介电系数、表观电导率与土壤含水率、有机质含量、孔隙大小等理化参数的关系

Table 1 Relationship between soil dielectric constant, apparent conductivity and physicochemical parameters such as soil moisture content, organic matter, and pore size

土壤理化参数 Soil physicochemical parameter	介电系数 Dielectric constant		表观电导率 Apparent conductivity
	实部 Real part	虚部 Imaginary part	
土壤含水率 Soil moisture content	+++ ^[30]	++ ^[31]	+++ ^[32]
土壤有机质含量 Soil organic matter content	++ ^[33]	+ ^[34]	++ ^[35]
孔隙大小 Pore size	—(干样); +(湿样) ^[36]	^[37]	^[37]
粒径 Particle size	+ ^[38]	+ ^[39]	— ^[40] , + ^[41]
土壤含盐量 Soil salinity	— ^[42]	++(低频区域) ^[43]	+++ ^[44]
温度 Temperature	+ ^[45]	+ ^[46]	+ ^[47]

注：+，代表正相关；—，代表负相关；“空白”，代表关系非单调的复杂相关。介电系数的实部反映电介质在电场作用下储存电能的能力，与电介质的极化程度直接相关。虚部反映电介质在电场作用下因电导或弛豫极化而消耗电能的能力^[48]。

Note: ‘+’ represents positive correlation, ‘—’ represents negative correlation, and ‘empty’ represents a non-monotonic complex correlation. The real part of the dielectric constant reflects the ability of the dielectric to store electrical energy under the influence of an electric field, which is directly related to the degree of polarization of the dielectric. The imaginary part reflects the ability of the dielectric to consume electrical energy due to conductivity or relaxation polarization under the action of the electric field^[48].

图 2 五层深度神经网络的结构示意^[51]Fig. 2 The structure of a five-layer deep neural network^[51]

室建模方法往往还需要将土壤进行烘干、研磨、过筛等处理，以保证关联光谱信息的精度。这些关键问题严重阻碍了 SOM、STN 等参数原位信息的大范围、多时相的精细反演。

为克服使用可见-近红外光谱预测土壤参数时环境因素影响，国内外研究人员采用了各种方法，例如直接标准化 (Direct standardization, DS)、分段直接

标准化 (Piecewise direct standardization, PDS)、外部参数正交化 (External parameter orthogonalization, EPO)、正交信号校正 (Orthogonal signal correction, OSC) 和光谱空间变换 (Spectral space transformation, SST)^[73-75]。Ji 等^[76]使用 DS 算法对样本田间光谱进行转换，并结合局部加权回归模型进行 SOM、STN 的含量预测，预测决定系数 R^2 分别

表2 不同调查区域、土壤类型下SOM在可见-近红外波段重叠关键特征波段

Table 2 Key characteristic bands of SOM in the visible-near infrared spectrum under different regions and soil types

特征波段/nm Spectral characteristic band	调查区域 Investigation area	土壤类型 Soil type
400~405	中国三江源地区 ^[57] 、中国华北平原 ^[58]	草甸土、壤土
490~520	美国堪萨斯州和伊利诺伊州 ^[59] 、中国东北平原 ^[60] 、 中国华北平原、中国湖北江汉平原 ^[61]	水稻土、壤土、黑土
540~550	中国华北平原、中国中东部地区 ^[62]	壤土、淋溶土、潮湿土、正盐土
570~600	中国新疆的艾比湖地区 ^[63] 、摩洛哥特里法平原 ^[64] 、 中国东北平原 ^[64] 、中国长江中下游平原 ^[65] 、德国 北部 ^[66]	正盐土、砂质新成土、腐殖土、黑土， 水稻土、砂质壤土、壤土、砂土、泥炭土
650~660	美国堪萨斯州和伊利诺伊州、中国湖北江汉平原	壤土、水稻土
770~820	中国新疆的艾比湖地区、中国东北平原、美国堪萨斯 州和伊利诺伊州、中国湖北江汉平原	正盐土、砂质新成土、黑土、壤土、水稻土
875~900	伊朗 Charmahal va Bakhtiari 省 ^[67] 、中国东北平原、中 国长江中下游平原	钙质土、黑土、水稻土
930~950	中国华北平原 ^[68-69] 、美国堪萨斯州和伊利诺伊州	壤土
995~1 005	中国新疆艾比湖地区、中国华北地区	正盐土、砂质新成土、黄壤
1 080~1 100	德国北部、中国华北平原、中国新疆艾比湖地区	砂质壤土、壤土、砂土、泥炭土、正盐土、 砂质新成土
1 350~1 450	中国华北平原、英国贝德福德郡 ^[70] 、中国东北松嫩 平原 ^[71] 、黄河三角洲地区 ^[72] 、中国中东部地区、中国 长江中下游平原、中国三江源地区、中国湖北江汉平 原、摩洛哥特里法平原	壤质土、黑土、盐碱土、潮湿土、正盐土、 水稻土、草甸土、等湿土
1 580~1 630	华北平原、德国北部	砂质壤土、壤土、砂土、泥炭土
1 860~1 910	中国新疆的艾比湖地区、英国贝德福德郡、中国东北 松嫩平原、黄河三角洲地区、中国长江中下游平原、 中国湖北江汉平原、中国三江源地区	正盐土、砂质新成土、黑土和黑钙土 盐碱土水稻土、草甸土
2 200~2 220	中国三江源地区、英国贝德福德郡、中国东北松嫩平 原、黄河三角洲地区、德国北部、中国湖北江汉平原	草甸土、雏形土、淋溶土、黑土、盐碱土、 壤土、砂土、泥炭土、水稻土
2 315~2 350	中国三江源地区、伊朗 Charmahal va Bakhtiari 省、中 国湖北江汉平原	草甸土、钙质土、水稻土

达到 0.641 和 0.658。Cao 等^[77]在研究内蒙古草原土壤时发现,EPO 算法在不同水分梯度条件下对低土壤有机碳(Soil organic carbon,SOC)样本表现出更强的适应性,构建的 EPO-RF 模型对 SOC 的预测效果最优。Roudier 等^[78]通过分析不同水分梯度下的新西兰土壤样本,比较 EPO 和 DS 消除水分干扰的效果,研究结果发现当使用大量的样本用于水分

校正时,EPO 和 DS 的效果相似,但使用小样本时,EPO 的消除效果优于 DS。Ji 等^[79]进一步采用 PDS 方法对田间光谱进行校准,相较于直接利用原始光谱数据,SOC 预测决定系数 R^2 由 0.03 提高至 0.71,并且所需校准样本数量少于 DS 方法。杨斌^[80]利用辐射传输模型对野外条件采集的光谱进行水分消除,然后对 SOM 含量进行预测,水分校正之后模型

的预测决定系数 R^2 和相对分析误差分别提升了 59.61% 和 67.13%。然而,传统校正方法如 DS、PDS、EPO、OSC 与 SST 等均属于线性校正范畴,其精度高度依赖于特定时空背景下的土壤特性。这类方法在应对跨时空场景的皮肤信息反演时存在显著局限性:以 EPO 校正为例,其通过强化 SOM 预测能力需构建干扰因素投影矩阵,但该过程要求预先采集相同 SOM 含量、不同含水率的土壤波谱数据。当反演区域发生时空迁移时,必须重新采集数据并重构投影矩阵,导致方法可移植性受限。

随着深度学习的发展和应用,基于数据驱动的参数解耦或校正方法或基于跨时空海量数据训练的大型深度学习模型进一步得到重视。这类方法依托深度神经网络的非线性拟合能力与高容量特征提取优势,有望突破传统线性校正方法适应性差

的瓶颈,为复杂时空场景下的皮肤信息精准反演提供全新解决方案。如 Zhao 等^[81]开发了一种基于深度学习的 MIRNet 模型,实现了水分干扰效应的非线性生成,有效抑制水分对可见/近红外光谱中有机碳预测的干扰,该模型构架见图 3,采集到的土壤原始光谱数据会同时输入到上下文提取模块和光谱提取模块,提取原始光谱的光谱特征和上下文信息。然后,通过连接层将提取的参数进行结合,拼接后的数据会输入到频谱重建模块,从而得到只包含水分信息的光谱。将原始光谱数据与水分相关的光谱数据相减,得到估计的干土光谱。通过计算测量的干土光谱和估计的干土光谱之间的 D-S 损失 (Distance-shape loss),调整模型的反向传播参数。模型预测决定系数 R^2 达到 0.926,整体性能优于 EPO 与 OSC 等传统校正方法。

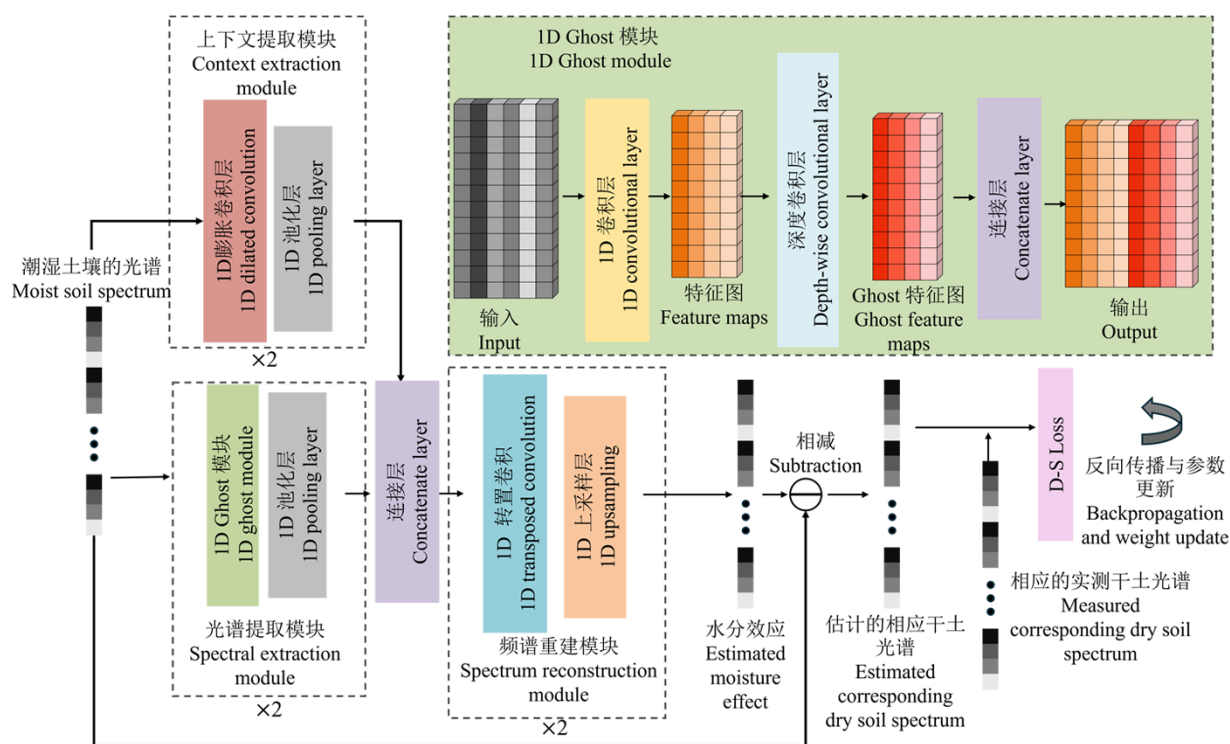


图 3 MIRNet 模型构架^[81]

Fig.3 MIRNet model architecture^[81]

即使使用线性校正方法,深度学习仍有强化模型泛化效果的潜力, Bao 等^[82]提出了一种结合 Kubelka-Munk 辐射传输模型水分消除策略 (Moisture elimination strategy, MSE) 和混合深度学习模型 (Multimodal transformer mechanism-CNN-

convolutional long short-term memory, MT-CNN-ConvLSTM) 的模型新范式, 依靠 LSTM 架构提取光谱特征、ConvLSTM 模块提取多尺度空间特征, 再利用自注意力机制对融合特征进行学习, 最终在湿润和半湿润地区均表现出优异的预测性能 ($R^2 \approx$

0.76~0.77),显著提升了模型的空间迁移能力。在模型的构建思路,部分学者利用深度学习的强大拟合能力,跳过校正步骤,直接对多时空背景下的海量土壤数据进行学习训练。如Singh等^[83]利用长短期记忆网络(LSTMs)结合主成分分析的方法和技术,利用深度学习自动捕捉土壤理化参数与光谱特征间的复杂映射关系,解决了从欧盟光谱库中的高光谱数据中量化土壤性质的问题,并在有机碳等多种土壤参数中实现了优异的预测效果,显著优于传统模型的效果。这些案例表明,相较于依赖先验假设的传统方法,依靠深度学习模型的高容量特征提取能力与强大的非线性拟合效果,可有效缓解跨区域土壤光谱变异性强、背景干扰因素复杂等问题。

深度学习模型也被用于融合多源土壤数据变相校正单一数据中存在的期望误差,实现更高的反演稳定性。如Gallios等^[84]利用低成本近红外扫描仪和地理空间协变量,通过双输入深度学习模型,解决了光谱传感器预测在大范围区域中预测性能不佳的问题,实现了表层SOC预测准确性的显著提升,平方根误差RMSE降低了30.56%。Hong等^[85]通过融合可见-近红外与近红外光谱数据,采用并行输入-卷积神经网络(Parallel input CNN)模型解决了单一传感器预测SOC的稳定性问题,在多区域土壤样本验证中实现了更精准的SOC预测效果。可以发现,得益于深度学习对数据耦合的强力辅助,土壤参数反演方法呈现多样化的趋势,并不局限于特定的研究思路与方法,既可利用深度学习用于强化土壤信息校正效果,也可基于深度学习模型利用足够样本丰度和数据源实现更好的反演稳定性。

基于便携式X射线诱导荧光、拉曼光谱、人工嗅觉等技术的土壤参数感知研究也具有相同的发展趋势。Yang等^[86]通过结合基于迭代自适应窗口经验小波变换和高斯卷积的信息预处理方法与分层深度神经网络技术,解决了土壤重金属定量分析中的背景干扰与多元素同步检测难题。Liu等^[87]采用基于热裂解-人工嗅觉系统的多特征优化方法,结合蒙特卡罗交叉验证异常样本剔除和遗传算法优化的反向传播神经网络特征降维技术,实现了土壤总氮含量更精准的定量预测,显著提升了人工嗅觉系统在土壤养分检测中的可靠性。

2 土壤信息空天遥感感知系统

星载和机载平台也是土壤信息监测的关键环节,星载平台根据采集的遥感波段可主要分为高光谱与多光谱成像(0.4~3 μm)、热红外遥感(3~1 000 μm)、和合成孔径雷达(Synthetic aperture radar, SAR)(5~1 000 mm)平台^[88-89]。而基于机载平台则多为高光谱、多光谱、RGB成像平台、激光雷达等传感器^[90]。表3示出2015—2025年不同深度学习模型在星载、机载平台的部分应用案例。利用星载、机载遥感数据实现土壤有机碳的精确反演具有较高的挑战性,不难发现,近年来研究人员基于深度学习技术通过庞大的土壤光谱数据库和联动近端遥感设备为高空遥感平台提供精准的波谱特征参考,以构建更精准的估算模型^[91-94]。

除了用于构建更加精细的反演模型,深度学习技术还被进一步用于辅助遥感数据的重建和校正。已有较多研究利用深度学习对离散数据进行复杂拟合,形成连续高精度的时空数据,弥补传感器在时空分辨率的不足,Wei等^[108]提出了一种物理约束的插值方法(PhyFill),该方法通过结合深度学习中的部分卷积神经网络技术和物理过程(如降水事件和土壤湿度干涸过程)来填充土壤湿度数据中的缺失部分,从而生成全球范围内连续且高精度的每日土壤湿度数据。Huang等^[109]提出了一种融合多源遥感数据的深度学习框架,通过结合降尺度辅助变量和偏差校正方法,生成了连续空间的土壤水分数据,该方法在奥地利HOAL传感器网络上的验证表明,其预测精度显著优于传统方法。Wei等^[110]提出了一种基于时空信息的残差密集网络(Spatiotemporal residual dense network, SMDN),通过建模低分辨率地球科学参数与土壤湿度的关系,并结合残差校正模块,生成了高精度的土壤湿度地图。此外,利用深度学习强大的特征挖掘能力,在实现遥感数据高精度压缩和降噪具有较高的可行性,如Zhao等^[111]通过构建基于深度强化学习的特征选择框架并结合多子集评估策略,利用马尔可夫决策过程建模与强化学习代理优化,有效解决了高光谱遥感图像在土壤有机物预测中的信息冗余与噪声干扰问题,预测精度与效率得到了显著提高。

表 3 2015—2025 年间部分星载、机载数据结合深度学习反演土壤参数的研究案例

Table 3 Recent research cases of soil parameter inversion using satellite and airborne data combined with deep learning from 2015 to 2025

模型框架 Model framework	数据类型 Data type	反演内容 Inversion content
BPNN	无人机多光谱图像 UAV multispectral imagery	土壤水分 ^[95] Soil moisture ^[95]
	星载高光谱和陆地成像仪 Satellite-based hyperspectral and land imager	土壤有机碳 ^[94] Soil organic carbon ^[94]
	星载高光谱图像 Satellite-based hyperspectral imagery	土壤有机碳 ^[96] Soil organic carbon ^[96]
		土壤含盐量 ^[97] Soil salinity ^[97]
	无人机高光谱图像 UAV hyperspectral imagery	土壤总砷 ^[98] Soil total arsenic ^[98]
		土壤有效含铜量 ^[99] Soil available copper content ^[99]
CNN	无人机多光谱图像、热力图和 RGB 图像 UAV multispectral imagery, thermal imagery, and RGB imagery	土壤含水率 ^[100] Soil water content ^[100]
	RNN (Recurrent neural network)	星载多光谱与高光谱成像 Satellite-based multispectral and hyperspectral imaging
		土壤有机碳 ^[93] Soil organic carbon ^[93]
	地面高光谱数据、星载多光谱与高光谱成像 Ground-based hyperspectral data, satellite-based multispectral and hyperspectral imaging	土壤有机碳 ^[91] Soil organic carbon ^[91]
	地面照片、航空高光谱成像与卫星数据 Ground-based photography, aerial hyperspectral imaging, and satellite data	田间作物残茬覆盖 ^[101] Field crop residue cover ^[101]
	星载多光谱成像和合成孔径雷达 Satellite-based multispectral imaging and synthetic aperture radar	黏土含量 ^[102] Clay content ^[102]
Transformer	星载高光谱和孔径雷达 Satellite-based hyperspectral and aperture radar	土壤有机碳 ^[103] Soil organic carbon ^[103]
	无人机 RGB 图像 UAV RGB imagery	土壤残膜含量 ^[99] Soil residual film content ^[99]
	无人机多光谱图像 UAV multispectral imagery	土壤盐分 ^[104] Soil salinity ^[104]
	星载多光谱图像、气象参数、地形参数 Satellite-based multispectral imagery, meteorological parameters, terrain parameters	土壤中黏土、淤泥和沙子的质量分数,电导率、有机碳含量、酸碱性和磷含量、钾含量 ^[105] Mass fractions of clay, silt, and sand in soil; organic carbon content; pH value; phosphorus content; potassium content ^[105]
	星载高光谱图像 Satellite-based hyperspectral imagery	土壤覆盖分类 ^[106] Soil cover classification ^[106]
		土壤质地 ^[107] Soil texture ^[107]

3 土壤多模态、多尺度与多时相的感测信息融合

基于多源信息融合以提升反演效果一直是土壤信息反演方法的重要研究方向^[112-113]。如美国 Veris 公司开发的 iScan 土壤传感装备同时测量土壤可见光反射率、红外反射率、土壤电导率等,拥有较好的土壤信息反演稳定性^[114]。Bonecke 等^[115]通过结合非商业化的 Geophylus 测量系统和商业化的 Veris MSP 平台采集土壤伽马辐射活动、pH、表观电阻率的数据生成高分辨率土壤酸化地图。Wang 等^[116]基于电流-电压六端法与近红外光谱技术,通过建立土壤电导率与光谱反射率的指数关系及敏感波长校正模型,开发了车载式土壤参数检测系统,实现了土壤电导率与含水量的高精度在线测量。然而传统的基于多源信息融合的土壤信息反演模型多依赖于特征对齐的思路,需要人工设计数据的对齐、配准流程,让数据在张量维度、分辨率上达到较高的一致性。Meng 等^[91]提出了一种土壤有机碳含量预测模型,通过结合 2009—2019 年无云裸土期多时相的 Landsat TM/OLI 数据和 2019 年无云裸土期高光谱数据,配合包含坡度、海拔、坡向、曲率和地形高差的数字高程模型进行几何配准,进一步基于区域加权离散小波变换 (Regional weighted discrete wavelet transform, RW-DWT),对时相-空间-光谱信息 (Temporal-spatial-spectral, TTS) 进行多维融合,其方法构架见图 4。

综合比较可见,基于特征对齐思路传统方法往往需要人为设计复杂繁琐的流程,与后续的模型结构存在割裂,这一问题使得传统融合方法在应用中存在数据压缩过程的信息丢失与数据配准过程中的误差累加问题。

与数据合并、加权融合、小波变化融合等传统的数据融合方法相比,深度学习系统性地推进了多模态的数据交互和融合,特别是具有空间、通道、时相维度的多源异构数据:图像(二维空间和光谱通道)、点云信息(三维空间)、多时相信息(包含时序维度的图像、点云)等信息。依靠深度学习的自动微分与参数优化器,精细地实现各类数据的特征提取与压缩融合,可以

避免关键特征的缺失和对齐误差,这些优势进一步影响了农情信息感知方法的设计与构建^[117-118]。Li 等^[119]通过融合特征波长、可见光图像和热成像图像的多模态数据,结合轻量级多模态网络 (MobileNet-LSTM 和 FCN 分支网络),解决了单传感器信息有限及田间土壤水分变化干扰的问题,实现了土壤有机质和水分含量的高精度实时预测,其网络架构见图 5,整体模型由 2 个分支网络和 1 个特征融合模块组成。第一个分支网络融合 RGB 图像和热成像数据,利用 Mobile Net V3-LSTM 模块进行高级特征映射;第二个分支网络处理光谱特征波长数据,通过全连接层进行非线性变化处理。最后,在特征融合模块中,采用交互注意力机制将 2 个分支网络提取到的特征张量进行融合。融合后的特征通过三层全连接层进行处理,最终实现对土壤水分、有机质和全氮含量的预测。

对于旋翼无人机平台,Yin 等^[100]通过包含 RGB、多谱系和热成像的多模态图像数据结合深度学习技术,准确估算了苜蓿根际的土壤湿度,其中深度神经网络模型在多模态数据融合和土壤湿度估计方面表现最佳,并在不同灌溉条件下表现稳定。相似地,Wu 等^[120]设计了多模态无人机遥感平台(包括 RGB、红外线和多光谱数据)结合卷积神经网络与长短期记忆网络的混合模型 (CNN-LSTM),实现了对柑橘果园不同深度土壤水分的快速反演。Jiang 等^[103]通过结合高光谱和雷达遥感数据,利用深度学习网络构建了土壤光谱校正策略,有效减少了土壤表面水分和粗糙度对土壤有机碳估算的耦合效应,显著提高了遥感图像对土壤光谱的预测精度和地图能力。针对多时相的时空光谱数据,Rukhovich 等^[121]利用多时相 Landsat 遥感数据与 U-Net 卷积神经网络,结合光谱邻域土壤线技术和地理信息系统,解决了传统土壤退化检测方法耗时且难以在大范围内应用的问题,实现了裸土表面的自动识别和土壤退化地图的高精度构建,其中退化分布图的准确率达到了 90%。利用深度学习模型对多维张量的强大支持性,可以有效将频谱、图像等多源异构数据进行特征对齐和特征融合,进一步提高反演的稳定性与精度。

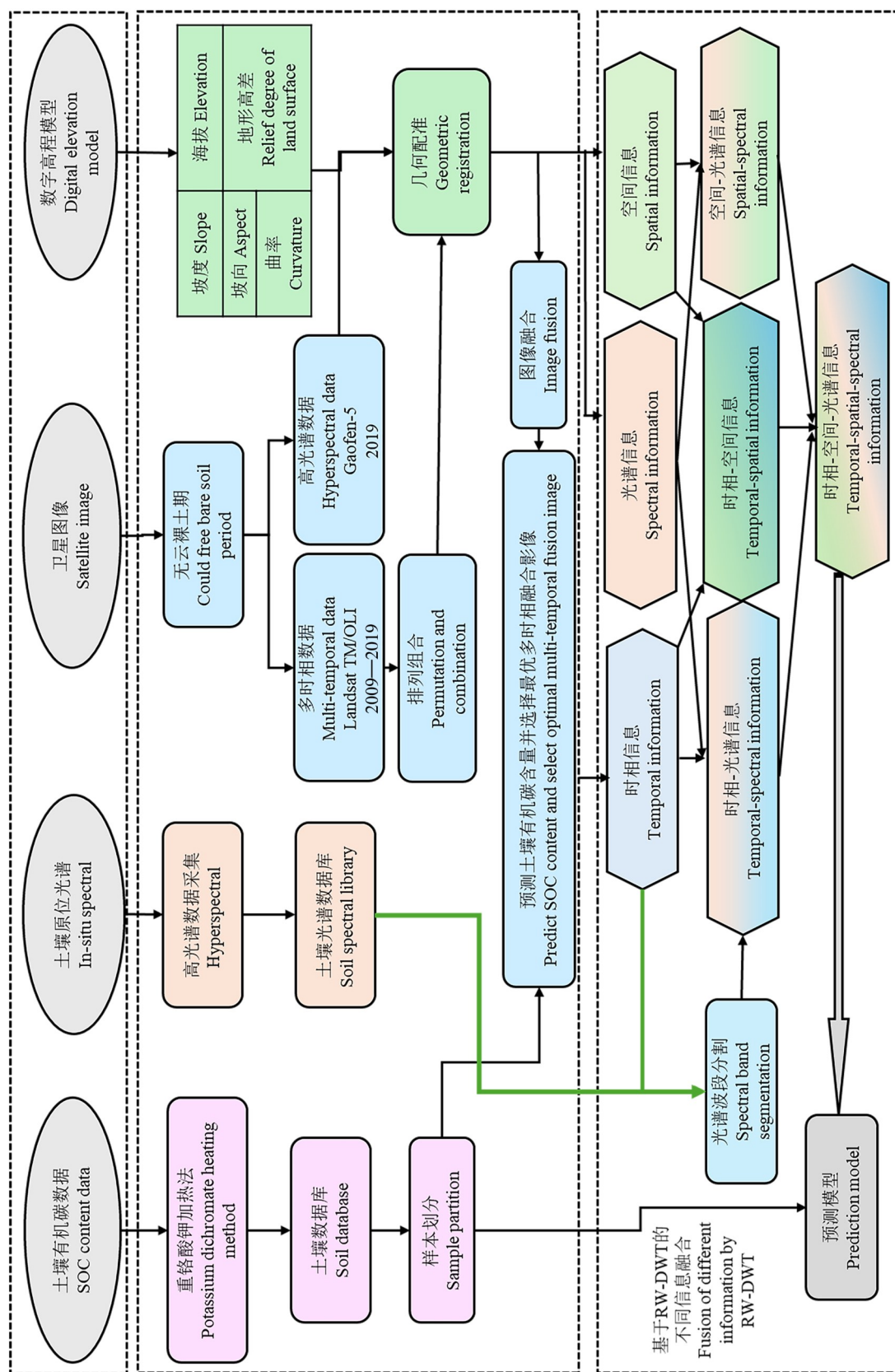
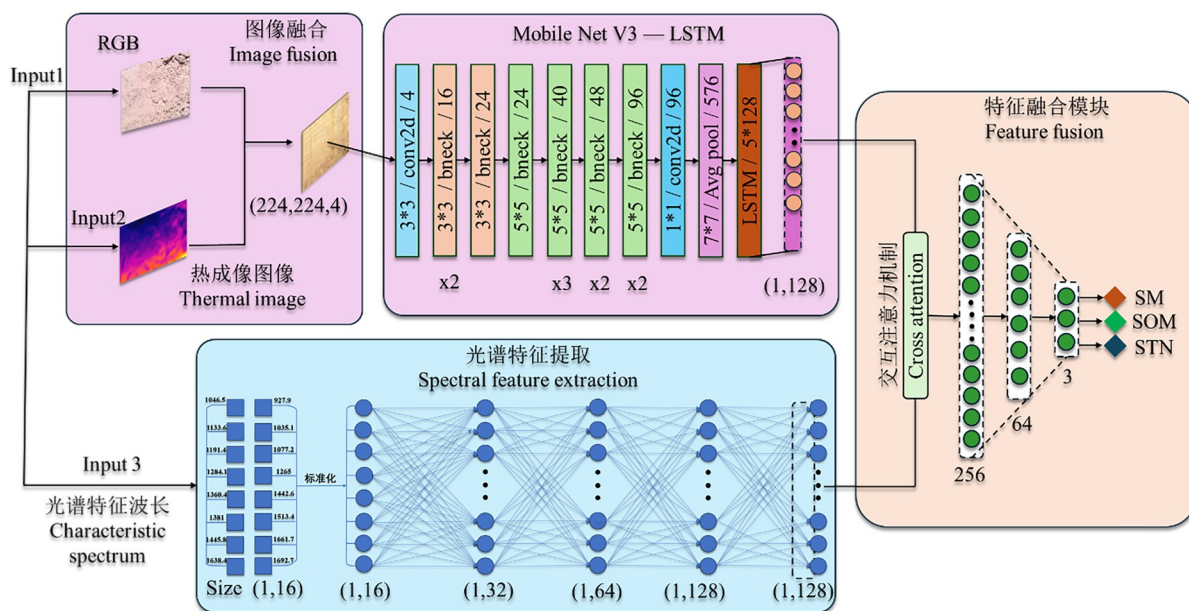


图 4 基于机器学习和深度学习算法的 TSS 信息融合土壤有机碳含量预测模型架构^[91]
 Fig.4 Framework of TSS information fusion soil organic carbon content prediction model based on machine learning and deep learning algorithms^[91]

图5 土壤多模态感测信息融合网络架构^[119]Fig. 5 Soil multimodal sensing information fusion network architecture^[119]

4 未来与展望

当下研究呈现出适应性强、多参数耦合的土壤参数反演模型的建模趋势,以及多尺度、多模态的信息交互与融合的遥感、传感趋势。本文综述了人工智能驱动下的大田土壤信息感知技术,特别是在土壤参数反演模型建模以及遥感、传感领域多尺度、多模态信息交互与融合方面的最新进展。通过回顾与分析,可以明确了2个核心发展趋势:一是基于深度学习技术实现适应性强、多参数耦合的土壤参数反演模型的趋势;二是多尺度、多模态的信息交互与融合的传感系统设计。在土壤参数反演模型建模方面,随着深度学习技术的兴起,传统的基于人工推导和预设规则的方法逐渐被数据驱动、模型自适应的方法所取代。这些新型模型不仅能够处理复杂的非线性关系,而且能有效融合多源异构数据,提高反演精度和泛化能力,形成连续精细的时空反演数据。联动多尺度、多单位、多平台的农情协作感知(Cooperative sensing)与群智感知(Crowd sensing)将会是未来土壤参数农情感知系统发展的重要思路。

随着土壤参数获取精度和便利性的提升,如何利用丰富的土壤数据量化土壤菌群与不同农艺间的作用关系可能是一个关键研究方向。传统的观

点认为土壤有机质(SOM)的持久性主要归因于某些难分解的有机碳形式^[122]。然而,这些“难以分解的腐殖质大分子”在现代分析技术中并未得到证实,因此其存在性越来越受到质疑。针对这一问题,Lehmann等^[123]提出了土壤连续体模型(Soil continuum model, SCM),认为土壤有机质是一个从完整植物材料到高度氧化的羧酸中“碳的连续体”。这一模型强调分解者生物对土壤有机质的可接近性,以及土壤矿物质对有机质分解的保护作用。Lehmann等^[124]认为传统上通过增加“稳定腐殖质”池来提高土壤有机质的策略可能是徒劳的,因为土壤有机质是一个动态分解的连续体。因此,管理土壤有机质的关键在于促进其周转而非积累。大田土壤中的微生物活性和种类丰富度显著影响着土壤有机质的积累与循环^[125],不同于森林土壤的SOM构成,草地与农田的SOM来源是真菌和细菌,二者占比总和均超过了55%,远高于森林土壤的33.4%^[126]。由微土壤菌群加工的低分子量化合与矿物表面结合而受保护而进一步形成的矿物结合态有机质(Mineral-associated organic matter, MAOM),拥有更长的持久性,是农田、牧场等低碳土壤的主要SOM来源^[127]。但由于种植和耕作的影响,农田MAOM表现出较高的脆弱性,长期的耕作与化肥的过度施加会导致农田土壤菌群的失衡与

MAOM 的快速流失,进而造成土壤的退化与板结。因此,高质量农田的建设仅仅关注当前农田的水分、SOM 含量和全氮等元素类指标可能存在不足,土壤菌落健康程度的监测方法和其与 SOM 的时空联系在未来应当得到学者的重视和研究。

5 结 论

1)近端土壤感知系统通过深度学习技术显著提升了土壤参数反演的精度与适应性。基于电性能、光谱等多源传感数据,深度神经网络有效解决了传统校准方法中环境因素耦合困难、现场校准频繁等问题,实现了介电常数、土壤水分及养分的高精度预测。自校准方法与多频段数据融合技术进一步降低了传感器成本,推动了原位土壤信息的高效获取。

2)空天遥感土壤感知系统依托星载/机载平台的高光谱、多光谱及 SAR 数据,结合深度学习模型显著提升了土壤有机碳、水分、盐分等参数的大范围反演能力。深度学习不仅优化了光谱校正与信息融合流程,还通过物理约束插值、残差网络等技术实现了遥感数据的缺失填补与高精度重建,为全球土壤湿度监测提供了连续、高分辨率的数据支持。

3)多模态、多尺度与多时相信息融合技术通过深度学习系统性整合了光谱、图像、点云及时序数据,有效解决了单传感器信息有限及环境干扰问题。各类轻量级网络与混合模型实现了可见光、热成像、光谱数据的交互融合,显著提升了土壤有机质、水分等参数的实时预测精度。多时相遥感数据与深度学习的结合进一步增强了模型的时空泛化能力。

4)在模型方法层面,发展适应复杂农田环境的强泛化能力反演模型,通过多源数据融合与跨尺度学习提升模型对时空变异的适应性,同时探索群智感知与协同感知技术,构建覆盖近端-机载-星载多尺度的土壤信息感知网络;展望未来,随着海量感测数据的采集与应用,在机理认知层面,结合土壤连续体理论,需加强土壤微生物菌群动态与有机质周转过程的关联研究,开发针对 MAOM 的原位监测技术,并探索菌群结构、农艺措施与土壤健康指标的定量关系模型,以实现从单一理化参数监测向土壤生态系统功能评估的跨越。

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