Supplementary materials for:

Exploring the Applications of Convolutional Neural Networks in Analyzing Multispectral Satellite Imagery: A Systematic Review

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This systematic review examines the application of 1D, 2D, 3D, and 4D convolutional neural networks (CNNs) to multispectral satellite imagery (MSI) in various domains. It follows PRISMA guidelines to address the successful application domains of different CNN models, commonly used MSI datasets for training, and the impact of CNN complexity on performance. The review finds that most studies focus on agriculture using Sentinel-2 data and primarily utilize classification for 1D, 2D, and 3D CNNs, while limited studies on 4D-CNNs employ segmentation techniques.

Table S1. PRISMA 2020 checklist

Topic	No.	Item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	1
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist	✓
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	1-2
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	3
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	5
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	5
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	5-6
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	6
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	6
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	7

Topic	No.	Item	Location where item is reported
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	N/A
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	6
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	7
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item 5)).	7
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	N/A
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	N/A
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	N/A
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	N/A
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	N/A
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	N/A
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	N/A
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	7-8

Topic	No.	Item	Location where item is reported
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	N/A
Study characteristics	17	Cite each included study and present its characteristics.	S6-S9
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	N/A
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	9-13
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	N/A
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	13-17
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	17-21
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	N/A
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	N/A
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	N/A
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	10-16
	23b	Discuss any limitations of the evidence included in the review.	10-16
	23c	Discuss any limitations of the review processes used.	16
	23d	Discuss implications of the results for practice, policy, and future research.	22
OTHER INFORMATION			

Topic	No.	Item	Location where item is reported
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	N/A
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	N/A
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	N/A
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	22
Competing interests	26	Declare any competing interests of review authors.	N/A
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	22

Table S2. PRISMA 2020 abstract checklist

Topic	No.	Item	Reported?
TITLE			
Title	1	Identify the report as a systematic review.	Yes
BACKGROUND			
Objectives	2	Provide an explicit statement of the main objective(s) or question(s) the review addresses.	Yes
METHODS			
Eligibility criteria	3	Specify the inclusion and exclusion criteria for the review.	Yes
Information sources	4	Specify the information sources (e.g. databases, registers) used to identify studies and the date when each was last searched.	Yes
Risk of bias	5	Specify the methods used to assess risk of bias in the included studies.	No
Synthesis of results	6	Specify the methods used to present and synthesize results.	No
RESULTS			
Included studies	7	Give the total number of included studies and participants and summarise relevant characteristics of studies.	Yes
Synthesis of results	8	Present results for main outcomes, preferably indicating the number of included studies and participants for each. If meta-analysis was done, report the summary estimate and confidence/credible interval. If comparing groups, indicate the direction of the effect (i.e. which group is favoured).	Yes
DISCUSSION			
Limitations of evidence	9	Provide a brief summary of the limitations of the evidence included in the review (e.g. study risk of bias, inconsistency and imprecision).	Yes
Interpretation	10	Provide a general interpretation of the results and important implications.	Yes
OTHER			
Funding	11	Specify the primary source of funding for the review.	Yes
Registration	12	Provide the register name and registration number.	No

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. MetaArXiv. 2020, September 14. DOI: 10.31222/osf.io/v7gm2. For more information, visit: www.prisma-statement.org

Table S3. Web of Science search strategy

Web of Science	Search term(s)
1D-CNN (n=190)	(((((ALL=(1d-cnn)) OR ALL=(1d cnn)) OR ALL=(1d convolutional))) AND ALL=(remote sensing)) AND (LA==("ENGLISH") AND DT==("ARTICLE" OR "PROCEEDINGS PAPER")) AND DOP=1990-01-01/2024-03-31
2D-CNN (n=421)	(((((ALL=(2d-cnn)) OR ALL=(2d cnn)) OR ALL=(2d convolutional))) AND ALL=(remote sensing)) AND (LA==("ENGLISH") AND DT==("ARTICLE" OR "PROCEEDINGS PAPER")) AND DOP=1990-01-01/2024-03-31
3D-CNN (n=769)	(((((ALL=(3d-cnn)) OR ALL=(3d cnn)) OR ALL=(3d convolutional))) AND ALL=(remote sensing)) AND (LA==("ENGLISH") AND DT==("ARTICLE" OR "PROCEEDINGS PAPER")) AND DOP=1990-01-01/2024-03-31
4D-CNN (n=10)	(((((ALL=(4d-cnn)) OR ALL=(4d cnn)) OR ALL=(4d convolutional))) AND ALL=(remote sensing)) AND (LA==("ENGLISH") AND DT==("ARTICLE" OR "PROCEEDINGS PAPER")) AND DOP=1990-01-01/2024-03-31

Table S4. IEEE Xplore search strategy

IEEE Xplore	Search term(s)
1D-CNN (n=63)	(((("All Metadata":"1d-cnn" OR "All Metadata":"1d cnn" OR "All Metadata":"1d convolutional") AND ("All Metadata":"remote sensing")))) AND ("ContentType":"Journals" OR "ContentType":"Conferences")
2D-CNN (n=72)	(((("All Metadata":"2d-cnn" OR "All Metadata":"2d cnn" OR "All Metadata":"2d convolutional") AND ("All Metadata":"remote sensing")))) AND ("ContentType":"Journals" OR "ContentType":"Conferences")
3D-CNN (n=132)	(((("All Metadata":"3d-cnn" OR "All Metadata":"3d cnn" OR "All

	Metadata":"3d convolutional") AND ("All Metadata":"remote sensing")))) AND ("ContentType":"Journals" OR "ContentType":"Conferences")
4D-CNN (n=2)	(((("All Metadata":"4d-cnn" OR "All Metadata":"4d cnn" OR "All Metadata":"4d convolutional") AND ("All Metadata":"remote sensing")))) AND ("ContentType":"Journals" OR "ContentType":"Conferences")

Table S5. Scopus search strategy

Scopus	**Search term(s)**
1D-CNN (n=425)	((TITLE-ABS-KEY (1d-cnn) OR TITLE-ABS-KEY (1d AND cnn) OR TITLE-ABS-KEY (1d AND convolutional)) AND ALL (remote AND sensing)) AND ((PUBYEAR > 1992 AND PUBYEAR < 2024) OR PUBDATETXT (january 2024) OR PUBDATETXT (february 2024) OR PUBDATETXT (march 2024)) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SRCTYPE , "j") OR LIMIT-TO (SRCTYPE , "p")) AND (EXCLUDE (EXACTKEYWORD , "3D Modeling") OR EXCLUDE (EXACTKEYWORD , "Fault Diagnosis") OR EXCLUDE (EXACTKEYWORD , "Hyperspectral Images") OR EXCLUDE (EXACTKEYWORD , "Electrocardiogram") OR EXCLUDE (EXACTKEYWORD , "Faults Diagnosis") OR EXCLUDE (EXACTKEYWORD , "Human Activity Recognition") OR EXCLUDE (EXACTKEYWORD , "Radar Target Recognition") OR EXCLUDE (EXACTKEYWORD , "Electrocardiography") OR EXCLUDE (EXACTKEYWORD , "Seismology") OR EXCLUDE (EXACTKEYWORD , "Diagnosis") OR EXCLUDE (EXACTKEYWORD , "Antennas") OR EXCLUDE (EXACTKEYWORD , "Hyperspectral") OR EXCLUDE (EXACTKEYWORD , "Diseases") OR EXCLUDE (EXACTKEYWORD , "Seismic Waves") OR EXCLUDE (EXACTKEYWORD , "Hyperspectral Image") OR EXCLUDE (EXACTKEYWORD , "Signal Processing") OR EXCLUDE (EXACTKEYWORD , "Brain") OR EXCLUDE (EXACTKEYWORD , "Hyperspectral Data") OR EXCLUDE (EXACTKEYWORD , "Hyperspectral Imaging") OR EXCLUDE (EXACTKEYWORD , "HyperSpectral") OR EXCLUDE (EXACTKEYWORD , "Hyperspectral Image Classification") OR EXCLUDE (EXACTKEYWORD , "Human") OR EXCLUDE (EXACTKEYWORD , "Humans") OR EXCLUDE (

	EXACTKEYWORD , "Biomedical Signal Processing") OR EXCLUDE (EXACTKEYWORD , "Seismic Response") OR EXCLUDE (EXACTKEYWORD , "Seismic Data"))
2D-CNN (n=720)	((TITLE-ABS-KEY (2d-cnn) OR TITLE-ABS-KEY (2d AND cnn) OR TITLE-ABS-KEY (2d AND convolutional)) AND ALL (remote AND sensing)) AND ((PUBYEAR > 1992 AND PUBYEAR < 2024) OR PUBDATETXT (january 2024) OR PUBDATETXT (february 2024) OR PUBDATETXT (march 2024)) AND (LIMIT-TO (SRCTYPE , "j") OR LIMIT-TO (SRCTYPE , "p")) AND (LIMIT-TO (LANGUAGE , "English")) AND (EXCLUDE (EXACTKEYWORD , "Aircraft Detection") OR EXCLUDE (EXACTKEYWORD , "Agricultural Robots") OR EXCLUDE (EXACTKEYWORD , "Computer Aided Diagnosis") OR EXCLUDE (EXACTKEYWORD , "Tumors") OR EXCLUDE (EXACTKEYWORD , "LiDAR") OR EXCLUDE (EXACTKEYWORD , "Optical Resolving Power") OR EXCLUDE (EXACTKEYWORD , "Nuclear Magnetic Resonance Imaging") OR EXCLUDE (EXACTKEYWORD , "Seismology") OR EXCLUDE (EXACTKEYWORD , "Seismic Response") OR EXCLUDE (EXACTKEYWORD , "Diseases") OR EXCLUDE (EXACTKEYWORD , "Seismic Data") OR EXCLUDE (EXACTKEYWORD , "Synthetic Aperture Radar") OR EXCLUDE (EXACTKEYWORD , "Attention Mechanism") OR EXCLUDE (EXACTKEYWORD , "Unmanned Aerial Vehicles (UAV)") OR EXCLUDE (EXACTKEYWORD , "3D Point Cloud") OR EXCLUDE (EXACTKEYWORD , "Computerized Tomography") OR EXCLUDE (EXACTKEYWORD , "Diagnosis") OR EXCLUDE (EXACTKEYWORD , "Radar Imaging") OR EXCLUDE (EXACTKEYWORD , "Brain") OR EXCLUDE (EXACTKEYWORD , "Diagnostic Imaging") OR EXCLUDE (EXACTKEYWORD , "Seismic Waves") OR EXCLUDE (EXACTKEYWORD , "Cameras") OR EXCLUDE (EXACTKEYWORD , "Magnetic Resonance Imaging") OR EXCLUDE (EXACTKEYWORD , "Hyperspectral Image") OR EXCLUDE (EXACTKEYWORD , "Attention Mechanisms") OR EXCLUDE (EXACTKEYWORD , "Semantic Web") OR EXCLUDE (EXACTKEYWORD , "Medical Imaging") OR EXCLUDE (EXACTKEYWORD , "Three Dimensional Computer Graphics") OR EXCLUDE (EXACTKEYWORD , "3D Modeling") OR EXCLUDE (EXACTKEYWORD , "Humans") OR EXCLUDE (EXACTKEYWORD , "Antennas") OR EXCLUDE (EXACTKEYWORD , "Optical Radar") OR EXCLUDE (EXACTKEYWORD , "HyperSpectral") OR EXCLUDE (EXACTKEYWORD , "Hyperspectral Imaging") OR EXCLUDE (EXACTKEYWORD , "Human") OR EXCLUDE (

	EXACTKEYWORD , "Hyperspectral Image Classification"))
3D-CNN (n=1112)	((TITLE-ABS-KEY (3d-cnn) OR TITLE-ABS-KEY (3d AND cnn) OR TITLE-ABS-KEY (3d AND convolutional)) AND ALL (remote AND sensing)) AND ((PUBYEAR > 1992 AND PUBYEAR < 2024) OR PUBDATETXT (january 2024) OR PUBDATETXT (february 2024) OR PUBDATETXT (march 2024)) AND (LIMIT-TO (SRCTYPE , "j") OR LIMIT-TO (SRCTYPE , "p")) AND (LIMIT-TO (LANGUAGE , "English")) AND (EXCLUDE (EXACTKEYWORD , "Three Dimensional Computer Graphics") OR EXCLUDE (EXACTKEYWORD , "Hyperspectral Image Classification") OR EXCLUDE (EXACTKEYWORD , "Human") OR EXCLUDE (EXACTKEYWORD , "Optical Radar") OR EXCLUDE (EXACTKEYWORD , "Hyperspectral Imaging") OR EXCLUDE (EXACTKEYWORD , "Antennas") OR EXCLUDE (EXACTKEYWORD , "HyperSpectral") OR EXCLUDE (EXACTKEYWORD , "Humans") OR EXCLUDE (EXACTKEYWORD , "Cameras") OR EXCLUDE (EXACTKEYWORD , "Medical Imaging") OR EXCLUDE (EXACTKEYWORD , "Magnetic Resonance Imaging") OR EXCLUDE (EXACTKEYWORD , "Hyperspectral Image") OR EXCLUDE (EXACTKEYWORD , "Computerized Tomography") OR EXCLUDE (EXACTKEYWORD , "Diagnostic Imaging") OR EXCLUDE (EXACTKEYWORD , "Unmanned Aerial Vehicles (UAV)") OR EXCLUDE (EXACTKEYWORD , "Radar Imaging") OR EXCLUDE (EXACTKEYWORD , "Diagnosis") OR EXCLUDE (EXACTKEYWORD , "LiDAR") OR EXCLUDE (EXACTKEYWORD , "Attention Mechanism") OR EXCLUDE (EXACTKEYWORD , "Brain") OR EXCLUDE (EXACTKEYWORD , "Semantic Web") OR EXCLUDE (EXACTKEYWORD , "Photogrammetry") OR EXCLUDE (EXACTKEYWORD , "Nuclear Magnetic Resonance Imaging") OR EXCLUDE (EXACTKEYWORD , "Robotics") OR EXCLUDE (EXACTKEYWORD , "Lidar") OR EXCLUDE (EXACTKEYWORD , "Tumors") OR EXCLUDE (EXACTKEYWORD , "Synthetic Aperture Radar") OR EXCLUDE (EXACTKEYWORD , "Male") OR EXCLUDE (EXACTKEYWORD , "Female") OR EXCLUDE (EXACTKEYWORD , "Aircraft Detection") OR EXCLUDE (EXACTKEYWORD , "X-ray Computed Tomography") OR EXCLUDE (EXACTKEYWORD , "Autonomous Vehicles") OR EXCLUDE (EXACTKEYWORD , "Seismic Waves") OR EXCLUDE (EXACTKEYWORD , "Major Clinical Study") OR EXCLUDE (EXACTKEYWORD , "Adult") OR EXCLUDE (EXACTKEYWORD , "Optical Resolving Power") OR

	EXCLUDE (EXACTKEYWORD , "Seismology") OR EXCLUDE (EXACTKEYWORD , "3D Printers") OR EXCLUDE (EXACTKEYWORD , "Security Systems") OR EXCLUDE (EXACTKEYWORD , "Optimization") OR EXCLUDE (EXACTKEYWORD , "Gesture Recognition") OR EXCLUDE (EXACTKEYWORD , "E-learning") OR EXCLUDE (EXACTKEYWORD , "Topology") OR EXCLUDE (EXACTKEYWORD , "Synthetic Data") OR EXCLUDE (EXACTKEYWORD , "Learning Approach") OR EXCLUDE (EXACTKEYWORD , "Additive Manufacturing") OR EXCLUDE (EXACTKEYWORD , "Palmprint Recognition") OR EXCLUDE (EXACTKEYWORD , "Laser Applications") OR EXCLUDE (EXACTKEYWORD , "Intelligent Robots") OR EXCLUDE (EXACTKEYWORD , "Computer Aided Design"))
4D-CNN (n=36)	((TITLE-ABS-KEY (4d-cnn) OR TITLE-ABS-KEY (4d AND cnn) OR TITLE-ABS-KEY (4d AND convolutional)) AND ALL (remote AND sensing)) AND ((PUBYEAR > 1992 AND PUBYEAR < 2024) OR PUBDATETXT (january 2024) OR PUBDATETXT (february 2024) OR PUBDATETXT (march 2024)) AND (LIMIT-TO (SRCTYPE , "j") OR LIMIT-TO (SRCTYPE , "p")) AND (LIMIT-TO (LANGUAGE , "English")) AND (EXCLUDE (EXACTKEYWORD , "Human") OR EXCLUDE (EXACTKEYWORD , "Seismology") OR EXCLUDE (EXACTKEYWORD , "Seismic Data") OR EXCLUDE (EXACTKEYWORD , "Security Systems") OR EXCLUDE (EXACTKEYWORD , "Medical Imaging"))

Table S6. Publications used in analysis - 1D CNN

No	Authors	Article Title	Year	Author Keywords	Research Category	Domain	ML Technique	Complex
1	Zhang, YH; Ge, TT; Tian, W; Liou, YA	Debris Flow Susceptibility Mapping Using Machine-Learning Techniques in Shigatse Area, China	2019	debris flow susceptibility; remote sensing; GIS; oversampling methods; back propagation neural network; one-dimensional convolutional neural network; decision tree; random forest; extreme gradient boosting	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Geohazards	Classification	no
2	Y. Song; Z. Zhang; R. K. Baghbaderani; F. Wang; Y. Qu; C. Stuttsy; H. Qi	Land Cover Classification for Satellite Images Through 1D CNN	2019	Satellite Image;Land Cover Classification;1D CNN;Deep Learning;Spectral Unmixing	N/A	Urban	Classification	no
3	Luo, X; Tong, XH; Hu, ZW; Wu, GF	Improving Urban Land Cover/Use Mapping by Integrating A Hybrid Convolutional Neural Network and An Automatic Training Sample Expanding Strategy	2020	remote sensing; land cover classification; spectral feature; context feature; convolutional neural networks	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Urban	Classification	no
4	Zhang, WC; Liu, HB; Wu, W; Zhan, LQ; Wei, J	Mapping Rice Paddy Based on Machine Learning with Sentinel-2 Multi-Temporal Data: Model Comparison and Transferability	2020	rice; convolutional neural network; F1 score; sentinel-2; transfer	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science &	Vegetation	Classification	no

* Column **Complex** indicates the complexity of the CNN model. "Yes" denotes models that incorporate additional techniques beyond basic 1D, 2D, 3D, or 4D architectures. "No" refers to models that consist solely of pure 1D, 2D, 3D, or 4D CNN architectures.

					Photographic Technology			
5	Russwurm, M; Korner, M	Self-attention for raw optical Satellite Time Series Classification	2020	Self-attention; Transformer; Time series classification; Multitemporal Earth observation; Crop type mapping; Vegetation monitoring; Deep learning	Geography, Physical; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
6	Liao, CH; Wang, JF; Xie, QH; Al Baz, A; Huang, XD; Shang, JL; He, YJ	Synergistic Use of Multi-Temporal RADARSAT-2 and VEN mu S Data for Crop Classification Based on 1D Convolutional Neural Network	2020	crop classification; RADARSAT-2; VEN mu S; data fusion; deep learning; convolutional neural network	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
7	Cordova K.M.N.; Sritarapipat T.; Piyatadsananon P.	APPLICATION of CNN on LANDSLIDE SUSCEPTIBILITY ANALYSIS: CASE STUDY on 2018 HOKKAIDO EASTERN IBURI EARTHQUAKE	2021	convolutional neural network; deep learning; landslides	N/A	Geohazards	Classification	no
8	Ma, N; Sun, L; Zhou, CH; He, YW	Cloud Detection Algorithm for Multi-Satellite Remote Sensing Imagery Based on a Spectral Library and 1D Convolutional Neural Network	2021	ASTER spectral library; hyperspectral data; 1D convolutional neural network; cloud detection; data simulation; multi-satellite remote sensing images	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Others	Classification	yes

* Column **Complex** indicates the complexity of the CNN model. "Yes" denotes models that incorporate additional techniques beyond basic 1D, 2D, 3D, or 4D architectures. "No" refers to models that consist solely of pure 1D, 2D, 3D, or 4D CNN architectures.

9	Pérez-Carabaza S.; Syrris V.; Kempeneers P.; Soille P.	CROP CLASSIFICATION FROM SENTINEL-2 TIME SERIES WITH TEMPORAL CONVOLUTIONAL NEURAL NETWORKS	2021	Convolutional Neural Networks; Crop classification; Multi-temporal remote sensing images	N/A	Vegetation	Classification	no
10	X. Wan; J. Wan; M. Xu; S. Liu; H. Sheng; Y. Chen; X. Zhang	Enteromorpha Coverage Information Extraction by 1D-CNN and Bi-LSTM Networks Considering Sample Balance From GOCI Images	2021	Enteromorpha prolifera (EP);geostationary ocean color imager (GOCI);neural network;sample balance	N/A	Water	Classification	no
11	Ding C.; Zhang X.; Ma S.; Han W.; Lu Y.; Yin J.	Estuary water quality classification through deep learning image segmentation, an example of Hangzhou Bay	2021	convolutional neural networks; image segmentation; Suspended sediment concentration; UNet	N/A	Water	Classification	no
12	Zhao, HW; Duan, SB; Liu, J; Sun, L; Reymondin, L	Evaluation of Five Deep Learning Models for Crop Type Mapping Using Sentinel-2 Time Series Images with Missing Information	2021	crop type mapping; Sentinel-2; missing information; time series data; CNN; LSTM; GRU	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
13	Sun, HR; Wang, L; Lin, RC; Zhang, Z; Zhang, BZ	Mapping Plastic Greenhouses with Two-Temporal Sentinel-2 Images and 1D-CNN Deep Learning	2021	plastic greenhouses; sustainable agriculture; sentinel-2; 1D-CNN; red-edge bands	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Urban	Classification	no

* Column **Complex** indicates the complexity of the CNN model. "Yes" denotes models that incorporate additional techniques beyond basic 1D, 2D, 3D, or 4D architectures. "No" refers to models that consist solely of pure 1D, 2D, 3D, or 4D CNN architectures.

14	Debella-Gilo, M; Gjertsen, AK	Mapping Seasonal Agricultural Land Use Types Using Deep Learning on Sentinel-2 Image Time Series	2021	multilayer perceptron; CNN; hyperparameter tuning; cereal; grass	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
15	Qadeer M.U.; Saeed S.; Taj M.; Muhammad A.	SPATIO-TEMPORAL CROP CLASSIFICATION ON VOLUMETRIC DATA	2021	CNN; Crop Classification; Satellite data	N/A	Vegetation	Classification	yes
16	Maier, PM; Keller, S; Hinz, S	Deep Learning with WASI Simulation Data for Estimating Chlorophyll a Concentration of Inland Water Bodies	2021	machine learning; regression; CNN; artificial neural network; radiative transfer model; WASI; hyperspectral data; algae; chlorophyll a; downsampling	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Water	Regression	no
17	Vulova, S; Meier, F; Rocha, AD; Quanz, J; Nouri, H; Kleinschmit, B	Modeling urban evapotranspiration using remote sensing, flux footprints, and artificial intelligence	2021	Urban water; Eddy covariance; Latent heat flux; 1D convolutional neural networks (CNN); Deep learning; Harmonized Landsat and Sentinel-2	Environmental Sciences	Urban	Regression	no
18	Zhou, Xuewen; Xin, Qinchuan; Dai, Yongjiu; Li, Wanjing	A deep-learning-based experiment for benchmarking the performance of global terrestrial vegetation phenology models	2021	convolutional neural network; land surface process; phenology metrics; remote sensing; vegetation phenology modelling	Ecology; Geography, Physical	Vegetation	Regression	yes

* Column **Complex** indicates the complexity of the CNN model. "Yes" denotes models that incorporate additional techniques beyond basic 1D, 2D, 3D, or 4D architectures. "No" refers to models that consist solely of pure 1D, 2D, 3D, or 4D CNN architectures.

19	Rawat, A; Kumar, A; Upadhyay, P; Kumar, S	A Comparative Study of 1D-Convolutional Neural Networks with Modified Possibilistic c-Mean Algorithm for Mapping Transplanted Paddy Fields Using Temporal Data	2022	Image classification; Temporal; 1D-CNN; MPCM; Fuzzy-based algorithm; Learning-based algorithm	Environmental Sciences; Remote Sensing	Vegetation	Classification	no
20	Moncrieff, GR	Continuous Land Cover Change Detection in a Critically Endangered Shrubland Ecosystem Using Neural Networks	2022	land cover change; land cover monitoring; deep learning; Renosterveld; threatened ecosystems; Sentinel 2; planet labs	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	yes
21	Tao, WC; Dong, Y; Su, W; Li, JY; Xuan, F; Huang, JX; Yang, JY; Li, XC; Zeng, YL; Li, BG	Mapping the Corn Residue-Covered Types Using Multi-Scale Feature Fusion and Supervised Learning Method by Chinese GF-2 PMS Image	2022	crop residue covering; multi-scale image features; machine learning; GF-2 PMS image; high spatial resolution remote sensing	Plant Sciences	Vegetation	Classification	no
22	Afira N.; Wijayanto A.W.	Mono-temporal and multi-temporal approaches for burnt area detection using Sentinel-2 satellite imagery (a case study of Rokan Hilir Regency, Indonesia)	2022	Burnt area detection; Deep learning algorithms; Fire; Machine learning algorithms; Sentinel-2	N/A	Geohazards	Classification	no
23	Sabir A.; Kumar A.	Optimized 1D-CNN model for medicinal Psyllium Husk crop mapping with temporal optical satellite data	2022	1D-CNN (convolutional neural network); Deep learning; FERM (fuzzy error matrix); MSAVI2 (modified	N/A	Vegetation	Classification	no

* Column **Complex** indicates the complexity of the CNN model. "Yes" denotes models that incorporate additional techniques beyond basic 1D, 2D, 3D, or 4D architectures. "No" refers to models that consist solely of pure 1D, 2D, 3D, or 4D CNN architectures.

				soil vegetation index); Psyllium Husk				
24	Gunen, MA	Performance comparison of deep learning and machine learning methods in determining wetland water areas using EuroSAT dataset	2022	1D CNN; Remote sensing; Classification; Wetland; Sentinel-2	Environmental Sciences	Water	Classification	no
25	Fang, J; He, GH; Zhu, ZJ; Attaher, BIM; Xue, J	Spatial-Spectral Decoupling Interaction Network for Multispectral Imagery Change Detection	2022	Mathematical models; Feature extraction; Geoscience and remote sensing; Neural networks; Fuses; Deep learning; Convolutional neural networks; Multispectral imagery change detection; spatial-spectral decoupling interaction network	Geochemistry & Geophysics; Engineering, Electrical & Electronic; Remote Sensing; Imaging Science & Photographic Technology	Others	Classification	yes
26	Florath, J; Keller, S	Supervised Machine Learning Approaches on Multispectral Remote Sensing Data for a Combined Detection of Fire and Burned Area	2022	remote sensing; classification; burned area mapping; fire detection; deep learning; Sentinel-2 images; self-organizing maps; undersampling; imbalanced dataset; convolutional neural network	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Geohazards	Classification	no
27	Fan, DL; He, HC; Wang, RS; Zeng, Y; Fu, BL; Xiong, YK; Liu, LL; Xu, Y; Gao, ET	CHLNET: A novel hybrid 1D CNN-SVR algorithm for estimating ocean surface chlorophyll-a	2022	chlorophyll-a inversion; hybrid algorithm; one-dimensional convolution neural network; feature	Environmental Sciences; Marine & Freshwater Biology	Water	Regression	no

* Column **Complex** indicates the complexity of the CNN model. "Yes" denotes models that incorporate additional techniques beyond basic 1D, 2D, 3D, or 4D architectures. "No" refers to models that consist solely of pure 1D, 2D, 3D, or 4D CNN architectures.

				extraction; ocean color; cross-water types				
28	Mukonza, SS; Chiang, JL	Micro-Climate Computed Machine and Deep Learning Models for Prediction of Surface Water Temperature Using Satellite Data in Mundan Water Reservoir	2022	water quality; water temperature; machine and deep learning; uncertainties; Landsat-8; Sentinel-3	Environmental Sciences; Water Resources	Water	Regression	yes
29	Jeong, S; Ko, J; Yeom, JM	Predicting rice yield at pixel scale through synthetic use of crop and deep learning models with satellite data in South and North Korea	2022	Crop yield prediction; Data driven model; Crop model; Remote sensing; Korean peninsula	Environmental Sciences	Vegetation	Regression	yes
30	Bahl G.; Lafarge F.	Scanner Neural Network for On-Board Segmentation of Satellite Images	2022	Cloud Segmentation; ConvLSTM; Image Segmentation; On-board processing; Recurrent Convolutional Network; Satellite Imagery	N/A	Others	Segmentation	yes
31	B. Yang; J. Guo; J. Liu; X. Ye	PPCE: A Practical Loss for Crop Mapping Using Phenological Prior	2023	Crop mapping;crop phenology;deep learning;loss function;remote sensing	N/A	Vegetation	Classification	no
32	Li, Qianjing; Tian, Jia; Tian, Qingjiu	Deep Learning Application for Crop Classification via Multi-Temporal Remote Sensing Images	2023	crop type classification; deep learning; multi-temporal; remote sensing	Agronomy	Vegetation	Classification	no
33	Bai, Maoyang; Peng, Peihao; Zhang, Shiqi; Wang, Xueman;	Mountain Forest Type Classification Based on One-Dimensional	2023	mountain forest; classification; one-dimensional convolutional	Forestry	Vegetation	Classification	no

* Column **Complex** indicates the complexity of the CNN model. "Yes" denotes models that incorporate additional techniques beyond basic 1D, 2D, 3D, or 4D architectures. "No" refers to models that consist solely of pure 1D, 2D, 3D, or 4D CNN architectures.

	Wang, Xiao; Wang, Juan; Pellikka, Petri	Convolutional Neural Network		neural network; Sentinel-1; Sentinel-2				
34	Fan, Xiangsuo; Chen, Lin; Xu, Xinggui; Yan, Chuan; Fan, Jinlong; Li, Xuyang	Land Cover Classification of Remote Sensing Images Based on Hierarchical Convolutional Recurrent Neural Network	2023	pixel classification; CNN; RNN; RS image classification	Forestry	Urban	Classification	no
35	Kanwal, Rida; Rafaqat, Warda; Iqbal, Mansoor; Weiguo, Song	Data-Driven Approaches for Wildfire Mapping and Prediction Assessment Using a Convolutional Neural Network (CNN)	2023	machine learning; wildfire assessment; CNN; random forest; fire occurrence	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Geohazards	Classification	yes
36	Ma, Ye; Zhen, Zhen; Li, Fengri; Feng, Fujuan; Zhao, Yinghui	An innovative lightweight 1D-CNN model for efficient monitoring of large-scale forest composition: a case study of Heilongjiang Province, China	2023	1D-CNN; SEM; large-scale mapping; forest composition change monitoring; Landsat	Geography, Physical; Remote Sensing	Vegetation	Classification	yes
37	Nguyen, Chi; Tan, Chang Wei; Daly, Edoardo; Pauwels, Valentijn R. N.	Efficient analysis of hydrological connectivity using 1D and 2D Convolutional Neural Networks	2023	Convolutional neural network; Functional connectivity; Potential connection length	Water Resources	Water	Classification	no
38	Tsangaratos, Paraskevas; Ilia, Ioanna; Chrysafi, Aikaterini-Alexandra;	Applying a 1D Convolutional Neural Network in Flood Susceptibility Assessments-The Case of	2023	flood susceptibility; remote sensing; convolutional neural network; geoinformatics; Euboea; Greece	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing;	Geohazards	Classification	no

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	Matiatos, Ioannis; Chen, Wei; Hong, Haoyuan	the Island of Euboea, Greece			Imaging Science & Photographic Technology			
39	Zhang, Hankui K.; Roy, David P.; Luo, Dong	Demonstration of large area land cover classification with a one dimensional convolutional neural network applied to single pixel temporal metric percentiles	2023	Land cover; Time series; Temporal metric percentiles; Convolutional neural network; Random forest; Deep learning; Large area classification; Landsat	Environmental Sciences; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
40	G. S. Phartiyal; L. S. Khangarot; D. Singh	Impact of Permuted Spectral Neighborhood of High-Dimensional Msts Rs Data on Crop Classification Performance with DNN Models	2023	localized spectral information;CNNs;multi-sensor;crop classification;time-series	N/A	Vegetation	Classification	no
41	Li H.; Di L.; Zhang C.; Lin L.; Guo L.; Zhao H.	Prediction of Crop Planting Map Using One-dimensional Convolutional Neural Network and Decision Tree Algorithm	2023	CDL; crop map prediction; decision tree; one-dimensional CNN	N/A	Vegetation	Classification	yes
42	Ojaghi, S; Bouroubi, Y; Foucher, S; Bergeron, M; Seynat, C	Deep Learning-Based Emulation of Radiative Transfer Models for Top-of-Atmosphere BRDF Modelling Using Sentinel-3 OLCI	2023	deep learning; RTMSs; emulator; BRDF; 1D-CNN; PROSAIL; 6S; Sentinel-3 OLCI	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Others	Regression	no
43	Salah, Muhammad; Higa,	1D Convolutional Neural Network-based	2023	chlorophyll-a; Sentinel-2; MultiSpectral Instrument;	Instruments & Instrumentation;	Water	Regression	no

* Column **Complex** indicates the complexity of the CNN model. "Yes" denotes models that incorporate additional techniques beyond basic 1D, 2D, 3D, or 4D architectures. "No" refers to models that consist solely of pure 1D, 2D, 3D, or 4D CNN architectures.

	Hiroto; Ishizaka, Joji; Salem, Salem Ibrahim	Chlorophyll-a Retrieval Algorithm for Sentinel-2 MultiSpectral Instrument in Various Trophic States		deep learning; convolutional neural network; ocean color	Materials Science, Multidisciplinary			
44	Fathi, Mahdiyeh; Shah-Hosseini, Reza; Moghimi, Armin	3D-ResNet-BiLSTM Model: A Deep Learning Model for County-Level Soybean Yield Prediction with Time-Series Sentinel-1, Sentinel-2 Imagery, and Daymet Data	2023	soybean; yield prediction; Conv3D; ResNet; BiLSTM; Sentinel 1-2; Daymet; Google Earth Engine (GEE)	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Regression	yes
45	Ivanda, Antonia; Seric, Ljiljana; Zagar, Dusan; Ostir, Kristof	An application of 1D convolution and deep learning to remote sensing modelling of Secchi depth in the northern Adriatic Sea	2023	Secchi; Sentinel-3; OLCI; 1D-CNN; Adriatic sea	Computer Science, Information Systems; Geosciences, Multidisciplinary; Remote Sensing	Water	Regression	no
46	Sabo, Filip; Meroni, Michele; Waldner, Francois; Rembold, Felix	Is deeper always better? Evaluating deep learning models for yield forecasting with small data	2023	Convolutional neural networks; Agriculture; Remote sensing; Food security	Environmental Sciences	Vegetation	Regression	no
47	Xu, Zhenheng; Sun, Hao; Zhang, Tian; Xu, Huanyu; Wu, Dan; Gao, JinHua	Evaluating established deep learning methods in constructing integrated remote sensing drought index: A case study in China	2023	Agricultural drought; Remote sensing; Data driven; Deep learning; Machine learning; Inductive bias	Agronomy; Water Resources	Agriculture	Regression	no
48	Zeng, You; Liang, Tianlong; Fan,	A Novel Algorithm for the Retrieval of Chlorophyll a	2023	marine; chlorophyll a; remote sensing inversion; deep learning	Environmental Sciences; Water Resources	Water	Regression	no

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	Donglin; He, Hongchang	in Marine Environments Using Deep Learning						
49	M. Salah; H. Higa; J. Ishizaka; S. I. Salem	B1D-CNN: A Novel Convolution Neural Network-Based Chlorophyll-A Retrieval Algorithm for Sentinel-2 Data	2023	Chlorophyll-a;CNN;MSI;Ocean Color	N/A	Water	Regression	yes

Table S7. Publications used in analysis - 2D CNN

No	Authors	Article Title	Year	Author Keywords	Research Category	Domain	ML Technique	Complex
1	Ji, SP; Zhang, C; Xu, AJ; Shi, Y; Duan, YL	3D Convolutional Neural Networks for Crop Classification with Multi-Temporal Remote Sensing Images	2018	3D convolution; convolutional neural networks; crop classification; multi-temporal remote sensing images; active learning	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
2	Bergamasco L.; Bovolo F.; Bruzzone L.	A novel deep learning data structure for multispectral remote sensing images	2020	Convolutional neural network; Data-cube analysis; Deep-learning classification; Remote sensing; Spatial-spectral analysis	N/A	Vegetation	Classification	yes
3	Kang J.; Demir B.	Band-Wise Multi-Scale CNN Architecture for Remote Sensing Image Scene Classification	2020	convolutional neural networks; Deep learning; feature extraction; remote	N/A	Vegetation	Classification	yes

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				sensing; scene classification				
4	Shakya, A; Biswas, M; Pal, M	CNN-based fusion and classification of SAR and Optical data	2020	N/A	Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
5	Park S.; Park N.-W.	Effects of class purity of training data on crop classification using 2D-CNn	2020	Deep learning; Patch-based classification; Training data	N/A	Vegetation	Classification	no
6	Park S.; Park N.-W.	Effects of class purity of training patch on classification performance of crop classification with convolutional neural network	2020	Class purity; Convolutional neural network; Patch-based classification; Training samples	N/A	Vegetation	Classification	no
7	Chelali, M; Kurtz, C; Puissant, A; Vincent, N	Image Time Series Classification based on a Planar Spatio-temporal Data Representation	2020	Satellite Image Time Series; Spatio-temporal Features; Space-filling Curves; Convolutional Neural Networks	Computer Science, Software Engineering	Vegetation	Classification	yes
8	Luo, X; Tong, XH; Hu, ZW; Wu, GF	Improving Urban Land Cover/Use Mapping by Integrating A Hybrid Convolutional Neural Network and An Automatic Training Sample Expanding Strategy	2020	remote sensing; land cover classification; spectral feature; context feature; convolutional neural networks	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Urban	Classification	no
9	Zhang, WC; Liu, HB; Wu, W; Zhan, LQ; Wei, J	Mapping Rice Paddy Based on Machine Learning with Sentinel-2	2020	rice; convolutional neural network; F1 score; sentinel-2; transfer	Environmental Sciences; Geosciences,	Vegetation	Classification	no

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		Multi-Temporal Data: Model Comparison and Transferability			Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology			
10	M. Pal; Akshay; H. Rohilla; B. C. Teja	Patch Based Land Cover Classification: A Comparison of Deep Learning, SVM and NN Classifiers	2020	2D-CNN;SVM;neural network;patch size;classification accuracy	N/A	Vegetation	Classification	no
11	Wang, L; Wu, YX; Xu, JP; Zhang, HY; Wang, XY; Yu, JB; Sun, Q; Zhao, ZY	STATUS PREDICTION BY 3D FRACTAL NET CNN BASED ON REMOTE SENSING IMAGES	2020	Fractal Net; 3D CNN; Status Prediction; Remote Sensing Images; Eutrophication	Mathematics, Interdisciplinary Applications; Multidisciplinary Sciences	Water	Classification	no
12	Lee, J; Im, J; Cha, DH; Park, H; Sim, S	Tropical Cyclone Intensity Estimation Using Multi-Dimensional Convolutional Neural Networks from Geostationary Satellite Data	2020	tropical cyclones; multispectral imaging; 2D; 3D convolutional neural networks	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Geohazards	Regression	no
13	M. Chelali; C. Kurtz; A. Puissant; N. Vincent	Classification of spatially enriched pixel time series with convolutional neural networks	2021	N/A	N/A	Vegetation	Classification	yes
14	A. Shakya; M. Biswas; M. Pal	CNN-Based Fusion and Classification of Multi-Temporal Sentinel-1 & -2 Satellite Data	2021	Fusion;Classification;Convolutional Neural Network (CNN);Bayesian Optimization	N/A	Vegetation	Classification	yes
15	Corbane C.; Syrris V.; Sabo F.; Politis	Convolutional neural networks for global human	2021	Built-up areas; Convolutional neural	N/A	Urban	Classification	yes

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	P.; Melchiorri M.; Pesaresi M.; Soille P.; Kemper T.	settlements mapping from Sentinel-2 satellite imagery		networks; Human settlements; Image segmentation; Remote sensing				
16	Chelali, M; Kurtz, C; Puissant, A; Vincent, N	Deep-STaR: Classification of image time series based on spatio-temporal representations	2021	Image time series; Spatio-temporal features; Planar image representation; Space filling curves; Random walk; CNN; Remote sensing	Computer Science, Artificial Intelligence; Engineering, Electrical & Electronic	Vegetation	Classification	yes
17	Moreno-Revelo M.Y.; Guachi-Guachi L.; Gómez-Mendoza J.B.; Revelo-Fuelagán J.; Peluffo-Ordóñez D.H.	Enhanced convolutional-neural-network architecture for crop classification	2021	Convolutional neural network (CNN); Crop classification; Post-processing; Satellite images	N/A	Vegetation	Classification	no
18	Ding C.; Zhang X.; Ma S.; Han W.; Lu Y.; Yin J.	Estuary water quality classification through deep learning image segmentation, an example of Hangzhou Bay	2021	convolutional neural networks; image segmentation; Suspended sediment concentration; UNet	N/A	Water	Classification	yes
19	Sagan, V; Maimaitijiang, M; Bhadra, S; Maimaitiyiming, M; Brown, DR; Sidike, P; Fritschi, FB	Field-scale crop yield prediction using multi-temporal WorldView-3 and PlanetScope satellite data and deep learning	2021	PlanetScope; WorldView-3; Deep learning; Convolutionneural network; ResNet; Artificial intelligence; Food security	Geography, Physical; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Regression	yes
20	Debella-Gilo, M; Gjertsen, AK	Mapping Seasonal Agricultural Land Use Types Using Deep	2021	multilayer perceptron; CNN; hyperparameter tuning; cereal; grass	Environmental Sciences; Geosciences,	Vegetation	Classification	no

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		Learning on Sentinel-2 Image Time Series			Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology			
21	Adrian, J; Sagan, V; Maimaitijiang, M	Sentinel SAR-optical fusion for crop type mapping using deep learning and Google Earth Engine	2021	3D U-Net; Denoising neural networks; Sentinel-1; Sentinel-2; Data fusion	Geography, Physical; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	yes
22	Papadomanolaki, M; Christodoulidis, S; Karantzalos, K; Vakalopoulou, M	Unsupervised Multistep Deformable Registration of Remote Sensing Imagery Based on Deep Learning	2021	spatial gradients; deformation; satellite; very high resolution imagery; urban and periurban; learning-based registration; dense displacements; alignment	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Others	Regression	yes
23	Seydi, ST; Amani, M; Ghorbanian, A	A Dual Attention Convolutional Neural Network for Crop Classification Using Time-Series Sentinel-2 Imagery	2022	crop mapping; deep learning; convolutional neural networks (CNN); attention modules (AM); dual attention CNN; Sentinel-2; multi-temporal	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
24	Azeez, OS; Shafri, HZM; Alias, AH; Haron, NA	A Joint Bayesian Optimization for the Classification of Fine Spatial Resolution	2022	object-based convolution neural networks; deep learning; Bayesian	Environmental Studies	Urban	Classification	no

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		Remotely Sensed Imagery Using Object-Based Convolutional Neural Networks		optimization; decision-level fusion; Worldview-3				
25	Virnodkar S.S.; Pachghare V.K.; Patil V.C.; Jha S.K.	CaneSat dataset to leverage convolutional neural networks for sugarcane classification from Sentinel-2	2022	Convolutional neural network; Deep network; Multi-temporal remote sensing images; Sugarcane classification	N/A	Vegetation	Classification	no
26	Sanchez, AMS; Gonzalez-Piqueras, J; de la Ossa, L; Calera, A	Convolutional Neural Networks for Agricultural Land Use Classification from Sentinel-2 Image Time Series	2022	deep learning; remote sensing; land use classification; sentinel; time series	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
27	Aldabbagh, YAN; Shafri, HZM; Mansor, S; Ismail, MH	Desertification prediction with an integrated 3D convolutional neural network and cellular automata in Al-Muthanna, Iraq	2022	Desertification prediction; Convolutional neural networks; Cellular automata; Al-Muthanna	Environmental Sciences	Geohazards	Classification	no
28	Shakya, A; Biswas, M; Pal, M	Fusion and classification of multi-temporal SAR and optical imagery using convolutional neural network	2022	Fusion; Convolutional Neural Network (CNN); Support Vector Machine (SVM); Bayesian Optimisation	Remote Sensing	Vegetation	Classification	yes
29	Z. Zhu; Y. Tao; X. Luo	HCNNet: A Hybrid Convolutional Neural Network for Spatiotemporal Image Fusion	2022	Feature fusion;hybrid convolution (Conv);spatiotemporal fusion (STF);spectral correlation	N/A	Others	Regression	yes

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30	Yang, ZW; Zhang, HB; Lyu, XX; Du, WB	Improving Typical Urban Land-Use Classification with Active-Passive Remote Sensing and Multi-Attention Modules Hybrid Network: A Case Study of Qibin District, Henan, China	2022	land-use classification; convolutional neural networks (CNN); active and passive remote sensing; data fusion	Green & Sustainable Science & Technology; Environmental Sciences; Environmental Studies	Urban	Classification	no
31	Voelsen, M; Teimouri, M; Rottensteiner, F; Heipke, C	INVESTIGATING 2D AND 3D CONVOLUTIONS FOR MULTITEMPORAL LAND COVER CLASSIFICATION USING REMOTE SENSING IMAGES	2022	land cover classification; remote sensing; FCN; multi-temporal images; 3D-CNN	Geography, Physical; Remote Sensing; Imaging Science & Photographic Technology	Urban	Classification	yes
32	Li, R; Zheng, SY; Duan, CX; Wang, LB; Zhang, C	Land cover classification from remote sensing images based on multi-scale fully convolutional network	2022	Spatio-temporal remote sensing images; Multi-Scale Fully Convolutional Network; land cover classification	Remote Sensing	Vegetation	Segmentation	yes
33	Zhang, E; Fu, YH; Wang, J; Liu, L; Yu, K; Peng, JY	MSAC-Net: 3D Multi-Scale Attention Convolutional Network for Multi-Spectral Imagery Pansharpening	2022	deep learning; multi-spectral image; 3D convolutional; multi-scale cost	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Others	Regression	no
34	Zhong, J; Sun, J; Lai, ZL; Song, Y	Nearshore Bathymetry from ICESat-2 LiDAR and Sentinel-2 Imagery Datasets Using Deep Learning Approach	2022	nearshore bathymetry; ICESat-2; Sentinel-2; 2D CNN; deep learning	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science &	Water	Regression	no

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					Photographic Technology			
35	Wang, CY; Zhang, YJ; Wu, XF; Yang, W; Qiang, HY; Lu, BB; Wang, JL	R-IMNet: Spatial-Temporal Evolution Analysis of Resource-Exhausted Urban Land Based on Residual-Intelligent Module Network	2022	remote sensing image; convolutional neural network; land use; driving force; resource depletion	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Urban	Classification	no
36	Ghandorh, H; Boulila, W; Masood, S; Koubaa, A; Ahmed, F; Ahmad, J	Semantic Segmentation and Edge Detection-Approach to Road Detection in Very High Resolution Satellite Images	2022	deep learning; convolutional neural networks; 2D attention; satellite images; road segmentation; edge detection	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Urban	Segmentation	yes
37	Saralioglu, E; Gungor, O	Semantic segmentation of land cover from high resolution multispectral satellite images by spectral-spatial convolutional neural network	2022	Remote sensing; classification; deep learning; semantic segmentation	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Segmentation	yes
38	J. Fang; G. He; Z. Zhu; B. I. M. Attaher; J. Xue	Spatial–Spectral Decoupling Interaction Network for Multispectral Imagery Change Detection	2022	Multispectral imagery change detection;spatial–spectral decoupling interaction network	N/A	Others	Classification	yes
39	Ball, JGC; Petrova, K; Coomes, DA; Flaxman, S	Using deep convolutional neural networks to forecast spatial patterns	2022	Amazon; artificial intelligence; convolutional neural networks; deep	Ecology	Vegetation	Classification	no

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		of Amazonian deforestation		learning; deforestation forecasting; machine learning; spatial forecasting; tropical forests				
40	Zhou, XY; Zhou, WZ; Li, F; Shao, ZL; Fu, XL	Vegetation Type Classification Based on 3D Convolutional Neural Network Model: A Case Study of Baishuijiang National Nature Reserve	2022	vegetation types; classification; 3D convolutional neural network; Baishuijiang National Nature Reserve	Forestry	Vegetation	Classification	no
41	S. M. M. Nejad; D. Abbasi-Moghadam; A. Sharifi; N. Farmonov; K. Amankulova; M. Lászlź	Multispectral Crop Yield Prediction Using 3D-Convolutional Neural Networks and Attention Convolutional LSTM Approaches	2023	3D-CNN;ConvLSTM;forecasting;LSTM attention;skip connection	N/A	Vegetation	Regression	yes
42	Li, Qianjing; Tian, Jia; Tian, Qingjiu	Deep Learning Application for Crop Classification via Multi-Temporal Remote Sensing Images	2023	crop type classification; deep learning; multi-temporal; remote sensing	Agronomy	Vegetation	Classification	no
43	Luo, Dong; Zhang, Hankui K.; Houborg, Rasmus; Ndekelu, Lina M. N.; Maimaitijiang, Maitiniyazi; Tran, Khuong H.; McMaine, John	Utility of daily 3 m Planet Fusion Surface Reflectance data for tillage practice mapping with deep learning	2023	Planet fusion; Tillage practice; Tillage date; Deep learning classification; Deep learning interpretation	Environmental Sciences; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
44	Fathi, Mahdiyeh; Shah-Hosseini,	3D-ResNet-BiLSTM Model: A Deep Learning Model for County-Level Soybean	2023	soybean; yield prediction; Conv3D; ResNet; BiLSTM;	Environmental Sciences; Geosciences,	Vegetation	Regression	yes

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	Reza; Moghimi, Armin	Yield Prediction with Time-Series Sentinel-1, Sentinel-2 Imagery, and Daymet Data		Sentinel 1-2; Daymet; Google Earth Engine (GEE)	Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology			
45	Nguyen, Chi; Tan, Chang Wei; Daly, Edoardo; Pauwels, Valentijn R. N.	Efficient analysis of hydrological connectivity using 1D and 2D Convolutional Neural Networks	2023	Convolutional neural network; Functional connectivity; Potential connection length	Water Resources	Water	Classification	no
46	Kanwal, Rida; Rafaqat, Warda; Iqbal, Mansoor; Weiguo, Song	Data-Driven Approaches for Wildfire Mapping and Prediction Assessment Using a Convolutional Neural Network (CNN)	2023	machine learning; wildfire assessment; CNN; random forest; fire occurrence	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Geohazards	Classification	yes
47	Zhao, Xin; Ma, Yi; Xiao, Yanfang; Liu, Jianqiang; Ding, Jing; Ye, Xiaomin; Liu, Rongjie	Atmospheric correction algorithm based on deep learning with spatial-spectral feature constraints for broadband optical satellites: Examples from the HY-1C Coastal Zone Imager	2023	Atmospheric correction; Broadband optical satellite; HY-1C coastal zone imager (CZI); Convolution neural network (CNN); Spatial-spectral feature constraint	Geography, Physical; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Others	Regression	yes
48	Wang, Zhiyuan; Fang, Shuai; Zhang, Jing	Spatiotemporal Fusion Model of Remote Sensing Images Combining Single-Band and Multi-Band Prediction	2023	spatiotemporal fusion; remote sensing; deep learning; ConvNeXt; convolutional neural network (CNN)	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science &	Others	Regression	yes

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					Photographic Technology			
49	Papadopoulou, Eleni; Mallinis, Giorgos; Siachalou, Sofia; Koutsias, Nikos; Thanopoulos, Athanasios C.; Tsaklidis, Georgios	Agricultural Land Cover Mapping through Two Deep Learning Models in the Framework of EU's CAP Activities Using Sentinel-2 Multitemporal Imagery	2023	crop classification; entropy; land cover mapping; neural networks; random forest; remote sensing; Sentinel-2 images; uncertainty	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	yes
50	Hussain, Muhammad Afaq; Chen, Zhanlong; Zheng, Ying; Zhou, Yulong; Daud, Hamza	Deep Learning and Machine Learning Models for Landslide Susceptibility Mapping with Remote Sensing Data	2023	convolutional neural network; recurrent neural networks; landslide susceptibility mapping; extreme gradient boosting; random forest	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Others	Classification	no
51	Sabo, Filip; Meroni, Michele; Waldner, Francois; Rembold, Felix	Is deeper always better? Evaluating deep learning models for yield forecasting with small data	2023	Convolutional neural networks; Agriculture; Remote sensing; Food security	Environmental Sciences	Vegetation	Regression	no
52	Fan, Xiangsuo; Chen, Lin; Xu, Xinggui; Yan, Chuan; Fan, Jinlong; Li, Xuyang	Land Cover Classification of Remote Sensing Images Based on Hierarchical Convolutional Recurrent Neural Network	2023	pixel classification; CNN; RNN; RS image classification	Forestry	Urban	Classification	yes
53	Wang, Chunyang; Yang, Kui; Yang, Wei; Qiang, Haiyang; Xue,	R-MFNet: Analysis of Urban Carbon Stock Change against the Background of Land-Use	2023	residual connection; attention mechanism; carbon density; spatio-	Environmental Sciences; Geosciences, Multidisciplinary;	Urban	Classification	no

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	Huiyuan; Lu, Bibo; Zhou, Peng	Change Based on a Residual Multi-Module Fusion Network		temporal change; deep learning	Remote Sensing; Imaging Science & Photographic Technology			
54	Zhang, Kaixin; Yuan, Da; Yang, Huijin; Zhao, Jianhui; Li, Ning	Synergy of Sentinel-1 and Sentinel-2 Imagery for Crop Classification Based on DC-CNN	2023	convolutional neural network; synthetic aperture radar (SAR); multispectral imagery; feature fusion; crop classification; polarimetric decomposition	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
55	Kou, Wenqi; Shen, Zhanfeng; Liu, Diyou; Liu, Zhe; Li, Junli; Chang, Wanqiu; Wang, Haoyu; Huang, Lan; Jiao, Shuhui; Lei, Yating; Zhang, Chi	Crop classification methods and influencing factors of reusing historical samples based on 2D-CNN	2023	reusing historical samples; crop classification; irregular satellite image time series; 2D-CNN; influencing factors	Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
56	Y. Xie; J. Tian	Multimodal Co-learning: A Domain Adaptation Method for Building Extraction from Optical Remote Sensing Imagery	2023	building extraction;multimodal data;co-learning;domain adaptation;transfer learning	Conference paper	Urban	Classification	yes
57	Patel T.; Jones M.W.; Redfern T.	Manifold Explorer: Satellite Image Labelling and Clustering Tool with Using Deep Convolutional Autoencoders	2023	dimension reduction; labelling samples; manifold exploration; remote sensing data	Computer Science, Artificial Intelligence; Computer Science, Theory & Methods	Others	Classification	yes

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58	G. S. Phartiyal; L. S. Khangarot; D. Singh	Impact of Permuted Spectral Neighborhood of High-Dimensional Msts Rs Data on Crop Classification Performance with DNN Models	2023	localized spectral information;CNNs;multi-sensor;crop classification;time-series	Conference paper	Vegetation	Classification	no

Table S8. Publications used in analysis - 3D CNN

No	Authors	Article Title	Year	Author Keywords	Research Category	Domain	ML Technique	Complex
1	Ji, SP; Zhang, C; Xu, AJ; Shi, Y; Duan, YL	3D Convolutional Neural Networks for Crop Classification with Multi-Temporal Remote Sensing Images	2018	3D convolution; convolutional neural networks; crop classification; multi-temporal remote sensing images; active learning	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
2	Xu, ZW; Guan, KY; Casler, N; Peng, B; Wang, SW	A 3D convolutional neural network method for land cover classification using LiDAR and multi-temporal Landsat imagery	2018	Big data analysis; Convolutional neural network; Land cover classification; LiDAR; Multi-temporal Landsat imagery	Geography, Physical; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Urban	Classification	yes
3	Jiang, H; Lu, N	Multi-Scale Residual Convolutional Neural	2018	haze removal; multi-scale context aggregation; residual learning;	Environmental Sciences; Geosciences,	Others	Regression	yes

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		Network for Haze Removal of Remote Sensing Images		convolutional neural network; Landsat 8 OLI	Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology			
4	Li N.; Wang R.; Zhao H.; Wei W.	AN IMPROVED FEATURE EXTRACTION METHOD BASED on CONTEXT FEATURES for MULTI-SPECTRAL REMOTE SENSING IMAGERY	2019	3D convolution network; context information; feature extraction; multi-spectral remote sensing images; small objects	N/A	Others	Classification	yes
5	A. B. Molini; D. Valsesia; G. Fracastoro; E. Magli	Deep Learning For Super-Resolution Of Unregistered Multi-Temporal Satellite Images	2019	Multi-image superresolution;convolutional neural networks;multi-temporal images	N/A	Others	Regression	yes
6	Sun, ZC; Zhao, XW; Wu, MF; Wang, CZ	Extracting Urban Impervious Surface from WorldView-2 and Airborne LiDAR Data Using 3D Convolutional Neural Networks	2019	WorldView-2; Airborne light detection and ranging (LiDAR); Impervious surface; Convolutional neural networks (CNNs); Support vector machine (SVM)	Environmental Sciences; Remote Sensing	Urban	Classification	no
7	A. S. Terliksiz; D. T. Altýlar	Use Of Deep Neural Networks For Crop Yield Prediction: A Case Study Of Soybean Yield in Lauderdale County, Alabama, USA	2019	crop yield prediction;deep neural networks;convolutional neural networks	N/A	Vegetation	Regression	no
8	Bergamasco, L; Bovolo, F; Bruzzone, L	A Novel Deep-Learning Data Structure for Multispectral Remote Sensing Images	2020	Spatial-spectral analysis; Deep-learning classification; Data-cube analysis; Convolutional	Remote Sensing; Optics; Imaging Science &	Vegetation	Classification	yes

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				Neural Network; Remote Sensing	Photographic Technology			
9	Jiang, ZC; Ma, Y	Accurate extraction of offshore raft aquaculture areas based on a 3D-CNN model	2020	N/A	Remote Sensing; Imaging Science & Photographic Technology	Water	Classification	yes
10	Chen Y.; Tang L.; Kan Z.; Latif A.; Yang X.; Bilal M.; Li Q.	Cloud and cloud shadow detection based on multiscale 3D-CNN for high resolution multispectral imagery	2020	Cloud detection; cloud shadow; convolution neural networks; multiscale 3D-CNN	Computer Science, Information Systems; Engineering, Electrical & Electronic; Telecommunicati ons	Others	Classification	no
11	Han, YL; Wei, C; Zhou, RY; Hong, ZH; Zhang, Y; Yang, SH	Combining 3D-CNN and Squeeze-and-Excitation Networks for Remote Sensing Sea Ice Image Classification	2020		Engineering, Multidisciplinary; Mathematics, Interdisciplinary Applications	Water	Classification	yes
12	M. S. Aydemir; A. N. Keyik; F. Kahraman; E. Aptoula	Land Cover Map Production of the Sakarya Basin from Multi-Temporal Satellite Images	2020	Remote sensing;convolutional neural networks;land cover;land use;CORINE	N/A	Vegetation	Classification	yes
13	Yılmaz; M. İmamoğlu; G. Özbulak; F. Kahraman; E. Aptoula	Large Scale Crop Classification from Multi-temporal and Multi-spectral Satellite Images	2020	crop classification;remote sensing;deep learning;random forest	N/A	Vegetation	Classification	yes
14	Ji, SP; Zhang, ZL; Zhang, C; Wei, SQ; Lu, M; Duan, YL	Learning discriminative spatiotemporal features for precise crop	2020		Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	yes

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		classification from multi-temporal satellite images						
15	Zhang, WC; Liu, HB; Wu, W; Zhan, LQ; Wei, J	Mapping Rice Paddy Based on Machine Learning with Sentinel-2 Multi-Temporal Data: Model Comparison and Transferability	2020	rice; convolutional neural network; F1 score; sentinel-2; transfer	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
16	Salvetti, F; Mazzia, V; Khaliq, A; Chiaberge, M	Multi-Image Super Resolution of Remotely Sensed Images Using Residual Attention Deep Neural Networks	2020	deep learning; multi-image super-resolution; attention networks; 3D convolutional neural networks	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Others	N/A It is image enhancement.	yes
17	Chen G.; Pei Q.; Kamruzzaman M.M.	Remote sensing image quality evaluation based on deep support value learning networks	2020	3D convolutional neural networks; Deep support value learning networks; Feature extraction; Remote sensing image	N/A	Others	Regression	yes
18	Dorr, F	Satellite Image Multi-Frame Super Resolution Using 3D Wide-Activation Neural Networks	2020	multi-frame super resolution; wide activation super resolution; 3D convolutional neural network; deep learning	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Others	N/A It is image enhancement.	yes
19	Wang, L; Wu, YX; Xu, JP; Zhang, HY;	STATUS PREDICTION BY 3D FRACTAL NET CNN	2020	Fractal Net; 3D CNN; Status Prediction; Remote	Mathematics, Interdisciplinary	Water	Classification	no

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	Wang, XY; Yu, JB; Sun, Q; Zhao, ZY	BASED ON REMOTE SENSING IMAGES		Sensing Images; Eutrophication	Applications; Multidisciplinary Sciences			
20	Lee, J; Im, J; Cha, DH; Park, H; Sim, S	Tropical Cyclone Intensity Estimation Using Multi-Dimensional Convolutional Neural Networks from Geostationary Satellite Data	2020	tropical cyclones; multispectral imaging; 2D; 3D convolutional neural networks	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Geohazards	Regression	no
21	Kalinicheva, E; Sublime, J; Trocan, M	Unsupervised Satellite Image Time Series Clustering Using Object-Based Approaches and 3D Convolutional Autoencoder	2020	satellite image time series; unsupervised learning; clustering; segmentation; 3D convolutional network; autoencoder	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Segmentation	yes
22	Song, Ahram; Choi, Jaewan	Fully Convolutional Networks with Multiscale 3D Filters and Transfer Learning for Change Detection in High Spatial Resolution Satellite Images	2020	multiscale three-dimensional filters; transfer learning; change detection; high spatial resolution satellite image; fully convolutional network; convolutional long short-term memory	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Urban	Classification	yes
23	Mohammadi S.; Belgiu M.; Stein A.	3D FULLY CONVOLUTIONAL NEURAL NETWORKS WITH INTERSECTION OVER UNION LOSS FOR CROP MAPPING FROM MULTI-	2021	Crop mapping; deep learning; fully convolutional neural networks; time series	N/A	Vegetation	Segmentation	yes

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		TEMPORAL SATELLITE IMAGES						
24	Meshkini K.; Bovolo F.; Bruzzone L.	AN UNSUPERVISED CHANGE DETECTION APPROACH FOR DENSE SATELLITE IMAGE TIME SERIES USING 3D CNN	2021	3D convolutional neural network; Deep learning; High resolution image; Land cover change map; Satellite image time series	N/A	Vegetation	Segmentation	no
25	Zhang Q.; Yuan Q.; Li Z.; Sun F.; Zhang L.	Combined deep prior with low-rank tensor SVD for thick cloud removal in multitemporal images	2021	Deep prior; Low-rank tensor SVD; Multitemporal images; Spatio-temporal; Thick cloud removal	N/A	Others	Regression	yes
26	Qiao, MJ; He, XH; Cheng, XJ; Li, PL; Luo, HT; Zhang, LH; Tian, ZH	Crop yield prediction from multi-spectral, multi-temporal remotely sensed imagery using recurrent 3D convolutional neural networks*	2021	Crop yield prediction; 3D convolutional neural network; Long short-term memory; Multi-temporal images	Remote Sensing	Vegetation	Regression	yes
27	He, S; Zhou, RQ; Li, SH; Jiang, S; Jiang, WS	Disparity Estimation of High-Resolution Remote Sensing Images with Dual-Scale Matching Network	2021	high-resolution remote sensing images; disparity estimation; stereo matching; convolutional neural network; dual-scale matching	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Others	Regression	yes
28	Sagan, V; Maimaitijiang, M; Bhadra, S; Maimaitiyiming, M; Brown, DR; Sidike, P; Fritschi, FB	Field-scale crop yield prediction using multi-temporal WorldView-3 and PlanetScope satellite data and deep learning	2021	PlanetScope; WorldView-3; Deep learning; Convolutionneural network; ResNet; Artificial intelligence; Food security	Geography, Physical; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Regression	no

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29	Wang D.; Bai Y.; Bai B.; Wu C.; Li Y.	Heterogeneous two-stream network with hierarchical feature Prefusion for multispectral pan-sharpening	2021	Heterogeneous network; Hierarchical feature prefusion; Pan-sharpening; Two-stream network	N/A	Others	N/A It is image enhancement	yes
30	Zhang, L; Liu, P; Wang, LZ; Liu, JB; Song, BZ; Zhang, YW; He, GJ; Zhang, H	Improved 1-km-Resolution Hourly Estimates of Aerosol Optical Depth Using Conditional Generative Adversarial Networks	2021	aerosol; conditional generative adversarial network; spatio-temporal estimation	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Others	Regression	yes
31	Fernandez-Beltran, R; Baidar, T; Kang, J; Pla, F	Rice-Yield Prediction with Multi-Temporal Sentinel-2 Data and 3D CNN: A Case Study in Nepal	2021	Sentinel-2; rice-yield estimation; regression; deep learning; Nepal	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Regression	no
32	Adrian, J; Sagan, V; Maimaitijiang, M	Sentinel SAR-optical fusion for crop type mapping using deep learning and Google Earth Engine	2021	3D U-Net; Denoising neural networks; Sentinel-1; Sentinel-2; Data fusion	Geography, Physical; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	yes
33	Qadeer M.U.; Saeed S.; Taj M.; Muhammad A.	SPATIO-TEMPORAL CROP CLASSIFICATION ON VOLUMETRIC DATA	2021	CNN; Crop Classification; Satellite data	N/A	Vegetation	Classification	yes

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34	Kong, Fanqiang; Hu, Kedi; Li, Yunsong; Li, Dan; Zhao, Shunmin	Spectral-Spatial Feature Partitioned Extraction Based on CNN for Multispectral Image Compression	2021	spectral-spatial feature; multispectral image compression; partitioned extraction; group convolution; rate-distortion	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Others	Compression	yes
35	Ibrahim, MR; Benavente, R; Lumbreras, F; Ponsa, D	3DRRDB: Super Resolution of Multiple Remote Sensing Images using 3D Residual in Residual Dense Blocks	2022	N/A	Computer Science, Artificial Intelligence; Computer Science, Theory & Methods	Others	Regression	yes
36	Jamali A.; Mahdianpari M.; Brisco B.; Mao D.; Salehi B.; Mohammadimanesh F.	3DUNetGSFormer: A deep learning pipeline for complex wetland mapping using generative adversarial networks and Swin transformer	2022	Convolutional neural networks; Deep learning; Generative adversarial network; Swin transformer; Vision transformers; Wetland mapping	N/A	Water	Classification	yes
37	Meshkini K.; Bovolo F.; Bruzzone L.	A 3D CNN APPROACH FOR CHANGE DETECTION IN HR SATELLITE IMAGE TIME SERIES BASED ON A PRETRAINED 2D CNN	2022	3D Convolutional Neural Network (CNN); Change Detection (CD); Change Vector Analysis (CVA); Deep Learning; High Resolution (HR) Image; Transfer Learning	N/A	Vegetation	Segmentation	yes
38	Jamali, A; Mahdianpari, M; Mohammadimanesh, F; Homayouni, S	A deep learning framework based on generative adversarial networks and vision transformer for complex wetland	2022	Generative adversarial network; Convolutional neural network; Wetland classification; New Brunswick; Vision	Remote Sensing	Water	Classification	yes

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		classification using limited training samples		Transformer (ViT); Deep learning				
39	Seydi, ST; Amani, M; Ghorbanian, A	A Dual Attention Convolutional Neural Network for Crop Classification Using Time-Series Sentinel-2 Imagery	2022	crop mapping; deep learning; convolutional neural networks (CNN); attention modules (AM); dual attention CNN; Sentinel-2; multi-temporal	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
40	Fei, TH; Huang, BH; Wang, X; Zhu, JX; Chen, Y; Wang, HZ; Zhang, WM	A Hybrid Deep Learning Model for the Bias Correction of SST Numerical Forecast Products Using Satellite Data	2022	SST; bias correction; deep learning; ConvLSTM; 3D-C BAM	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Water	Regression	yes
41	Azeez, OS; Shafri, HZM; Alias, AH; Haron, NA	A Joint Bayesian Optimization for the Classification of Fine Spatial Resolution Remotely Sensed Imagery Using Object-Based Convolutional Neural Networks	2022	object-based convolution neural networks; deep learning; Bayesian optimization; decision-level fusion; Worldview-3	Environmental Studies	Urban	Classification	no
42	Igeta T.; Iwasaki A.	An Unsupervised Network for Stereo Matching of Very High Resolution Satellite Imagery	2022	disparity estimation; high-resolution remote sensing imagery; stereo matching; unsupervised learning	N/A	Others	Regression	yes
43	Aldabbagh, YAN; Shafri, HZM;	Desertification prediction with an integrated 3D convolutional neural	2022	Desertification prediction; Convolutional neural	Environmental Sciences	Geohazards	Classification	no

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	Mansor, S; Ismail, MH	network and cellular automata in Al-Muthanna, Iraq		networks; Cellular automata; Al-Muthanna				
44	Phan, A; Takejima, K; Hirakawa, T; Fukui, H	FOREST-RELATED SDG ISSUES MONITORING FOR DATA-SCARCE REGIONS EMPLOYING MACHINE LEARNING AND REMOTE SENSING - A CASE STUDY FOR ENA CITY, JAPAN	2022	Forest; Tree species; Tree age; SDG; CNN; Sentinel 1/2; 3D Atrous Convolution; Ena City	Geosciences, Multidisciplinary; Remote Sensing	Vegetation	Classification	yes
45	S. Yang; L. Gu; X. Li; F. Gao; T. Jiang	Fully Automated Classification Method for Crops Based on Spatiotemporal Deep-Learning Fusion Technology	2022	Active learning;Crops;Classification algorithms;Data fusion;Deep learning;Training samples	IEEE Journals	Vegetation	Classification	no
46	Seydi, ST; Saeidi, V; Kalantar, B; Ueda, N; van Genderen, JL; Maskouni, FH; Aria, FA	Fusion of the Multisource Datasets for Flood Extent Mapping Based on Ensemble Convolutional Neural Network (CNN) Model	2022		Engineering, Electrical & Electronic; Instruments & Instrumentation	Water	Classification	no
47	Teimouri, M; Mokhtarzade, M; Baghdadi, N; Heipke, C	Fusion of time-series optical and SAR images using 3D convolutional neural networks for crop classification	2022	Crop classification; fusion; time-series radar images; time-series optical images; 3D-CNN	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Classification	no
48	Z. Zhu; Y. Tao; X. Luo	HCNNet: A Hybrid Convolutional Neural Network for	2022	Feature fusion;hybrid convolution (Conv);spatiotemporal	IEEE Journals	Others	Regression	yes

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		Spatiotemporal Image Fusion		fusion (STF);spectral correlation				
49	Yang, ZW; Zhang, HB; Lyu, XX; Du, WB	Improving Typical Urban Land-Use Classification with Active-Passive Remote Sensing and Multi-Attention Modules Hybrid Network: A Case Study of Qibin District, Henan, China	2022	land-use classification; convolutional neural networks (CNN); active and passive remote sensing; data fusion	Green & Sustainable Science & Technology; Environmental Sciences; Environmental Studies	Urban	Classification	no
50	Voelsen, M; Teimouri, M; Rottensteiner, F; Heipke, C	INVESTIGATING 2D AND 3D CONVOLUTIONS FOR MULTITEMPORAL LAND COVER CLASSIFICATION USING REMOTE SENSING IMAGES	2022	land cover classification; remote sensing; FCN; multi-temporal images; 3D-CNN	Geography, Physical; Remote Sensing; Imaging Science & Photographic Technology	Urban	Classification	yes
51	Li, R; Zheng, SY; Duan, CX; Wang, LB; Zhang, C	Land cover classification from remote sensing images based on multi-scale fully convolutional network	2022	Spatio-temporal remote sensing images; Multi-Scale Fully Convolutional Network; land cover classification	Remote Sensing	Urban	Segmentation	yes
52	Zhang, E; Fu, YH; Wang, J; Liu, L; Yu, K; Peng, JY	MSAC-Net: 3D Multi-Scale Attention Convolutional Network for Multi-Spectral Imagery Pansharpening	2022	deep learning; multi-spectral image; 3D convolutional; multi-scale cost	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Others	Regression	no
53	Wang, L; Wang, XY; Zhao, ZY; Wu, YX; Xu, JP; Zhang,	MULTI-FACTOR STATUS PREDICTION BY 4D FRACTAL CNN BASED ON	2022	Fractal Net; 4D CNN; Status Prediction; Remote Sensing Images; Eutrophication	Mathematics, Interdisciplinary Applications;	Water	Segmentation	no

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	HY; Yu, JB; Sun, Q; Bai, YT	REMOTE SENSING IMAGES			Multidisciplinary Sciences			
54	Saralioglu, E; Gungor, O	Semantic segmentation of land cover from high resolution multispectral satellite images by spectral-spatial convolutional neural network	2022	Remote sensing; classification; deep learning; semantic segmentation	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Segmentation	yes
55	Jamali, A; Mahdianpari, M	Swin Transformer and Deep Convolutional Neural Networks for Coastal Wetland Classification Using Sentinel-1, Sentinel-2, and LiDAR Data	2022	Swin transformer; 3D convolutional neural network; coastal wetlands; New Brunswick; random forest; support vector machine; deep learning	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Water	Classification	no
56	Ball, JGC; Petrova, K; Coomes, DA; Flaxman, S	Using deep convolutional neural networks to forecast spatial patterns of Amazonian deforestation	2022	Amazon; artificial intelligence; convolutional neural networks; deep learning; deforestation forecasting; machine learning; spatial forecasting; tropical forests	Ecology	Vegetation	Classification	no
57	Zhou, XY; Zhou, WZ; Li, F; Shao, ZL; Fu, XL	Vegetation Type Classification Based on 3D Convolutional Neural Network Model: A Case Study of Baishuijiang National Nature Reserve	2022	vegetation types; classification; 3D convolutional neural network; Baishuijiang National Nature Reserve	Forestry	Vegetation	Classification	no

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58	Gallo I.; Ranghetti L.; Landro N.; La Grassa R.; Boschetti M.	In-season and dynamic crop mapping using 3D convolution neural networks and sentinel-2 time series	2023	3D fully convolutive CNN; Crop mapping; Sentinel-2 time series; Short and long-term crop mapping	N/A	Vegetation	Segmentation	yes
59	S. M. M. Nejad; D. Abbasi-Moghadam; A. Sharifi; N. Farmonov; K. Amankulova; M. LÃ¡szlÅº	Multispectral Crop Yield Prediction Using 3D-Convolutional Neural Networks and Attention Convolutional LSTM Approaches	2023	3D-CNN;ConvLSTM;forecasting;LSTM attention;skip connection	N/A	Vegetation	Regression	yes
60	Liu, Mengmeng; Liu, Jiping; Xu, Shenghua; Chen, Cai; Bao, Shuai; Wang, Zhuolu; Du, Jun	3DCNN landslide susceptibility considering spatial-factor features	2023	3DCNN; spatial-factor features; landslide susceptibility; trigger factos; scale comparison	Environmental Sciences	Geohazards	Classification	no
61	Mohammadi, Sina; Belgiu, Mariana; Stein, Alfred	Improvement in crop mapping from satellite image time series by effectively supervising deep neural networks	2023	Crop mapping; Deep learning; Fully convolutional neural networks; Supervised contrastive learning; Loss function; Time series	Geography, Physical; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Segmentation	yes
62	Wang, Li; Li, Wenhao; Wang, Xiaoyi; Xu, Jiping	Remote sensing image analysis and prediction based on improved Pix2Pix model for water environment protection of smart cities	2023	Prediction; Remote sensing; Image analysis; Pix2Pix model; Water environment; Smart cities; Artificial intelligence; Deep learning; Spatial-	Computer Science, Artificial Intelligence; Computer Science, Information Systems;	Water	Regression	yes

* Column **Complex** indicates the complexity of the CNN model. "Yes" denotes models that incorporate additional techniques beyond basic 1D, 2D, 3D, or 4D architectures. "No" refers to models that consist solely of pure 1D, 2D, 3D, or 4D CNN architectures.

				temporal data; Neural network	Computer Science, Theory & Methods			
63	G. S. Phartiyal; L. S. Khangarot; D. Singh	Impact of Permuted Spectral Neighborhood of High-Dimensional Msts Rs Data on Crop Classification Performance with DNN Models	2023	localized spectral information;CNNs;multi-sensor;crop classification;time-series	N/A	Vegetation	Classification	no
64	N. Wang; Z. Ma; P. Huo; X. Liu	Predicting Crop Yield Using 3D Convolutional Neural Network with Dimension Reduction and Metric Learning	2023	crop yield prediction;metric learning;3D convolutional neural network;feature constraint;multitask learning	N/A	Vegetation	Regression	yes
65	Zhao, Xin; Ma, Yi; Xiao, Yanfang; Liu, Jianqiang; Ding, Jing; Ye, Xiaomin; Liu, Rongjie	Atmospheric correction algorithm based on deep learning with spatial-spectral feature constraints for broadband optical satellites: Examples from the HY-1C Coastal Zone Imager	2023	Atmospheric correction; Broadband optical satellite; HY-1C coastal zone imager (CZI); Convolution neural network (CNN); Spatial-spectral feature constraint	Geography, Physical; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Others	Regression	yes
66	Wang N.; Ma Z.; Huo P.; Liu X.	3D Convolutional Neural Network with Dimension Reduction and Metric Learning for Crop Yield Prediction Based on Remote Sensing Data	2023	crop yield prediction; metric learning; 3D convolutional neural network; feature constraint; multitask learning	Chemistry, Multidisciplinary; Engineering, Multidisciplinary; Materials Science, Multidisciplinary; Physics, Applied	Vegetation	Regression	no

* Column **Complex** indicates the complexity of the CNN model. "Yes" denotes models that incorporate additional techniques beyond basic 1D, 2D, 3D, or 4D architectures. "No" refers to models that consist solely of pure 1D, 2D, 3D, or 4D CNN architectures.

Table S9. Publications used in analysis - 4D CNN

No	Authors	Article Title	Year	Author Keywords	Research Category	Domain	ML Technique	Complex
1	Wang, L; Wang, XY; Zhao, ZY; Wu, YX; Xu, JP; Zhang, HY; Yu, JB; Sun, Q; Bai, YT	MULTI-FACTOR STATUS PREDICTION BY 4D FRACTAL CNN BASED ON REMOTE SENSING IMAGES	2022	Fractal Net; 4D CNN; Status Prediction; Remote Sensing Images; Eutrophication	Mathematics, Interdisciplinary Applications; Multidisciplinary Sciences	Water	Segmentation	no
2	Giannopoulos, M; Tsagkatakis, G; Tsakalides, P	4D U-Nets for Multi-Temporal Remote Sensing Data Classification	2022	remote sensing; u-nets; higher-order convolutional neural networks; multi-temporal data classification	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology	Vegetation	Segmentation	yes
3	Giannopoulos M.; Tsagkatakis G.; Tsakalides P.	4D CONVOLUTIONAL NEURAL NETWORKS FOR MULTI-SPECTRAL AND MULTI-TEMPORAL REMOTE SENSING DATA CLASSIFICATION	2022	Convolutional Neural Networks; Land-Cover Classification; Remote Sensing; Time-series	N/A	Vegetation	Segmentation	no

* Column **Complex** indicates the complexity of the CNN model. "Yes" denotes models that incorporate additional techniques beyond basic 1D, 2D, 3D, or 4D architectures. "No" refers to models that consist solely of pure 1D, 2D, 3D, or 4D CNN architectures.