REMOTE SENSING AND DEEP LEARNING INTEGRATION FOR SPATIAL INTELLIGENCE

Ventsislav Polimenov

Krassimira Ivanova

Institute of Mathematics and Informatics, Bulgarian Academy of Sciences, **Bulgaria**

ABSTRACT

This review article provides an overview of the combination of remote sensing with deep learning techniques in the last ten years. It specifically examines the emerging patterns and applications in both fields, highlighting their combined use in processing remote sensing data. It focuses on how these techniques have brought about significant changes in environmental monitoring, urban planning, agricultural management, security, and change detection. The article discusses various satellite probes, detailing their specific capabilities, technological attributes, and suitability for diverse observational tasks. Also, it stops attention on multispectral fusion techniques aimed to integrate data from multiple spectral bands or sensors to enhance the overall quality of remote sensing imagery. Additionally, it provides an overview of potential neural network architectures, highlighting the necessity for innovative algorithms that can effectively manage the growing amount and diversity of remote sensing datasets. The discussion revolves around the authors' aspirations for future research, employing advanced deep learning models for understanding complex spatial and spectral patterns.

Keywords: Remote Sensing, Deep Learning, Artificial Intelligence, Image Processing, Image Fusion

1. INTRODUCTION

The rapid development of technology especially in the last decade has led to a huge leap in the advancement of remote sensing technologies and their use in various disciplines including environmental monitoring, agriculture, urban planning, and disaster management. Technological innovations in the field of satellites and drones, as well as significant improvements in sensors for capturing various terrestrial features, have democratised access to remote sensing data and created the possibility of using the collected data to conduct intelligent analyses that support informed decision-making. Collaborative efforts between academia, industry, governments, and international organizations have led to a growing development of innovation in remote sensing technologies, resulting in improved spatial resolution, temporal coverage, and data processing techniques. Of great importance in this process is the integration of remote sensing with the disciplines related to the analysis of large volumes of data and artificial intelligence (in particular, deep learning), which has created new opportunities for extracting meaningful insights from huge and complex data sets.

The increased interest in remote sensing as well as the integration of this area with the capabilities of artificial intelligence techniques is also evidenced by the increasing

https://doi.org/10.5593/sgem2024/2.1/s10.33

number of articles indexed in Scopus. Figure 1 shows this trend based on the number of publications over the last ten years filtering in keywords by (1) “remote sensing” and (2) “remote sensing” in combination with (“artificial intelligence” OR “machine learning” OR “deep learning” OR “neural networks”). The number of publications for 2024 is approximated based on the first quarter of the year when this research is done. Figure 2 shows that generally the research is focused on proposing new or enhancing existing mathematical algorithms (about a quarter of research is in the area “Computer Science and Mathematics”), engineering (16%), as well as applying such techniques to support the research in Earth and Planetary Sciences, Astronomy, Environment, and Agricultural and Biological Sciences.

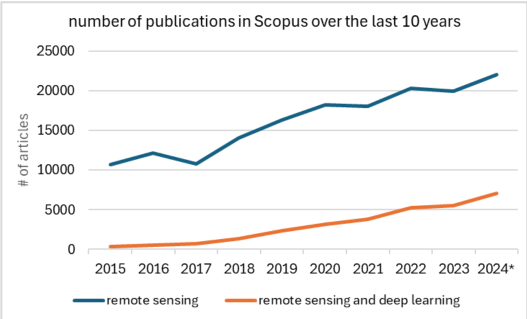

Figure 1: Number of publications in Scopus over the last ten years filtering in keywords by (1) “remote sensing” and (2) “remote sensing” in combination with (“artificial intelligence” OR “machine learning” OR “deep learning” OR “neural networks”). The number of publications for 2024 is approximated based on the first quarter of the year.

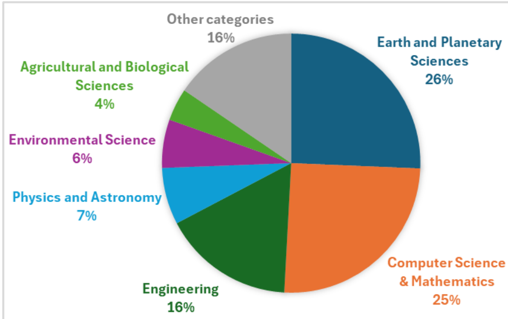

Figure 2: Publications in Scopus over the last ten years filtering in keywords by “remote sensing” in combination with (“artificial intelligence” OR “machine learning” OR “deep learning” OR “neural networks”) grouped by subject areas (some publications are classified in more than one area).

Due to the high interest over the last few years in this area, we are going to review the current state-of-the-art methods and methodologies to apply deep learning models to remote sensing data. Furthermore, we will identify gaps and misconceptions in the current understanding and applications of these satellite technologies. Additionally, we will outline potential solutions and improvements to enhance accuracy and efficiency.

In Chapter 2 we describe the current trends in Remote Sensing and Deep Learning as well as the combination of both fields. In Chapter 3 we discuss the benefits and optimisation strategies. And finally, we conclude with future directions and final remarks.

2. CURRENT TRENDS IN REMOTE SENSING AND DEEP LEARNING

The questions that we posed in this study can be summarised as follows:

1) what are the current trends in remote sensing and respective needs;
2) what is the current state of deep learning algorithms directly related to those needs;
3) how effective is deep learning in remote sensing.

In the next subsections we will try to answer these questions.

2.1. Trends in Remote Sensing

Remote sensing satellite missions are essential for land conservation and global sustainability by providing crucial data through multispectral imaging. Such images depict spectral signatures that represent distinct land cover features throughout the electromagnetic spectrum [10]. The increase in worldwide open data satellite missions has significantly expanded the use of remote land observation, leading to widespread accessibility to satellite imagery [2].

In remote sensing, the main types of images used are [17]:

- Panchromatic images (PAN) record data in a spectral band covering the visible spectrum and near-infrared region. These images are high-resolution single-channel grayscale and allow visual analysis of the Earth's surface.
- Multispectral images (MS) record data in multiple spectral bands in the electromagnetic spectrum. Multispectral imagery is commonly used in applications such as land cover classification, agricultural monitoring, and environmental analysis.

Furthermore, a crucial attribute is the radiometric resolution. The sensitivity of the sensors is defined as their ability to detect small variations in energy levels. This sensitivity is typically measured in bits, which enables a more precise distinction between similar, although not identical, targets.

PAN images can provide high spatial resolution but are composed of only one band. The MS images possess several spectral bands and contain an array of spectral information, but the spatial details are inferior to the details in the PAN images. On the other side, freely available satellite imagery generally has lower spatial resolution compared to commercial satellites, which can make extensive analysis more challenging.

During the last few decades, the availability of high spatial, temporal, spectral, and radiometric resolution imagery from low-orbiting small satellites has greatly improved, widening the remote sensing applications further with better precision and accuracy. Especially, satellites such as GeoEye, IKONOS, KOMPSAT-3, Landsat 8, Pleiades 1A, Pleiades 1B, QuickBird, Sentinel 2, and WorldView-3 have been effectively utilised in many agricultural applications [16]. These applications encompass but are not restricted to the retrieval of vegetation indices [12], the estimation of plant height [15], evapotranspiration [11], leaf/canopy chlorophyll content [6], and yield [7].

The diversity in spatial and temporal resolutions, spectral characteristics (Table 1 and Figure 3), and the varying shapes of output images from different satellite probes complicate the application of deep learning algorithms to remote sensing imagery. These variances need the creation of versatile, adaptable models that can effectively handle datasets with varying quality and dimensions.

Table 1: Spatial and temporal resolution and spectral differences between different satellite probes [10][17]

Satellite	Spatial resolution PAN (m)	Spatial resolution MS (m)	Spectral bands (#)	Temporal resolution (days)	Radiometric resolution (bits)	Swath width (km)	Wavelength range (nm)
GeoEye-1	0.41	1.65	4	1 – 3	11	15.2	250 – 800
IKONOS	0.82	3.2	4	1 – 3	11	11.3	445 – 853
KOMPSAT-3	0.7	2.8	5	1	14	15	450 – 900
Landsat 8	15	30	11	16	16	185	433 – 12500
Pleiades 1A, 1B	0.5	2	4	1	12	20	430 – 950
QuickBird	0.65	2.62	4	1 – 3.5	11	16.5	450 – 900
Sentinel 2	10	20	13	2 – 3	12	290	442 – 2186
WorldView-2	0.46	1.84	8	1.1	11	16.4	400 – 1040
WorldView-3	0.31	1.24	28	1	11	13.1	397 – 2373

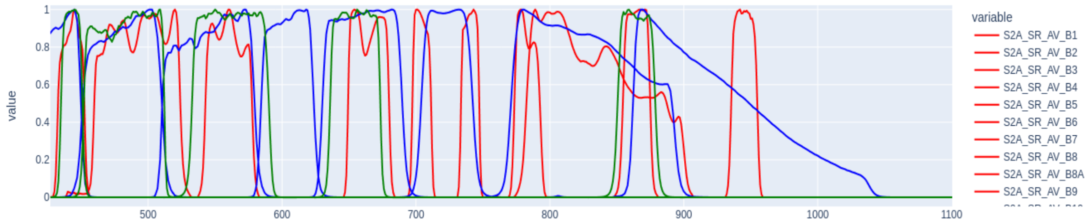

Figure 3: Differences between spectral bands of WorldView-3 (blue), Landsat 8 (green) and Sentinel 2 (red).

Regardless of the constant increase in the quality of multispectral imaging sensors, there is always a need for improving the spatial resolution of multispectral bands – a process called pansharpening. There are different image fusion methods used for pansharpening – some of them based on classical data mining methods, such as component substitution and multiresolution analysis, as well as the new deep learning techniques, which can generally be classified into three main groups – source image concatenation (the neural network directly combines MS and PAN images into one), feature concatenation (firstly as preprocessing step two different sub-networks filtered some redundant information and this way avoid spatial and spectral distortions in the fused image), and feature fusion (aimed to merge the complementary information of MS and PAN images in the feature domain by different fusion rules) [17]. For example, in [9] authors introduced a novel approach for applying image fusion across different satellite probes. They took advantage of the relationship between Land surface temperature and spectral indices to downscale the data from 1000 to 10 and 30 m resolutions.

2.2. Deep Learning

Recently, with the successful applications of deep learning in the field of computer vision, there has been a significant increase in research that invents or improves such methods in tasks involving the use of remote sensing data. According to [8] the following deep learning techniques and combinations of them are most frequently used in remote sensing applications:

- Convolutional Neural Network (CNN) is used as a basis of most models. CNN is designed to learn spatial hierarchies of features automatically and adaptively from input data. CNNs are successfully used for various tasks such as classification, object detection, and feature extraction. Wildly used varieties of CNN are FCN (where fully connected layers are replaced by convolutional layers allowing to preserve of spatial information across layers and this way very appropriate for tasks involving pixel-wise predictions), U-net (the most widely utilized model, which uses skip connections for facilitating the fusion of low-level and high-level features), and SegNet (which utilizes the max-pooling indices obtained during the downsampling in the encoder phase to perform efficient upsampling in the decoder phase) [8].
- Attention Mechanism is another prevalent technique, inspired by the idea of selective focus in human perception and cognition. It allows the model to dynamically focus on different parts of the input data, giving greater weight to certain features based on their applicability to the task at hand. Such mechanisms show better performance and interpretability against other models, especially in tasks involving sequential or structured data.

- Multi-Scale Strategy refers to the use of procedures that examine and interpret data at several levels or resolutions to encompass a broad spectrum of characteristics, ranging from fine details to more general patterns. By using multi-scale representations, models can enhance their ability to generalize across a wide range of input data sizes and forms, resulting in improved accuracy and robustness. Such models are very convenient for detecting objects, for instance – vehicles [5].
- Transformer was originally applied in the field of natural language processing but has been adapted to handle spatial data by transforming the images into non-overlapping patch sequences and has demonstrated remarkable performance in remote sensing tasks like classification, semantic segmentation, and change detection [8].
- Generative Adversarial Network (GAN) is a relatively new paradigm, that has gained a lot of popularity recently. GANs generate new synthetic data that resembles real data by pitting two neural networks (Generator and Discriminator) against each other. The generator tries to capture the true distribution of the data to generate new samples. On the other hand, the discriminator tries to distinguish the real from the generated samples as accurately as possible. In remote sensing, GANs are used for data augmentation, pansharpening, super-resolution, cloud removal, etc. [3]

Regardless of the improvements that each of the above mechanism provides, the classical application of neural networks assumes the presence of a vast amount of training data. For this reason, the transfer-learning methods have recently come into force. In transfer learning a pre-existing model created for one generic activity is used as a base for a model designed for a specific purpose. The use of it in remote sensing is particularly valuable because of the extensive variety and quantity of data, frequently accompanied by a lack of labelled samples for certain tasks [5]. Transfer learning, through the utilisation of pre-trained models on larger datasets, enables improved generalisation, reduces the requirement for substantial processing resources, and decreases the training time. This makes it highly efficient for remote sensing applications.

2.3. Remote Sensing and Deep Learning

Deep learning techniques have found wide application in remote sensing due to their ability to extract complex patterns and features from satellite or aerial imagery [1]. As the main tasks in which deep learning is used in remote sensing, we can single out:

- Classification: Categorising images into predefined categories, such as land cover types. Such applications are very useful in land use planning, environmental monitoring, and disaster management.
- Regression: Applying statistical methods to model and assess the relationships between spectral data captured by various sensors and the actual conditions on the ground. This could be fundamental for tasks such as predicting crop yields, which is a complex but crucial activity for managing agricultural lands effectively. The success of these predictions depends on multiple factors, including climate, weather conditions, soil properties, fertilizer usage, and the types of seeds used.
- Segmentation: Identifying objects or regions in the image to delineate buildings, water surfaces, agricultural fields, etc. In this case, each pixel of the image is assigned a class label (semantic segmentation [13]) or an object label (instance segmentation [14]).
- Change detection: Analysis of multiple images of the same location to identify ongoing changes such as urban growth, deforestation, change of riverbeds, etc. This type of task is particularly important for monitoring environmental trends.

Deep learning techniques are also extremely useful as elements in the preprocessing step of more complex tasks, such as:

- Enhancing the spatial resolution and improving the visual quality of remote sensing images (so-called techniques for super-resolution).
- Integrating information from different remote sensing modalities (so-called data fusion techniques).
- Extracting valuable insights and meaningful features from remote sensing images. Such tasks include using classification, anomaly detection, and feature extraction techniques.

3. DISCUSSIONS

The application of deep learning in remote sensing also encounters some specific obstacles and limitations [4], some of which are:

- Cost and accessibility – The high cost and limited accessibility of high-resolution satellite imagery pose significant challenges, especially for small-scale projects or researchers with limited funding. High-resolution images, which provide detailed information crucial for precise analysis, are typically more expensive because of the advanced technology required to capture them. Additionally, the best quality imagery is often controlled by private companies or governments, which can restrict access based on commercial interests or security concerns. This can inhibit the ability of researchers and organizations to conduct timely and effective environmental monitoring, urban planning, and disaster response initiatives.
- Data variability, volume, and management – The collection of remote sensing data under diverse environmental and temporal conditions leads to significant variability in the data, which presents challenges for deep learning models especially in regard of consistency. Variability can affect various aspects such as lighting, shadows, and atmospheric conditions, thus causing significant changes in data representation and making the task of consistency challenging. In addition, the large amount of data generated by remote sensing technologies requires the need of robust data management systems to store, process, and retrieve data effectively. This adds complexity to both operational logistics and computational processing.
- Model adaptability – Developing deep learning models that can effectively process and analyse data across multiple dimensions – spatial, spectral, and temporal is a difficult task. Each dimension adds complexity: spatial analysis must account for variations in scale and perspective, spectral analysis requires decoding information across different wavelengths (which may indicate vegetation types, water bodies, etc.), and temporal analysis tracks changes over time, adding dynamic behaviour to the model. The integration and simultaneous analysis of these dimensions require sophisticated algorithmic strategies and substantial computational resources, often challenging the limits of current technologies and methodologies.
- Transferability – Transferability is a significant challenge in remote sensing models, where a model trained on data from one geographic area or under specific conditions might fail to generalise to other areas or different environmental conditions. This constraint frequently arises due to the presence of various land cover types, atmospheric conditions, and seasonal fluctuations that are not accounted for in the training dataset. Thus, to improve the capacity of a model, it is necessary to train it

extensively on a wide range of datasets or use sophisticated methods such as domain adaptation, which would allow models to perform effectively in multiple domains.

CONCLUSION AND FUTURE DIRECTIONS

Our research presents an examination of the latest advancements in both remote sensing and deep learning as applied to image processing. We highlighted several critical limitations that need addressing to advance further. In addition, we have identified crucial areas that require more investigation and advancement to improve the capabilities and potential uses of these technologies in the future.

Developing a unified neural network capable of processing multispectral images across varying spatial resolutions and spectral characteristics would represent a significant advancement in remote sensing technology. Such a network would need to robustly handle the details and complexities of different image types, allowing for more flexible and comprehensive analysis. This would involve advanced techniques in image processing and neural network design, leveraging architectures that can dynamically adjust to the input image characteristics.

Furthermore, our research highlighted the significant differences in spectral bands across various satellite probes and their sensors. Moving forward, we anticipate conducting follow-up research aimed at developing methods to normalize these spectral variations, facilitating the creation of a unified analytical framework for multispectral image processing.

Advanced pansharpening algorithms are also increasingly necessary to enhance the accuracy and effectiveness of image fusion, improving both spatial and spectral quality. The development of these techniques requires the improvement of algorithms to successfully combine high-resolution spatial information with broad spectrum data, resulting in clearer and more detailed representations of targeted areas.

ACKNOWLEDGEMENTS

The research is partially supported by “NGIC – National Geoinformation Center for monitoring, assessment and prediction of natural and anthropogenic risks and disasters” under the Program “National Roadmap for Scientific Infrastructure 2017–2023”, financed by the Bulgarian Ministry of Education and Science.

REFERENCES

[1] Adegun A., S. Viriri, and J.-R. Tapamo. Review of deep learning methods for remote sensing satellite images classification: experimental survey and comparative analysis. Journal of Big Data, vol. 10, p. 93, Jun 2023.

[2] Agutu N., J. Awange, A. Zerihun, C. Ndehedehe, M. Kuhn, and Y. Fukuda. Assessing multi-satellite remote sensing, reanalysis, and land surface models’ products in characterizing agricultural drought in East Africa. Remote Sensing of Environment, vol. 194, pp. 287–302, 2017.

[3] Dash A., J. Ye, G. Wang. A review of generative adversarial networks (gans) and its applications in a wide variety of disciplines: from medical to remote sensing. IEEE Access, 12, pp. 18330–18357, art. no. 3346273, 2024.

[4] Han W., X. Zhang, Y. Wang, L. Wang, X. Huang, J. Li, S. Wang, W. Chen, X. Li, R. Feng, R. Fan, X. Zhang, and Y. Wang. A survey of machine learning and deep learning in remote sensing of geological environment: Challenges, advances, and

opportunities. ISPRS Journal of Photogrammetry and Remote Sensing, vol. 202, pp. 87–113, 2023.

[5] Hosseiny B., M. Mahdianpari, M. Hemati, A. Radman, F. Mohammadimanesh, and J. Chanussot. Beyond supervised learning in remote sensing: a systematic review of deep learning approaches. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 17, pp. 1035–1052, 2024.

[6] Houborg R., M. McCabe, A. Cescatti, F. Gao, M. Schull, and A. Gitelson. Joint leaf chlorophyll content and leaf area index retrieval from landsat data using a regularized model inversion system (regflec). Remote Sensing of Environment, vol. 159, pp. 203–221, 2015.

[7] Lai Y., M. Pringle, P. Kopittke, N. Menzies, T. Orton, and Y. Dang. An empirical model for prediction of wheat yield, using time-integrated landsat ndvi. International Journal of Applied Earth Observation and Geoinformation, vol. 72, pp. 99–108, 2018.

[8] Lv J., Q. Shen, M. Lv, Y. Li, L. Shi, and P. Zhang. Deep learning-based semantic segmentation of remote sensing images: a review. Frontiers in Ecology and Evolution, 11, art. no. 1201125, 2023.

[9] Mokhtari A., H. Noory, F. Pourshakouri, P. Haghighatmehr, Y. Afrasiabian, M. Razavi, F. Fereydooni, and A. Sadeghi Naeni. Calculating potential evapotranspiration and single crop coefficient based on energy balance equation using landsat 8 and sentinel-2. ISPRS Journal of Photogrammetry and Remote Sensing, vol. 154, pp. 231–245, 2019.

[10] Radočaj D., J. Obhođaš, M. Jurišić, and M. Gašparović. Global open data remote sensing satellite missions for land monitoring and conservation: A review. Land, vol. 9, no. 11, 2020.

[11] Reyes-Gonzalez A., J. Kjaersgaard, T. Trooien, C. Hay, and L. Ahiablame. Estimation of crop evapotranspiration using satellite remote sensing-based vegetation index. Advances in Meteorology, vol. 2018, p. 4525021, Feb 2018.

[12] Tattaris M., M. Reynolds, and S. Chapman. A direct comparison of remote sensing approaches for high-throughput phenotyping in plant breeding. Frontiers in Plant Science, vol. 7, 08 2016.

[13] Wang L., C. Zhang, R. Li, C. Duan, X. Meng, and P. M. Atkinson. Scale-aware neural network for semantic segmentation of multi-resolution remote sensing images. Remote Sensing, vol. 13, no. 24, 2021.

[14] Xu Z., T. Wang, A.K. Skidmore, and R. Lamprey. A review of deep learning techniques for detecting animals in aerial and satellite images. International Journal of Applied Earth Observation and Geoinformation, vol. 128, art. no. 103732, 2024.

[15] Yang Z., Y. Shao, K. Li, Q. Liu, L. Liu, and B. Brisco. An improved scheme for rice phenology estimation based on time-series multispectral hj-1a/b and polarimetric radarsat-2 data. Remote Sensing of Environment, vol. 195, pp. 184–201, 2017.

[16] Zhang C., A. Marzougui, and S. Sankaran. High-resolution satellite imagery applications in crop phenotyping: An overview. Computers and Electronics in Agriculture, vol. 175, p. 105584, 2020.

[17] Zhang, K., F. Zhang, W. Wan, H. Yu, J. Sun, J. Del Ser, E. Elyan, and A. Hussain. Panchromatic and multispectral image fusion for remote sensing and earth observation: Concepts, taxonomy, literature review, evaluation methodologies and challenges ahead. Information Fusion, 93, pp. 227-242, 2023.