Guest Editorial
Special Issue on Deep Learning for Earth and Planetary Geosciences

EARTH and planetary geosciences are essential for understanding and addressing many societal challenges and scientific questions. Increased availability of geoscience data creates an opportunity for deep learning to advance the methods and scientific understanding for tackling these challenges. However, the complex characteristics of geoscience problems and datasets necessitate the development of novel approaches and frameworks. This Special Issue aims at collecting new ideas and deep learning formulations to gain new earth and planetary insights. The contributions cover a wide range of topics, such as satellite and hyperspectral imaging, land monitoring, geophysical imaging, and subsurface analysis.

I. Overview of the Special Issue

Geosciences study the connection between the hydrological, biological, atmospheric, and lithospheric characterizations of the Earth and other planetary bodies. It plays a crucial role in addressing many pressing societal challenges. These include managing the risks of climate change and understanding its effects on hydrological, biological, and atmospheric processes. Other applications include underground carbon capture, energy development, and space exploration. Characterizations of these natural systems have relied traditionally on physical, chemical, and biological models. In addition to being computationally expensive, the available models are limited to processes that are well-understood and from which measurements can be directly acquired. Moreover, they struggle with noise in the data, due to sensors or [the inherent variability in the processes], and a potential mismatch between the assumed model structure and the characteristics of the modeled process. Machine learning, and deep learning in particular, has made great progress in managing these difficulties and has an opportunity to advance geoscience and augment the methods and models used.

Direct application of deep learning methods in geosciences is often difficult or has had limited impact, however. That is due to the complexity of geoscience data and the difficulties in meeting the needs of geoscience problems. The difficulties include high dimensionality, strong spatiotemporal correlations, and heterogeneity in the data. One usually also wants deep learning to integrate with available scientific models where they exist. Furthermore, ground-truth data in geosciences is scarce because of the high cost or impracticality of acquiring such data or the inherent rare or sparse nature of the elements of interest. This limits the applicability and robustness of supervised deep-learning methods. Therefore, resolving geoscience problems requires the development of new deep learning formulations and methods.

This Special Issue aims to provide a timely reference for future deep learning research in geosciences. The articles collected herein tackle several of the aforementioned difficulties. These include the development of physics-guided models, handling high-dimensional imagery, and reducing different forms of noise. These are then applied to foundational aspects of geoscience, such as the characterization of ocean temperatures, the Earth's subsurface, or land-cover recognition. A summary of the accepted articles is provided in the following sections.

II. Remote Sensing, Imaging, and Land Characterization

Given the large scale of geoscience processes, the ability to image the planet's surface from satellite hyperspectral sensor measurements accurately and at higher resolutions is crucial. Toward that end, Vandal and Nemani [A1] propose a deep learning-based optical flow method for temporal upsampling of geostationary satellite imagery. While this problem has similarities to video frame interpolation, they address the high-dimensionality and varying spatial resolutions and characteristics of different spectral channels. This provides higher frequency observations needed, for example, for studying mesoscale weather events and improving weather tracking and forecasting of several convective events.

Noise in hyperspectral imaging (HSI) limits the usefulness of the resulting images and the performance of downstream analyses. Guan et al. [A2] handle the issue of stripe noise in such images. Unlike standard image denoising techniques which assume independent noise, stripe noise is spatially correlated making it harder to remove. They propose a recurrent convolutional neural network that utilizes the intrinsic spatial and spectral correlation structure of hyperspectral images to preserve both while denoising. Experiments on real data demonstrate the ability of their method to greatly improve the images compared to previous approaches.

A novel approach to HSI denoising is also proposed by Li et al. [A3]. Rather than treat the denoising step as an independent, separate step, they consider the downstream use of the images (e.g., classification). They present a framework for joint denoising and classification of hyperspectral images which accounts for the high dimensionality and varying noise statistics across spectral bands. They propose a compound loss

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function which ensures that denoising and classification jointly optimize the overall result.

Then, a major challenge in remote sensing is finding correspondences between images. Chen et al. [A4] present a novel neural network to address this issue. The proposed deep learning architecture learns correspondence by successively refining the matching of image features and the spatial correlation structure between the matched features. This enables the registration of images from different perspectives, scales, and modalities.

Remote sensing images are then frequently analyzed to understand land cover dynamics. Kaselimi et al. [A5] conduct such a study and demonstrate how a vision transformer can be used to monitor deforestation and understand the underlying factors. They approach the problem from a multilabel image classification perspective which simultaneously detects the different labels related to the drivers of deforestation observable on the areas at the edge of forests. This understanding is crucial for developing the correct forest conversation and management policies.

Another application of remote sensing is in urban land analysis. In particular, Liu et al. [A6] tackle the problem of automatic extraction of traffic roads. Attempts to achieve this from aerial images directly are fraught with many challenges, such as occlusions and imaging limitations. To solve this they propose a multistage cross-modal data fusion architecture which successively refines and shares information between modalities across the layers of the architecture. They demonstrate their approach for road extraction using aerial images and vehicle crowdsourced trajectories, which can inform future urban planning and land use development.

Of course, a challenge in training models for land analysis or classification is the limited availability of labeled data, which Kalita and Roy [A7] propose addressing by domain adaptation between datasets. Starting from a network trained on a dataset, their approach selects target images with high classification confidence. These are then used with the source images for learning a common subspace using a Siamese network. This enables learning a classifier using the source dataset labels which can also be robustly applied to other datasets.

The need for surface characterization also arises in planetary geosciences. Xiao et al. [A8] propose a method for rock detection in a Mars rover. They utilize a kernel-based methodology to handle the diverse morphology of Martian rocks from currently limited data and on tight computational constraints. Since interplanetary vehicles must operate largely autonomously, approaches such as this are crucial for vehicle navigation, obstacle avoidance, and determining which rocks or soil to sample.

III. Physics-Guided Modeling

In many geoscience aspects, physics models provide the best-known characterization of Earth processes but their numerical computation is slow and expensive. Duffy et al. [A9] provide a framework to train deep learning-based surrogate models to approximate high-resolution numerical models. The framework learns Bayesian deep learning models using variational Dropout for uncertainty quantification. When applied in a satellite-based atmospheric correction case study, they found that deep learning models can reproduce the predictions of a high-resolution model acceptably but are faster and able to estimate the predictive uncertainty.

Deep learning models can also be used in conjunction with physics models to augment the predictions and provide easy adaptation to new data, as presented by Meng et al. [A10]. They propose to first use the results of a numerical model of sea subsurface temperature to train a generative adversarial network (GAN) such that it emulates the spatial continuity and physical relationships between temperatures at different depths. The GAN model is then finetuned using remotely sensed sea surface temperature and sparse sea subsurface measurements, which enable the predictions to adapt to varying data conditions and limitations in the numerical model. Their approach enables widespread and frequent monitoring of sea subsurface temperatures.

IV. Subsurface Imaging and Characterization

Many geoscience studies need the ability to monitor the Earth's subsurface processes, such as those leading to earthquakes. One way to do this is through distributed acoustic sensing, but the signal is often mixed with many sources of noise. van den Ende et al. [A11] present a self-supervised deep learning method that both removes noise and enhances the signal. They use the fact that the signal of interest exhibits long-range coherence across the spatially distributed recording locations whereas the noise aspects do not. This spatial invariance property is used to self-supervise the training of a U-net model that infers the denoised, coherent signal from recordings at other locations. This enables, for example, monitoring and detection of microseismicity events in noisy environments, such as in urban settings.

Seismic interferometry can also be used to infer the Earth's structure by leveraging the cross-correlation between naturally occurring acoustic noise sources. In practice, the application of seismic interferometry is challenging because of correlated and inhomogeneous noise sources. Sun and Demanet [A12] propose to learn a neural network that transforms correlograms and yields the correct Green's function characterization of the subsurface. And, unlike previous work, their approach can determine this from short noise recordings and undistributed noise sources, enabling real-time monitoring of processes in the Earth's subsurface.

Seismic imaging using active sources is also frequently used, especially in applications requiring higher imaging resolution. A common issue is the presence of noise in the recorded seismic signals, which limits the quality of the subsurface imaging result. Iqbal [A13] proposes a noise reduction framework to filter out both correlated and uncorrelated noise. The method learns a sparse representation of time–frequency seismic signal segments using a deep convolutional neural network, which then uses to reconstruct the denoised signal.

Some forms of noise arise from specific seismic acquisition approaches. Simultaneous-source seismic acquisition reduces the cost of acquisition but causes the blending of seismic signals (i.e., superposition in time). Wang et al. [A14] tackle this problem by learning a neural network to minimize a self-supervised blending loss function. This enables training a deblending network without ground truth data. Since deblending is an under-determined problem, they further regularize the training by randomly masking traces out and ensuring that the network can recover them, which removes trace-wise independent blending noise.

Once the subsurface is imaged, the result must be analyzed to identify underground geologic features of interest, such as salt bodies. Saad et al. [A15] propose a deep convolutional neural network to automatically segment salt bodies, avoiding time-consuming manual analysis. The network uses squeeze-and-excitation blocks to control a self-attention mechanism which allows it to more efficiently extract the relevant information needed to identify salt from its context. They demonstrate the ability of their method to generalize between datasets.

Wells provide direct access to subsurface rocks. Still, the characterization of rock properties, such as porosity and permeability, often requires experiments from core samples which are costly and impractical to perform beyond localized well-depth intervals. To handle this, Yang et al. [A16] present a deep learning approach for estimating porosity and permeability from well logs. A novel aspect of their approach is the combination of convolutions for determining local context across well logs measurements and a bidirectional long short-term memory self-attention mechanism to infer relevant information at other depths.

V. Concluding Remarks

With this Special Issue, we aimed to bring together geoscientists and machine learning researchers to encourage future work and collaboration on these important topics. The articles compiled in this Special Issue provide examples and a timely overview of such methods. As these articles demonstrate, the machine learning community has a unique opportunity to help solve many technical issues, answer-related geoscience questions, and tackle associated societal challenges.

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Appendix: Related Articles

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