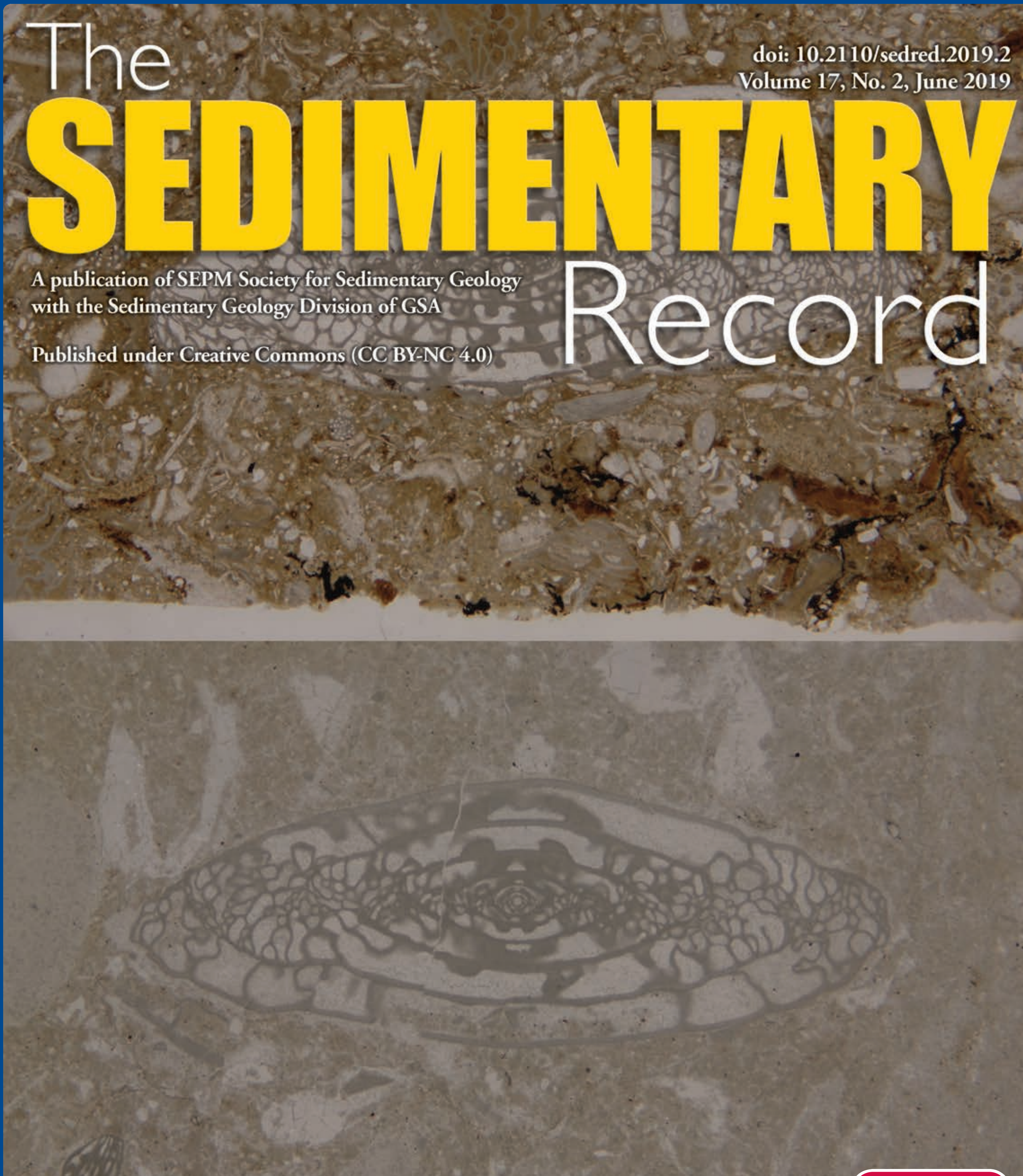
The SEDIMENTARY Record

doi: 10.2110/sedred.2019.2
Volume 17, No. 2, June 2019

A publication of SEPM Society for Sedimentary Geology
with the Sedimentary Geology Division of GSA



INSIDE: DEEP CONVOLUTIONAL NEURAL NETWORKS AS A GEOLOGICAL IMAGE CLASSIFICATION TOOL

PLUS: PRESIDENT'S COMMENTS, UPCOMING CONFERENCES, ISGC 2020

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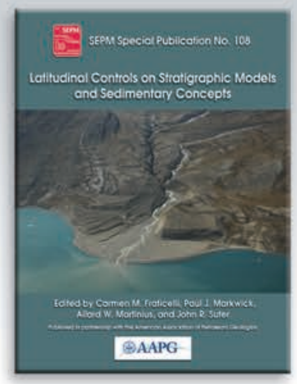


Special Publication #108

Latitudinal Controls on Stratigraphic Models and Sedimentary Concepts

Edited by: Carmen M. Fraticelli, Paul J. Markwick, Allard W. Martinius and John R. Suter

It is self-evident that a better understanding of depositional systems and analogs leads to better inputs for geological models and better assessment of risk for plays and prospects in hydrocarbon exploration, as well as enhancing interpretations of earth history. Depositional environments—clastic and carbonate, fine- and coarse-grained, continental, marginal marine and deep marine—show latitudinal variations, which are sometimes extreme. Most familiar facies models derive from temperate and, to a lesser extent, tropical examples. By comparison, depositional analogs from higher latitudes are sparser in number and more poorly understood. Numerous processes are amplified and/or diminished at higher latitudes, producing variations in stratigraphic architecture from more familiar depositional "norms." The joint AAPG/SEPM Hedberg Conference held in Banff, Alberta, Canada in October 2014 brought together broad studies looking at global databases to identify differences in stratigraphic models and sedimentary concepts that arise due to differences in latitude and to search for insights that may be applicable for subsurface interpretations. The articles in this Special Publication represent a cross-section of the work presented at the conference, along with the abstracts of the remaining presentations. This volume should be of great interest to all those working with stratigraphic models and sedimentary concepts.

Catalog #40108 • Hardcover POD • List Price: $100.00 • SEPM Member Price: $60.00

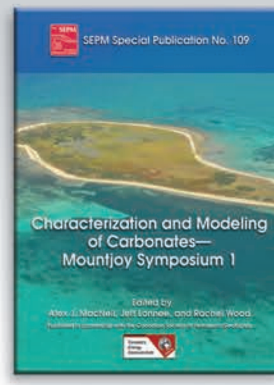
Special Publication #109

Characterization and Modeling of Carbonates—Mountjoy Symposium 1

Edited by: Alex J. MacNeil, Jeff Lonnee, and Rachel Wood

In August of 2015 the first Mountjoy Carbonate Conference, co-hosted by the Society for Sedimentary Geology (SEPM) and Canadian Society of Petroleum Geologists (CSPG), took place in Banff, Alberta. As the approaches to characterization and modeling of carbonate reservoirs are undergoing rapid changes, this was the theme of the meeting. This Special Publication, following the inaugural meeting, contains nine state-of-the art papers relating to the (1) characterization of carbonates and advances in analytical methods, (2) controls on carbonate reservoir quality and recovery factors, and (3) reservoir distribution, the modeling of dolostone geobodies, and reservoir prediction. The Introduction includes an overview of Eric Mountjoy's career and his many contributions to the science. The contents of this Special Publication should be useful to those engaged in the characterization and modeling of carbonate reservoirs, including unconventional carbonate reservoirs, and is highly recommended as one of the most impactful recent publications for those working in this area of sedimentary science.

Catalog #40109 • Hardcover POD • List Price: $197.00 • SEPM Member Price: $118.00



Special Publication #111

Geologic Problem Solving with Microfossils IV

Edited by: Richard A. Denne and Alicia Kahn

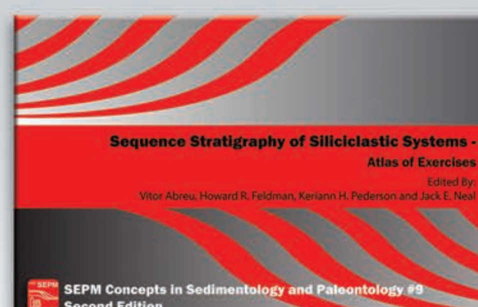
Every four years micropaleontologists from across the globe gather in Houston, Texas for the quadrennial conference of the North American Micropaleontology Section–SEPM (NAMS) to learn, share, and network on applied micropaleontology. Geologic Problem Solving with Microfossils IV was held on April 5–8, 2017 with 130 participants. Fourteen of the 95 presentations were selected for publication, which includes papers on geologic applications utilizing foraminifera (benthic and planktic), calcareous nannofossils, palynology, and conodonts, in studies of rocks and sediments ranging from the Pennsylvanian to the modern.

Catalog #40111 • Hardcover POD • List Price: $100.00 • SEPM Member Price: $60.00

Concepts in Sedimentology and Paleontology 9 (2nd edition)

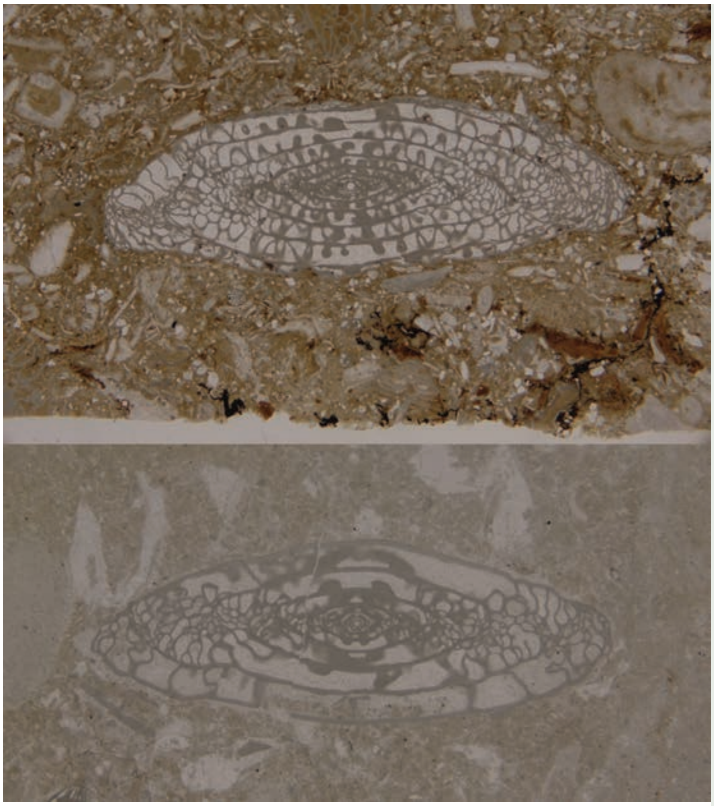
Sequence Stratigraphy of Siliciclastic Systems

Edited by: Vitor Abreu, Howard R. Feldman, Keriann H. Pederson, and Jack E. Neal



This publication is the result of more than 3 decades of sequence stratigraphy research and application. The objective is to emphasize the most important aspects of Sequence Stratigraphy—a method to guide geologic interpretation of stratigraphic data (seismic profiles, well-logs, cores and outcrops) across scales (from local to regional and global) and depositional environments (from continental to deep marine).The stratigraphic concept of a depositional sequence was introduced to the scientific literature by Peter Vail and his colleagues in the late 70s, building on the shoulders of giants like Chamberlain, Sloss and Wheeler. Since then, several papers compared and contrasted the original sequence-stratigraphic school published in the AAPG Memoir 26 in 1977 with other approaches to subdivide the geologic record, as well as, debating the model validity and impact on the community. At its core, the "model" is really a stratigraphic interpretation method, which was never explicitly documented in the literature. The objective of this book is to present the sequence stratigraphic method in its current form in an attempt to clarify its usage and application in diverse geologic data and depositional environments. This publication is the result of more than 3 decades of sequence stratigraphy research and application. The objective is to emphasize the most important aspects of Sequence Stratigraphy—a method to guide geologic interpretation of stratigraphic data (seismic profiles, well-logs, cores and outcrops) across scales (from local to regional and global) and depositional environments (from continental to deep marine). This book in an 11 x 17 format is designed to be easily used for teaching or self-learning experiences. In the second edition of the "Atlas", the book was divided in 2 separately bound volumes—Exercises and Solutions—to make it easier to use the publication as text book for sequence stratigraphy courses in universities. Also, a new exercise was added and several of the existing exercises went through major updating and editing.

Catalog #55020 • Softcover Print • List Price: $135.00 • SEPM Member Price: $81.00



Cover image: Thin Sections of Fusilinid Triticites spp.

CONTENTS

The Sedimentary Record (ISSN 1543-8740) is published quarterly by the Society for Sedimentary Geology with offices at 1621 S. Eucalyptus Ave., Suite 204, Broken Arrow, OK 74012, USA.

The Sedimentary Record is provided as part of membership dues to the Society for Sedimentary Geology.

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Deep convolutional neural networks as a geological image classification tool

Rafael Pires de Lima[1,2], Alicia Bonar[1], David Duarte Coronado[1], Kurt Marfurt[1], Charles Nicholson[3]

[1]School of Geology and Geophysics, The University of Oklahoma, 100 East Boyd Street, RM 710, Norman, Oklahoma, 73019, USA

[2]The Geological Survey of Brazil – CPRM, 55 Rua Costa, São Paulo, São Paulo, Brazil

[3]School of Industrial and Systems Engineering, The University of Oklahoma, 202 West Boyd Street, RM 124, Norman, Oklahoma, 73019, USA

Keywords

convolutional neural networks, transfer learning, automatization, microfossil identification, petrography

ABSTRACT

A convolutional neural network (CNN) is a deep learning (DL) method that has been widely and successfully applied to computer vision tasks including object localization, detection, and image classification. DL for supervised learning tasks is a method that uses the raw data to determine the classification features, in contrast to other machine learning (ML) techniques that require pre-selection of the input features (or attributes). In the geosciences, we hypothesize that deep learning will facilitate the analysis of uninterpreted images that have been neglected due to a limited number of experts, such as fossil images, slabbed cores, or petrographic thin sections. We use transfer learning, which employs previously trained models to shorten the development time for subsequent models, to address a suite of geologic interpretation tasks that may benefit from ML. Using two different base models, MobileNet V2 and Inception V3, we illustrate the successful classification of microfossils, core images, petrographic photomicrographs, and rock and mineral hand sample images. ML does not replace the expert geoscientist. The expert defines the labels (interpretations) needed to train the algorithm and also monitors the results to address incorrect or ambiguous classifications. ML techniques provide a means to apply the expertise of skilled geoscientists to much larger volumes of data.

INTRODUCTION

Machine learning (ML) techniques have been successfully applied, with considerable success, in the geosciences for almost two decades. Applications of ML by the geoscientific community include many examples such as seismic-facies classification (Meldahl et al., 2001; West et al., 2002; de Matos et al., 2011; Roy et al., 2014; Qi et al., 2016; Hu et al., 2017; Zhao et al., 2017), electrofacies classification (Allen and Pranter, 2016), and analysis of seismicity (Kortström et al., 2016; DeVries et al., 2018; Perol et al., 2018; Sinha et al., 2018), and classification of volcanic ash (Shoji et al., 2018), among others. Conventionally, ML applications rely on a set of attributes (or features) selected or designed by an expert. Features are specific characteristics of an object that can be used to study patterns or predict outcomes. In classification modeling, these features are chosen with the goal of distinguishing one object from another.

Typically, feature selection is problem dependent. For example, a clastic sedimentary rock is most broadly classified by its grain size; therefore a general classification for a rock sample (data) is sandstone if its grain sizes (features) lie from 0.06 mm to 2.0 mm following the Wentworth size class. In this example, a single feature is used to classify the sample, but more complex and/or detailed classification often requires analysis of multiple features exhibited by the sample. An inefficiency of traditional ML approaches is that many features may be constructed while only a subset of them are actually needed for the classification.

The use of explicitly designed features to classify data was the traditional approach in ML applications within the geosciences as in many other research areas. This classification approach works well when human interpreters know and can quantify the features that distinguish one object from another. However, sometimes an interpreter will subconsciously classify features and have difficulty describing what the distinguishing features might be, relying on "I'll know what the object is when I see it". In contrast to feature-driven ML classification algorithms, deep learning (DL) models extract information directly from the raw unstructured data rather than the data being manually transformed.

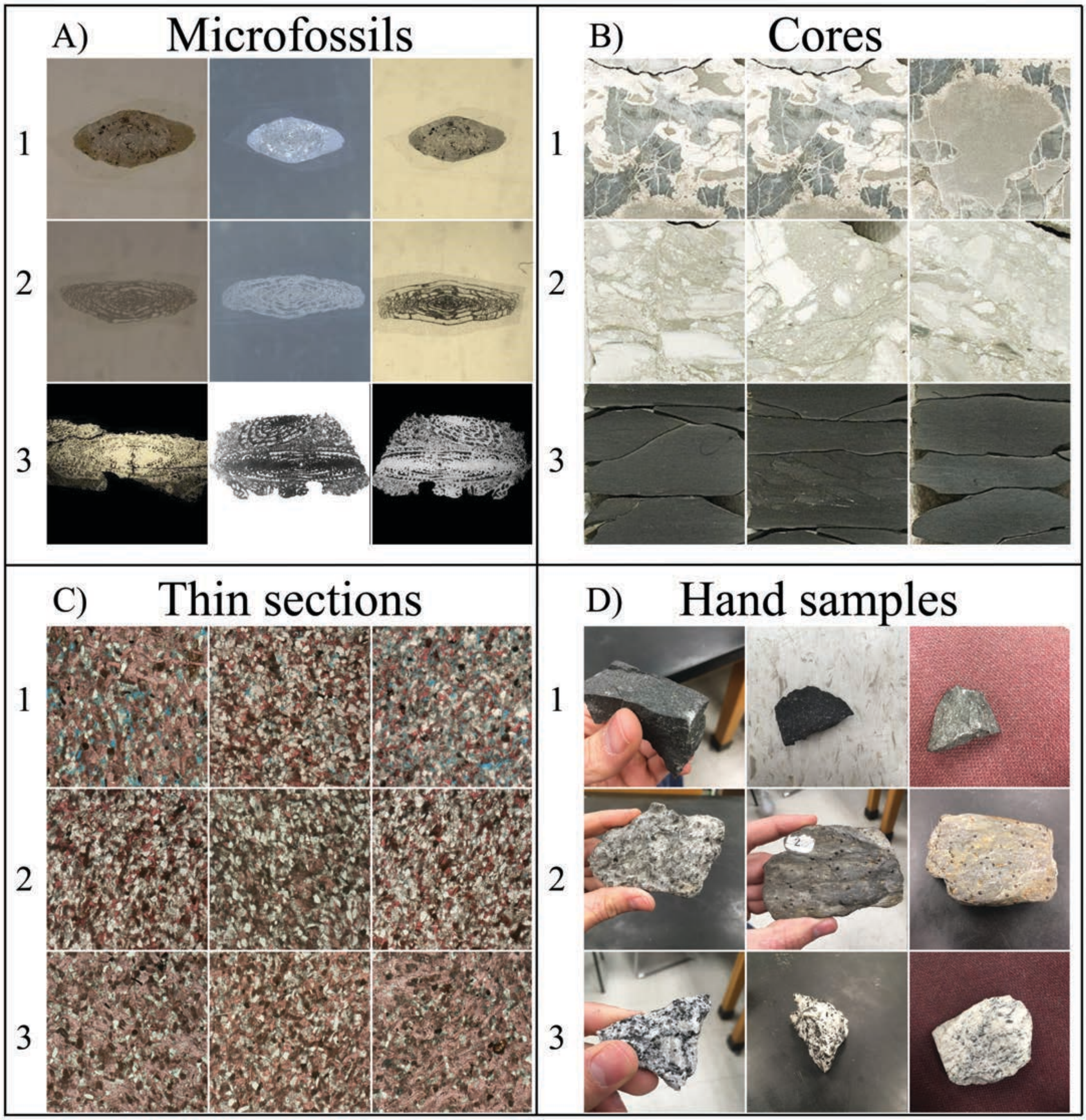


Figure 1: Examples of the data used in this study. A) Three of the seven Fusulinids groups (Beedeina (1), Fusulinella (2), and Parafusulina (3)). B) Three of the five lithofacies (bioturbated mudstone-wackestone (1), chert breccia (2), and shale (3)). C) Reservoir quality classes (high (1), intermediate (2), and low (3)) D) Three of the six rock sample groups (basalt (1), garnet schist (2), and granite (3)). Samples were interpreted by professionals working with each separate dataset.

Because of their greater complexity (and resulting flexibility and power) convolutional neural networks (CNN) usually requires more training data than traditional ML processes. However, when expert-labeled data are provided, non-experts can use the CNN models to generate highly accurate results (e.g. TGS Salt Identification Challenge | Kaggle, 2019).

DL applications in the geosciences require experts to first define the labels used to construct the necessary data sets as well as identify and address any ambiguous results and anomalies. In order to bring awareness and provide basic information regarding CNN models, DL techniques, and the necessity of expert-level knowledge needed to utilize these advancements, we applied these methods to four different geologic tasks. Figure 1 shows samples of different types of data that can be interpreted and labeled by experienced geologists. We use such interpretations to train our models. In this manuscript, we show how CNN can aid geoscientists with microfossil identification, core descriptions, petrographic analyses, and as a potential tool for education and outreach by creating a simple hand specimen identification application.

CONVOLUTIONAL NEURAL NETWORKS AND TRANSFER LEARNING

Recent CNN research has yielded significant improvements and unprecedented accuracy (the ratio between correct classifications and the total number of samples classified) in image classification and are recognized as leading methods for large-scale visual recognition problems, such as the annual ImageNet Large Scale Visual Recognition Challenge (ILSVRC, Russakovsky et al. (2015)). Specific CNN architectures have been the leading approach for several years now (e.g., Szegedy et al., 2014; Chollet, 2016; He et al., 2016; Huang et al., 2016; Sandler et al., 2018). Researchers noted that the parameters learned by the layers in many CNN models trained on images exhibit a common behavior – layers closer to the input data tend to learn general features, such as edge detecting/enhancing filters or color blobs, then there is a transition to more specific dataset features, such as faces, feathers, or object parts (Yosinski et al., 2014; Yin et al., 2017). These general-specific CNN layer properties are important points to be considered for the implementation of transfer learning (Caruana, 1995; Bengio, 2012; Yosinski et al., 2014). In transfer learning, first a CNN model is trained on a base dataset for a specific task. The learned features (model parameters) are repurposed, or transferred, to a second target CNN to be trained on a different dataset and task (Yosinski et al., 2014).

New DL applications often require large volumes of data, however the combination of CNNs and transfer learning allows the reuse of existing DL models to novel classification problems with limited data, as has been demonstrated in diverse fields, such as botany (Carranza-Rojas et al., 2017), cancer classification (Esteva et al., 2017), and aircraft detection (Chen et al., 2018). Analyzing medical image data, Tajbakhsh et al. (2016) and Qayyum et al. (2017) found that transfer learning achieved comparable or better results than training a CNN model with randomly initialized parameters. As an example, training the entire InceptionV3 (Szegedy et al., 2015) with 1000 images (five classes, 50 original images for each class, four copies of each original image) with randomly initialized parameters can be 10 times slower than the transfer learning process (11 minutes vs 1 minute on average for five executions) using a Nvidia Quadro M2000 (768 CUDA Cores). On a CPU (3.60 GHz clock speed), training the entire model can take up to 2 hours whereas transfer learning can be completed within a few minutes. We also noticed that transfer learning is easier to train. During the speed comparison test, transfer learning achieved high accuracies (close to 1.0) within 5 epochs (note the dataset is very simple with most of the samples being copies of each other). Successful applications of computer vision technologies in different fields suggest that ML models could be extremely beneficial for geologic applications, especially those in the category of image classification problems.

For the examples we present in this paper (Figure 1), we rely on the use of transfer learning (Yosinski et al., 2014) using the MobileNetV2 (Sandler et al., 2018) and InceptionV3 as our base CNN models. Both MobileNetV2 and InceptionV3 were trained on ILSVRC. Therefore, the CNN models we used were constructed based on inputs of 3-channels (RGB) of 2D photographic images. We randomly select part of the data to be used as a test set maintaining the same proportion of samples per class as in the training set. The data in the test set is not used during the

Table 1: Summary of test accuracy for the examples in this study.

Dataset	Number of training samples	Number of test samples	Number of output classes	MobileNetV2 Accuracy	InceptionV3 Accuracy
Microfossils (Fusulinids)	1480	184	7	1.00	1.00
Core	227	28	5	1.00	0.97
Petrographic thin-sections	194	31	3	0.81	0.81
Rock samples	1218	151	6	0.98	0.97

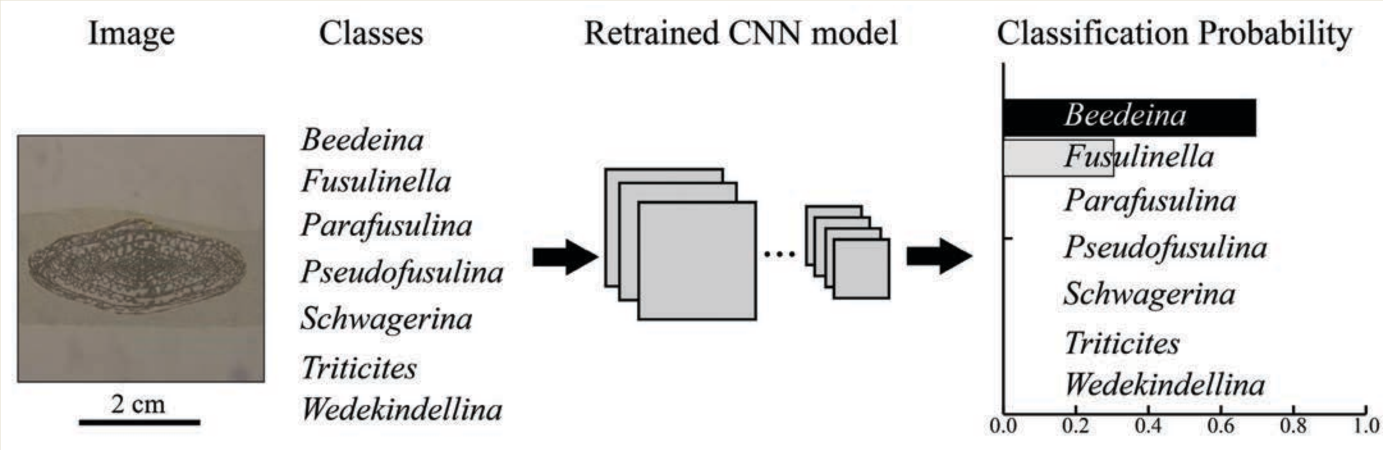


Figure 2: An example of the classification process. In this example, a thin-section image that should fit one of the seven fusulinid genera is analyzed by the model. The model outputs the probability assigned to each of the possible classes (all probabilities summing to 1.0). The term "classes" here is used in the ML sense rather than the biological one. In the example provided, our model provided a high probability for the same class as the human expert. Note that in the implementation we use the model will classify any image as one of the seven learned classes – even if the image is clearly not a fossil. This highlights the importance of a domain expert intervention.

computational process for model training; rather, it is used to evaluate the quality and robustness of the final model. Due to limited space, we refrained showing the CNN mistakes and many of the steps necessary for data preparation.

CNN-ASSISTED FOSSIL ANALYSIS

Biostratigraphy has become a less common focus of study in the discipline of paleontology (Farley and Armentrout, 2000, 2002), but the applications of biostratigraphy are necessary for understanding age-constraints for rocks that cannot be radiometrically dated. Access to a specific taxonomic expert to accurately analyze fossils at the species-level can be as challenging as data acquisition and preparation. Using labeled data from the University of Oklahoma Sam Noble Museum and iDigBio portal, we found that fusulinids (index fossils for the Late Paleozoic) can be accurately classified with the use of transfer learning. Accurate identification of a fusulinid depends on characteristics that must be observed and exposed along the long axis of the (prolate spheroid-shaped) fusulinid. We used a dataset of 1850 qualified images including seven different fusulinid genera. After retraining the CNN model, we obtained an accuracy for the test set (10% of the data) of 1.0 for both retrained MobileNetV2 and InceptionV3 (Table 1). Figure 2 shows a schematic view of the classification process.

CNN-ASSISTED CORE DESCRIPTION

Miles of drilled cores are stored in boxes in enormous warehouses, many of which have either been neglected for years or never digitally described. Core-based rock-type descriptions are important for understanding the lithology and structure of subsurface geology. Using several hundred feet of labeled core from a Mississippian limestone in Oklahoma (data from Suriamin and Pranter, 2018 and Pires de Lima et al., 2019), we selected a small sample of 285 images from five distinct lithofacies to be classified by the retrained CNN models. Pires de Lima et al. (2019) describes how a sliding window is used to generate CNN input data, cropping small sections from a standard core image. We used 10% of the data as the test set and achieved an accuracy of 1.0 using the retrained MobileNetV2 and an accuracy of 0.97 using the retrained InceptionV3 (Table 1).

CNN-ASSISTED RESERVOIR QUALITY CLASSIFICATION USING PETROGRAPHIC THIN SECTIONS

Petrography focuses on the microscopic description and classification of rocks and is one of the most important techniques in sedimentary and diagenetic studies. Potential information gained from thin section analysis compared to hand specimen descriptions include mineral distribution and percentage, pore space analysis, and cement composition. Petrographic analyses can be laborious even for experienced geologists. Using a total of 161 photomicrographs of parallel Nicol polarization of thin sections from the Sycamore Formation shale resource play in Oklahoma, we classified these images as representatives of high, intermediate, and low reservoir quality depending on the percent of calcite cement and pore space. We used 20% of the images in the test set and obtained a test set accuracy of 0.81 for both the retrained

MobileNetV2 and the retrained InceptionV3 (Table 1).

CNN-ASSISTED ROCK SAMPLE ANALYSIS

By creating a simple website, the general population could have immediate access to a rock identification tool using transfer learning technology. For this work in progress, we used smartphones to acquire 1521 pictures of six different rock types, using five different hand samples for each one of the rock types. We took pictures with different backgrounds, as visually depicted in Figure 1, however all pictures were taken in the same classroom. After retraining the CNN models, we obtained an accuracy for the test set (10% of original data) of 0.98 using the retrained MobileNetV2 and 0.97 using the retrained InceptionV3 (Table 1). We note that our model does not perform well with no-background images (i.e., pictures in which the rock sample is edited and seems to be within a white or black canvas) as such images were not used in training.

CONCLUSIONS AND FUTURE WORK

Although gaining popularity and becoming established as robust technologies in other scientific fields, transfer learning and CNN models are still novel with respect to application within the geoscience community. In this paper, we used CNN and transfer learning to address four potential applications that could improve data management, organization, and interpretation in different segments of our community. We predict that the versatile transfer learning and deep learning technologies will play a role in public education and community outreach, allowing the public to identify rock samples much as they currently can use smart phone apps to identify visitors to their bird feeder. Such public engagement will increase geological awareness and provide learning opportunities for elementary schools, outdoor organizations, and families.

For all of our examples, we were able to achieve high levels of accuracy (greater than 0.81) by repurposing two different CNN models originally assembled for generic computer vision tasks. We note that the examples and applications demonstrated here are curated, and therefore we expected highly accurate results. We presented demonstrations with limited classes and relatively well-controlled input images, so near perfect accuracies cannot necessarily be expected in an open, free-range deployment scenario. Regardless, the ability to create distinctive models for specific sets of images allows for a versatile application.

The techniques we have shown could greatly improve the speed of monotonous tasks such as describing miles of core data with very similar characteristics or looking at hundreds of thin sections from the same geologic formation. While the tasks are performed by the computer, the geoscience expert is still the most important element in every analysis in order to create the necessary datasets and provide quality control of the generated results. In the end, the expert validates the correctness of the results and looks for anomalies that are poorly represented by the target classes. We believe ML can help maintain consistency in interpretations and even provide a resource for less common observations and data variations, such as previously overlooked fossil subspecies and unique mineralogical assemblages in small communities and private collections, thereby building and reconciling a more complete international database. By combing expert knowledge and time efficient technology, ML methods can accelerate many data analysis processes for geologic research.

ACKNOWLEDGEMENTS

We thank the iDigBio initiative for providing access to the community for biodiversity collections data. Rafael acknowledges CNPq (grant 203589/2014-9) for the financial support and CPRM for granting the leave of absence allowing the pursuit of his Ph.D. studies. We thank Roger J. Burkhalter from the University of Oklahoma Sam Noble Museum of Natural History for providing the Fusulinids images used in this manuscript.

REFERENCES

ALLEN, D. B., AND M. J. PRANTER, 2016, Geologically constrained electrofacies classification of fluvial deposits: An example from the Cretaceous Mesaverde Group, Uinta and Piceance Basins: AAPG Bulletin, v. 100, no. 12, p. 1775–1801, doi:10.1306/05131614229.

BENGIO, Y., 2012, Deep Learning of Representations for Unsupervised and Transfer Learning, *in* I. Guyon, G. Dror, V. Lemaire, G. Taylor, and D. Silver, eds., Proceedings of ICML Workshop on Unsupervised and Transfer Learning: PMLR, Proceedings of Machine Learning Research, p. 17–36.

CARRANZA-ROJAS, J., H. GOEAU, P. BONNET, E. MATA-MONTERO, AND A. JOLY, 2017, Going deeper in the automated identification of Herbarium specimens: BMC Evolutionary Biology, v. 17, no. 1, p. 181, doi:10.1186/s12862-017-1014-z.

CARUANA, R., 1995, Learning Many Related Tasks at the Same Time with Backpropagation, *in* G. Tesauro, D. S. Touretzky, and T. K. Leen, eds., Advances in Neural Information Processing Systems 7: MIT Press, p. 657–664.

CHEN, Z., T. ZHANG, C. OUYANG, Z. CHEN, T. ZHANG, AND C. OUYANG, 2018, End-to-End Airplane Detection Using Transfer Learning in Remote Sensing Images: Remote Sensing, v. 10, no. 1, p. 139, doi:10.3390/rs10010139.

CHOLLET, F., 2016, Xception: Deep Learning with Depthwise Separable Convolutions: CoRR, v. abs/1610.0.

DEVRIES, P. M. R., F. VIÉGAS, M. WATTENBERG, AND B. J. MEADE, 2018,

Deep learning of aftershock patterns following large earthquakes: Nature, v. 560, no. 7720, p. 632–634, doi:10.1038/s41586-018-0438-y.
ESTEVA, A., B. KUPREL, R. A. NOVOA, J. KO, S. M. SWETTER, H. M. BLAU, AND S. THRUN, 2017, Dermatologist-level classification of skin cancer with deep neural networks: Nature, v. 542, no. 7639, p. 115–118, doi:10.1038/nature21056.
FARLEY, M. B., AND J. M. ARMENTROUT, 2000, Fossils in the Oil Patch: Geotimes, p. 14–17.
FARLEY, M. B., AND J. M. ARMENTROUT, 2002, Tools, Biostratigraphy becoming lost art in rush to find new exploration: Offshore, p. 94–95.
HE, K., X. ZHANG, S. REN, AND J. SUN, 2016, Deep Residual Learning for Image Recognition, *in* 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR): IEEE, p. 770–778, doi:10.1109/CVPR.2016.90.
HU, S., W. ZHAO, Z. XU, H. ZENG, Q. FU, L. JIANG, S. SHI, Z. WANG, AND W. LIU, 2017, Applying principal component analysis to seismic attributes for interpretation of evaporite facies: Lower Triassic Jialingjiang Formation, Sichuan Basin, China: Interpretation, v. 5, no. 4, p. T461–T475, doi:10.1190/INT-2017-0004.1.
HUANG, G., Z. LIU, AND K. Q. WEINBERGER, 2016, Densely Connected Convolutional Networks: CoRR, v. abs/1608.0.
KORTSTRÖM, J., M. USKI, AND T. TIIRA, 2016, Automatic classification of seismic events within a regional seismograph network: Computers & Geosciences, v. 87, p. 22–30, doi:10.1016/J.CAGEO.2015.11.006.
DE MATOS, M. C., M. (MOE) YENUGU, S. M. ANGELO, AND K. J. MARFURT, 2011, Integrated seismic texture segmentation and cluster analysis applied to channel delineation and chert reservoir characterization: Geophysics, v. 76, no. 5, p. P11–P21, doi:10.1190/geo2010-0150.1.
MELDAHL, P., R. HEGGLAND, B. BRIL, AND P. DE GROOT, 2001, Identifying faults and gas chimneys using multiattributes and neural networks: The Leading Edge, v. 20, no. 5, p. 474–482, doi:10.1190/1.1438976.
PEROL, T., M. GHARBI, AND M. DENOLLE, 2018, Convolutional neural network for earthquake detection and location: Science Advances, v. 4, no. 2, p. e1700578, doi:10.1126/sciadv.1700578.
PIRES DE LIMA, R., F. SURIANAM, K. J. MARFURT, AND M. J. PRANTER, 2019, Convolutional neural networks as aid in core lithofacies classification: Interpretation, v. 7, no. 3, doi:10.1190/int-2018-0245.1.
QAYYUM, A., S. M. ANWAR, M. AWAIS, AND M. MAJID, 2017, Medical image retrieval using deep convolutional neural network: Neurocomputing, v. 266, p. 8–20, doi:10.1016/J.NEUCOM.2017.05.025.
QI, J., T. LIN, T. ZHAO, F. LI, AND K. MARFURT, 2016, Semisupervised multiattribute seismic facies analysis: Interpretation, v. 4, no. 1, p. SB91–SB106, doi:10.1190/INT-2015-0098.1.
ROY, A., A. S. ROMERO-PELÁEZ, T. J. KWIATKOWSKI, AND K. J. MARFURT, 2014, Generative topographic mapping for seismic facies estimation of a carbonate wash, Veracruz Basin, southern Mexico: Interpretation, v. 2, no. 1, p. SA31–SA47, doi:10.1190/INT-2013-0077.1.
RUSSAKOVSKY, O. ET AL., 2015, ImageNet Large Scale Visual Recognition Challenge: International Journal of Computer Vision, v. 115, no. 3, p. 211–252, doi:10.1007/s11263-015-0816-y.
SANDLER, M., A. HOWARD, M. ZHU, A. ZHMOGINOV, AND L.-C. CHEN, 2018, MobileNetV2: Inverted Residuals and Linear Bottlenecks: ArXiv e-prints.
SHOJI, D., R. NOGUCHI, S. OTSUKI, AND H. HINO, 2018, Classification of volcanic ash particles using a convolutional neural network and probability: Scientific Reports, v. 8, no. 1, p. 8111, doi:10.1038/s41598-018-26200-2.
SINHA, S., Y. WEN, R. A. PIRES DE LIMA, AND K. MARFURT, 2018, Statistical controls on induced seismicity: Unconventional Resources Technology Conference, doi:10.15530/urtec-2018-2897507-MS.
SURIAMIN, F., AND M. J. PRANTER, 2018, Stratigraphic and lithofacies control on pore characteristics of Mississippian limestone and chert reservoirs of north-central Oklahoma: Interpretation, p. 1–66, doi:10.1190/int-2017-0204.1.
SZEGEDY, C., W. LIU, Y. JIA, P. SERMANET, S. E. REED, D. ANGUELOV, D. ERHAN, V. VANHOUCKE, AND A. RABINOVICH, 2014, Going Deeper with Convolutions: CoRR, v. abs/1409.4.
SZEGEDY, C., V. VANHOUCKE, S. IOFFE, J. SHLENS, AND Z. WOJNA, 2015, Rethinking the Inception Architecture for Computer Vision: CoRR, v. abs/1512.0.
TAJBAKHSH, N., J. Y. SHIN, S. R. GURUDU, R. T. HURST, C. B. KENDALL, M. B. GOTWAY, AND J. LIANG, 2016, Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning? IEEE Transactions on Medical Imaging, v. 35, no. 5, p. 1299–1312, doi:10.1109/TMI.2016.2535302.
TGS Salt Identification Challenge | Kaggle, n.d.: <https://www.kaggle.com/c/tgs-salt-identification-challenge> (accessed January 10, 2019).
WEST, B. P., S. R. MAY, J. E. EASTWOOD, AND C. ROSSEN, 2002, Interactive seismic facies classification using textural attributes and neural networks: The Leading Edge, v. 21, no. 10, p. 1042–1049, doi:10.1190/1.1518444.
YIN, X., W. CHEN, X. WU, AND H. YUE, 2017, Fine-tuning and visualization of convolutional neural networks, *in* 2017 12th IEEE Conference on Industrial Electronics and Applications (ICIEA): IEEE, p. 1310–1315, doi:10.1109/ICIEA.2017.8283041.
YOSINSKI, J., J. CLUNE, Y. BENGIO, AND H. LIPSON, 2014, How transferable are features in deep neural networks? Advances in Neural Information Processing Systems, v. 27, p. 3320–3328.
ZHAO, T., F. LI, AND K. J. MARFURT, 2017, Constraining self-organizing map facies analysis with stratigraphy: An approach to increase the credibility in automatic seismic facies classification: Interpretation, v. 5, no. 2, p. T163–T171, doi:10.1190/INT-2016-0132.1.

Accepted June 2019

PRESIDENT'S COMMENTS

Thanks to continued admirable efforts by the Foundation and Staff, SEPM is on excellent financial footing, and can count many accomplishments in the form of successful conference sessions, field trips, and publications (e.g. a record number of Red Books) this year. Despite this, SEPM faces several potentially existential threats shared by many other "boutique" scientific societies. Chief among these are wavering membership and the global push to gold open access which— although a lofty goal— may threaten our future viability, given SEPM's reliance on publication proceedings to fund other society activities. Our May Council meeting focused on these threats, as well as finalizing our Code of Conduct (viewable here https://www.sepm.org/MemberEthics). We are undertaking a major initiative on strategic planning, to assess who we (SEPM) are, what distinguishes us, and how we can add value as a scientific society (to ourselves and society in general). Part of this includes a fundamental overhaul of our digital resources, and assessing how we can best serve our student demographic. We also plan to investigate how SEPM can help inform a society facing the greatest challenges of the future —those laying at the confluence of energy and the environment.

In my last President's column, I noted the enthrall I experienced as a student upon discovering that sediments present a window to whole worlds of past "alternative Earths." Grains and bugs, facies and phylogeny, reveal evolutionary radiations, past orogenic events, and paleoatmospheric conditions; isotopes of protozoan tests preserve histories of sea level change, and ice volume; fungal proliferations archive the frightening aftermath of global kills. One of SEPM's "greatest hits" — the 1974 publication of Special Publication #22 — *Tectonics and Sedimentation*[1], captured this globalization, ended up selling out in both print and CD forms, and remains popular. What was it about THAT book? Perhaps its success relates to its correlation with a paradigm shift in our science— the movement from micro and local scales to an appreciation of sediments as a window to global processes.

Beyond this, the economic/applied side of sedimentary geology is that it has quite literally fueled civilization— enabled the Industrial Age, provided access to an energy density previously unimaginable, thus lifting many out of poverty and— quite likely— saving the whales, in addition to enabling urbanization.

But such an abundance of riches, we now realize, has exacted a cost. Ironically, the very science that helped discover and develop this energy density also informs our understanding of carbon's role in that system. Sedimentary geologists and paleontologists lie at the forefront of the greatest issues facing the future of humanity: Earth, energy, and sustainability. In *Lives of a Cell*[2], Lewis Thomas spoke metaphorically of the Earth as a cell, because, viewed from space it is a living system, insulated from the harshness of space by a "marvelous" atmosphere (membrane). We could power civilization for hundreds of years by combusting Carboniferous coal, for example (or other Phanerozoic hydrocarbons); but in so doing, we would "instantaneously" release to Earth's "marvelous" atmosphere carbon that was sequestered over tens of millions of years. This is a rate issue. The Earth system will survive this; Earth will scrub this excess CO_2 from the atmosphere, but at its own stately pace. And although Earth will sail through this perturbation, one of an entire history-book of storms Earth has weathered, the biosphere will not escape unscathed, and those least able to adapt will preferentially bear the costs. Our current climate-energy crisis has well-defined scientific and societal aspects.

Sedimentary geologists and paleontologists know the science, and know the consequences of past climate shifts. We have expertise in the nexus of the Earth system — the climate system — that "marvelous" atmosphere that serves as Earth's membrane and governs life on Earth, and the record of which lies archived in sedimentary rocks. We, the Society for Sedimentary Geology, thus bear a responsibility to state what we know to be supported by our science. SEPM exists in order to further the science of sedimentary geology and paleontology; what better way to further our science than by making it relevant to the human society so desperately in need of scientific guidance? It is time for SEPM to consider crafting position statements on issues relevant to our expertise. Council is taking up the matter of how SEPM should begin contributing to society in this larger way.

I wish to close by extending heartfelt thanks to previous presidents and council members, as well as SEPM staff, for guiding SEPM to date, and helping cultivate the ethical practice of a science so integral to life on Earth.

Lynn Soreghan,
SEPM President

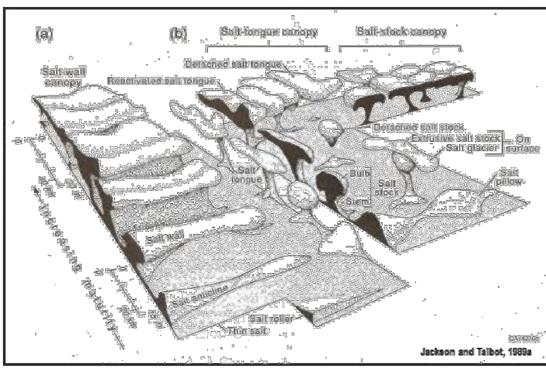
[1] Dickinson, William (Editor) (1974). *Tectonics and Sedimentation*, SEPM Special Publication No. 22.
[2] Thomas, Lewis (1974). *The Lives of a Cell*, The Viking Press.

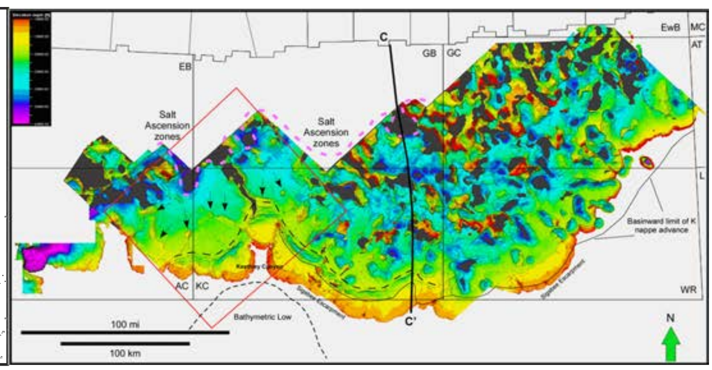
37th GCSSEPM Perkins-Rosen Research Conference

December 3-6, 2019
Charles Davidson Hall, Noble Energy,
1001 Noble Energy Way
Houston, Texas

Where were You in 1989?

Salt Tectonics, Associated Processes, and Exploration Potential: Revisited 1989-2019





The 37th Perkins-Rosen Research Conference of the Gulf Coast Section SEPM (GCSSEPM)celebrates thirty years of progress in the understanding of all aspects of salt tectonics. The 1989 conference emphasized the basics as interpreted at the time: the origin of the Gulf of Mexico, the extent of autochthonous and allochthonous salt, delineated regional salt provinces, described salt structural styles and internal salt characteristics, and salt-sediment interaction. The 2019 conference will focus on what has been learned from the GOM and salt basins globally over the past thirty years.

Organizers

Chairman: J. Carl Fiduk, Fiduk Consulting LLC
Co-Chairman: Van Mount, Anadarko
Co-Chairman: Thomas J. Hearon, EOG Resources

Registration will be opening this summer online at the SEPM web site: www.sepm.org. Full details concerning logistics, including maps and directions, suggested lodging and local restaurants, will be available at the registration, as well as the GCSSEPM website www.gcssepm.org.

THE PAST IS THE KEY TO A SUSTAINABLE FUTURE

Proposed Field Trips*

- Grand Canyon River Trip – 10 days
- Surface Process of Alluvial Stratigraphic Record – Death Valley-Owens Valley Area – 5 Days
- Contrasting Mesozoic Fluvial Systems of Utah – 4 Days
- Southern California Turbidite Depositional Environments – 4 Days
- Upper Cretaceous Tectonics, Stratigraphy, and Vertebrate Paleontology of the Kaiparowits Plateau – 5 Days
- Jurassic and Lower Cretaceous strata of Border Rift basins in SE Arizona and SW New Mexico – 5 Days
- Red rocks of Sedona: Day tour of late Paleozoic strata of the Mogollon Rim – 1 Day
- The Convergent Margin of Western North America – 6 Days
- Upper Cretaceous stratigraphy, depositional environments, and reservoir geology of the Henry Mountains region, southern Utah – 4 Days
- Rift Sedimentology of Death Valley and Owens Valley, California – 6 Days
- Jurassic of Kane County, Utah Revisited -2 Days
- Paleosols and Paleoenvironments in Petrified Forest National Park, Arizona – 2 Days
- Ice sheets in Earth's hottest deserts: the Neoproterozoic of Death Valley – 5 Days
- The Mural Limestone of Arizona: Depositional Facies and Implications for Reservoir Characterization – 2 Days
- Aeolian Sedimentary Structures, from wind ripples to compound dunes – 1 Day

Proposed Short Courses and Workshops*

- Paleoceanography & Cyclostratigraphy
- Storms and Tsunamis
- Isotopic tools for carbonate diagenesis
- Fluvial Paleohydraulics
- Applications of Ichnology
- Mudstone Diagenesis
- Sandstone Diagenesis
- Detrital Tools with Zircons
- Chemostratigraphy
- Ocean Chemistry of Carbonates
- Time in the Stratigraphic Record
- Machine Learning

*These lists of proposed trips and courses will be finalized before registration

SEPM 2020 ISGC – Flagstaff, AZ, April 26-29, 2020

Abstract Submission Instructions

https://cpaper-us.ctimeetingtech.com/sepm/login

First you must create a 'New User' Account so that you can submit an abstract. Once you have created an account you can submit multiple abstracts and edit your submissions. There are seven (7) steps in the abstract submission process and each must be completed to successfully submit an abstract.

Steps

1. **Title and Topic.** Enter your title as you want it to appear. Please use upper and lower case letters for your title (not all CAPS). Next select the appropriate Session Topic for your presentation from the drop down listing. An additional category is 'Other' if you do not think your abstract fits into any of the listed topics. Note that there is a PDF of the complete descriptions of the sessions available on that page for review – 'click here'.
2. **Presentation Preference.** You may select your presentation preference from the list noting that you may be offered a different presentation mode that you selected when the program is finalized. Options include: Oral; Poster-Printed; ePoster-PICO; and Any Format. The final program will be decided by the number of quality abstracts for each Session and the presentation plans of the Session chairs.
3. **Affirmation.** You must acknowledge the SEPM guidelines in our Code of Conduct which is designed to create a harassment free environment for this meeting. A PDF of the Code is available on this page from the link 'here'.
4. **Authors.** As usual please list all of the authors associated with the abstract and you must include: First and names; Institution/Company; Country; Email; and Phone contact for the presenter.
5. **Abstract.** Up to 3000 characters and you can include formulas using the special box at the top of the entry box. You can also cut and paste into the box.
6. **Keywords.** You may enter 'keywords or phrases' for your presentation here. Enter one in the text box and click the 'Add' button. You can then add additional keywords following the same process.
7. **Preview.** This will allow you to review your entries and to fill in any that are not complete. Your submission will not be accepted until all of the required entries are completed. Here make sure to click on "Finish Submission & Close" to finalize your submission. You can login and edit your submission until Abstract Submissions close.

The icons in the black circles – 'i' and '?' can supply help or technical support is available from Monday-Friday 8am-5pm CT either through phone or email. Email: sepm@support.ctimeetingtech.com or phone: 217.398.1792.

2020 PLENARY SESSIONS

"The Science of Science Communication"
Dr. Sara K. Yeo
Assistant Professor
Department of Communication
University of Utah

"Earth, Mars, and Comparative Planetary Evolution"
Dr. John Grotzinger
Fletcher Jones Professor of Geology
Ted and Ginger Jenkins Leadership Chair
Division of Geological and Planetary Sciences
California Institute of Technology

"Multi-proxy data to resolve source to sink dynamics"
Dr. Barbara Carrapa
Professor and Department of Geosciences Head
University of Arizona

"Life and Death by Impact: Drilling for Clues"
Dr. Sean Gulick
Research Professor
Institute for Geophysics & Department of Geological Sciences
University of Texas at Austin

1926 SEPM
Society for Sedimentary Geology

GRAND CANYON – COLORADO RIVER FIELD EXPERIENCE

A North American Geobucket-List Event.

A ten day motorized boat trip down the Colorado River experiencing all of the Grand Canyon's geological splendor.

Led by Dr. Gary Gianniny (Professor of Geosciences, Fort Lewis College, Durango, CO, USA), this trip focuses on the Neoproterozoic and Paleozoic carbonate and clastic sequences of the Southern Colorado Plateau as exposed along the Colorado River in the Grand Canyon. It also features exquisite outcrops of the Proterozoic metamorphic and igneous rocks of the inner gorge, and well exposed Neoproterozoic sediments of the Grand Canyon Super Group. These exceptional exposures provide robust analogs to many sedimentological and stratigraphic problems known only from the subsurface. Attendees will traverse the length of Grand Canyon National Park via a motorized raft which will serve as the base for short hikes to see the wide variety of geology exposed along the river.

**Recent sequence stratigraphic, diagenetic, porosity evolution, and karst aquifer research on the Mississippian Redwall Limestone will be highlighted, as well as some of the enigmatic parsequences of the Cambrian mixed carbonate-clastic strata in the Bright Angel Shale and Muave Limestone. Arthropod (mostly trilobite) traces in this transition are superbly preserved. Participants will visit spectacular incised paleovalleys filled by Devonian Temple Butte Limestone equivalent sediments, and Cambrian "sea stacks" of Proterozoic granite and quartzite enveloped by onlapping Cambrian Tapeats Sandstone Shorter visits will likely include the low gradient fluvial systems and paleosols of the Supai Group, and the astonishing "R" karst aquifer-hosted waterfall/springs. Participants will attend an afternoon seminar on Grand Canyon geology and stratigraphy on April 30th prior to spending the next ten days enveloped in some of the best geologic laboratories and classrooms on Earth, the Grand Canyon.

More information about this trip will be out soon, including details about fees and itinerary.
There will be very limited space for this trip so register for it as soon as it opens to insure your place.