PSApplications of Machine Learning Techniques in Assessing Cap Rock Efficiency Based on Surface Data*

Sanaz Salati¹, Frank J.A. van Ruitenbeek², and Freek D. van der Meer²

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Abstract

The presence of hydrocarbon seeps at the surface indicates the accumulation of oil and gas at subsurface and reflects hydrocarbon migration in a sedimentary basin. There have been various techniques for characterizing oil and gas reservoirs from seismic to logging techniques. However, less attention has been paid to characterizing petroleum basins based on surface data. Earth observation data offers the confidence-building benefit of iterative sampling. It plays an important role in providing valuable information of factors such as lithology and structures influencing cap rock efficiency. This presentation aims at presenting new technology for interpretation of petroleum basins based on remote sensing data. Machine learning techniques have recently been applied in reservoir characterization. Boosted regression tree (BRT) is a nonparametric classification method relates the response to the predictor variables (spectral bands) by recursive binary splits, and the boosting method combines large numbers of simple tree models to improve predictive performance (Friedl and Brodley, 1997). We implemented the BRT technique on Thermal Emission and Reflection Radiometer (ASTER) data to classify lithologies hosting different types of hydrocarbon seeps in the Zagros Basin. The BRT classification results show that oil seeps have a consistent spatial association with calcite and clay zones of the evaporite cap rock and there is high density of gas seeps within areas of the cap rock formation mainly consist of gypsum. The BRT algorithm provided high accuracy of classification based on the presence of different types of hydrocarbon seeps. We recommend petroleum industry adopt machine learning in basin interpretation.

References Cited

Breiman, L., J.H. Friedman, R.A. Olshen, and C.J. Stone, 1984, Classification and Regression Trees: Wadsworth International Group, Belmont, California, 358 p.

Efron, B., and R. Tibshirani, 1997, Improvements on Cross-Validation: The .632+ Bootstrap Method: Journal of the American Statistical Association, v. 92/438, p. 548-560. doi:10.2307/2965703

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Friedl, M.A., and C.E. Brodley, 1997, Decision Tree Classification of Land Cover from Remotely Sensed Data: Remote Sensing of Environment, v. 61, p. 399-409. doi.org/10.1016/S0034-4257(97)00049-7

R Development Core Team, 2006, R Version 2.15.3: A Language and Environment for Statistical Computing: R Foundation for Statistical Computing, Vienna.

Ridgeway, G., 2006. Generalized Boosted Regression Models. Documentation on the R 731 Package 'gbm', version 1.5-7.

Ridgeway, G., 1999, The State of Boosting: Computing Science and Statistics, v. 31, p. 172-181.

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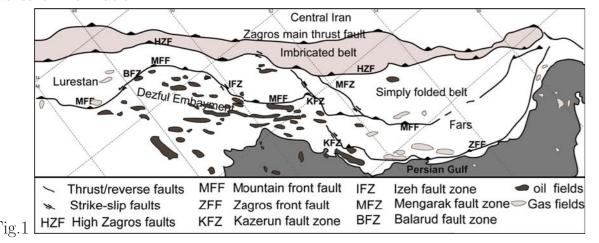
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Introduction

Machine learning methods play an important role in analyzing petroleum basins and exploring important geological factors controlling the productivity and integrity of basins which have been overlooked using traditional methods. The boosted regression tree (BRT) is a machine learning method fitting complex nonlinear relationship by combining two algorithms of classification and a regression tree (CART) (Breiman et al., 1984) and boosting. The persistent natural hydrocarbon seepage in onshore basins challenges observation and exploration technologies, which are required to document and assess these valuable indications of the presence of oil and gas in the subsurface. This poster presents the application of BRT in the classification of different types of hydrocarbon seeps using the multispectral Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data.

Geological setting

The study area is in the Zagros fold-thrust belt, southwest of Iran. Three giant oil fields were selected for this study; Masjid-Soleyman, Gachsaran, and Bibi-Hakimeh (Fig.1). The studied areas are in an arid environment without vegetation covers and hosts several oil and gas seeps. The Asmari reservoir is sealed by the evaporite Gachsaran Formation.

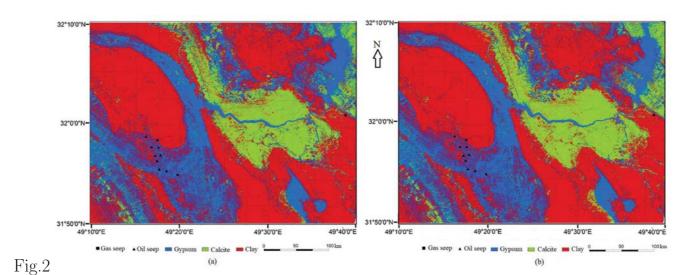


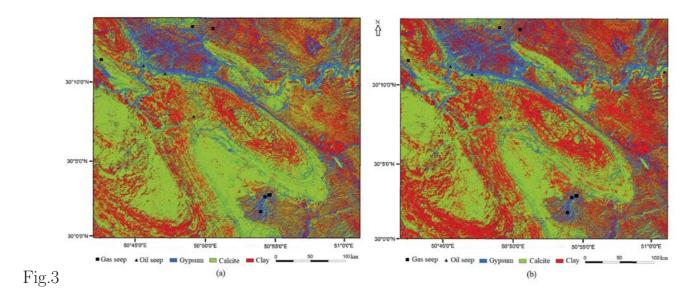
Method

The main purpose of the BRT classification was detecting target minerals and evaluating the spatial correspondence between classified lithologies and the location of oil and gas seeps. First, three region of interests (ROIs) representing the presence of gypsum, calcite, and clays were chosen from the ASTER imagery and mean spectra of these regions were selected as endmembers. Then, the training and test dataset (mean spectra) were produced by bootstrap method (Efron and Tibshirani, 1997) for each of the ROIs. The Relative Band Depth (RBD) and ratio images were integrated into the ASTER dataset to investigate whether they improve the classification accuracy. Generalized boosted regression models (GBM) package version 2.0-8 (Ridgeway, 2006) was used to fit the model in R version 2.15.3 (R development Core Team 2006). The classification accuracy performance was evaluated by Area Under Curve (AUC) of a receiver operating characteristic (ROC) plot.

Results

Figures 2 and 3 show the classification of the ASTER dataset obtained with the BRT method for the Gachsaran and Bibi-Hakimeh oil fields. The prediction power of classification using gas seeps co-located with gypsum zones is fair; the AUC has mean values of 60 percent (Table) The AUC value of the classification is improved to 70% using RBD/ratio images. This indicate the high density of gas seeps within areas of the cap rock formation mainly consist of gypsum. The BRT classification results show that oil seeps have a consistent spatial association with calcite zones of the evaporite cap rock; the AUC has a mean value of 76%. The AUC value of the classification using RBD/ratio layers is 70%. The predicted power of the classification using oil seeps co-located with clay zones of the ASTER image is good; the AUC has a mean value of 70% and using RBD/ratio images improves the AUC value to 76%. Figure 3 (a) shows the results of the BRT classification of ASTER data in the Masjid Soleyman oil field. The predicted power of the classification using oil seeps co-located with calcite zones is good; the AUC has mean values of 70% (Table). Results of the classification of the ASTER data using RBD/ratio images are shown in Figure 3 (b) with an AUC value of 60% (Table). The predicted power of the classification using oil seeps co-located with clay zones for both classification scenarios is fair; the AUC has mean values of 62%.





Results

Classification	Dataset	Types of seeps/Host rock	AUC (%)
1 (Figure 3 (a))	ASTER	Gas seep/gypsum	60
2 (Figure 3 (b))	ATER+ RBD/ratio	Gas seep/gypsum	70
3 (Figure 3 (a))	ASTER	Oil seep/calcite	76
4 (Figure 3 (b))	ATER +RBD/ratio	Oil seep/calcite	70
5 (Figure 3 (a))	ASTER	Oil seep/clays	70
6 (Figure 3 (b))	ATER+RBD/ ratio	Oil seep/clays	76
7 (Figure 4 (a))	ASTER	Oil seep/calcite	70
8 (Figure 4 (b))	ATER+RBD/ ratio	Oil seep/calcite	60
9 (Figure 4 (a))	ASTER	Oil seep/clays	62
10 (Figure 4 (b))	ATER+RBD/ ratio	Oil seep/clays	62

Remarks

One thing to consider in onshore basins is if the compositional variation of host rocks influences the types of seeps occurred at the surface. It would be most beneficial to determine the migration pathways of hydrocarbon seeps by study the spatial pattern of hydrocarbon seeps and their host rocks in any petroleum system. Such studies provide valuable information about the efficiency of cap rock and/or productivity of reservoirs. In addition, understanding the spatial distribution of seeps and diagenetic mineralization could provide geotechnical information, which may be of interest for planning of pipeline constructions over oil and gas fields.

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