Boletin de la Sociedad Geologica del Perú

journal homepage: www.sgp.org.pe ISSN 0079-1091

# APLICACIÓN DE MACHINE LEARNING PARA MEJORAR LA CARACTERIZACION SISMICA DE UN RESERVORIO FLUVIO-DELTAICO, CAMPO ZAPOTAL, CUENCA TALARA

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The development of a Mature Oil field as well as others in the world is a challenging task, and Talara Basin is one of them because of its growing depletion and its structural complexity, the latter made the seismic reflection image a little bit difficult to interpret. However, there are some areas where the seismic data plus well information could be used to get more reliable reservoir characterization using machine learning tools. The relation between different seismic attributes and acoustic impedance derived from well-logs using XGBoost (Extreme Gradient Boosting) regression algorithm is a compelling example of how machine learning could add extra information to predict reservoir sandstones. The aim of this study is to perform a machine learning model throughout the interaction of the extracted amplitude from the nine seismic attribute volumes as a log curves inside the reservoir with acoustic impedance log curve (Ip) in seven wells in the structural block (that contains 10 wells with Ip and 3 out of them are blind wells in the model). As a result, the model gives us the opportunity to predict Ip curves from seismic attributes with higher seismic resolution at each trace of the 3D seismic inside the block. Hence, the acoustic impedance volume from the XGBoost model due to its high resolution could be used to point out isolated sand bodies that will be difficult to predict with stochastic model that only use spaced wells. To be honest, this study does not attempt to replace other workflows of seismic inversion or more robust geostatistical model. On the contrary, the possibility to obtain nonlinear operators from the machine learning algorithm that could learn the anisotropic behavior of the wavefield propagation is the most prominent goal of this study. Furthermore, machine learning models could friendly and swiftly be used as a propagation guide of stochastic seismic inversion. For instance, Zapotal Field, in Talara Basin has a long history with several years of oil production, during its first year of exploitation the wells give enormous volume of hydrocarbon as the development of the fields have been growing, the difficulty to maintain a balance between costs of production by barrels turn out to be difficult which is the main reason why many expenses had to be cut off. Nevertheless, it was the opportunity to use alternative techniques such a machine learning which improve our reservoir models without acquiring commercial software tools that raise the cost, thus there is still remain room for machine learning applications in many areas.

## Dataset and Feature Engineering

The block area of the study is closed by faults in which there are 22 wells that has been drilling since 1979, for the machine learning model ten wells out of them that has density and sonic log information were used (Figure 1.) plus a seismic crop in the reservoir window.

The main goal of the study is to predict acoustic impedance (Output) from seismic attributes traces as input using XGBoost regression algorithm. Seven out of ten wells that has acoustic impedance were used in the regression model, and 3 wells as a blind. The Figure 2 attempts to describe the XGBoost model and shows the feature importance of all inputs in the prediction.

As a normal step in almost any machine learning begins by doing feature engineering, in this case the seismic traces of the attributes extracted in the ten wells were normalize by minimum and maximum due to some attributes by its calculus produce high values which are not suitable for reasonable predictions.

The data of 7 wells were split where the test size was 0.25 to catch the best training model without overfitting with accuracy score of 0.8361, Figure 3. As additional way to measure the predictability of the model 3 wells where use as a blind wells where the accuracy was as expected lower 0.7845 but high considering that is data not seen before in the training model.

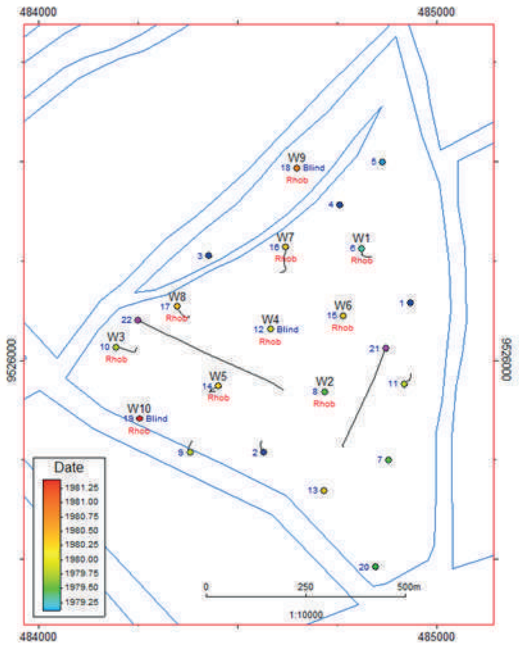


*Figure 1. Boundary of Structural map of Cabo Blanco's Top where 10 wells out of 22 total wells has density log curves (Rhob), and 7 out of the 10 wells with density log curves (Rhob) were used to deploy the Machine Learning Model.*

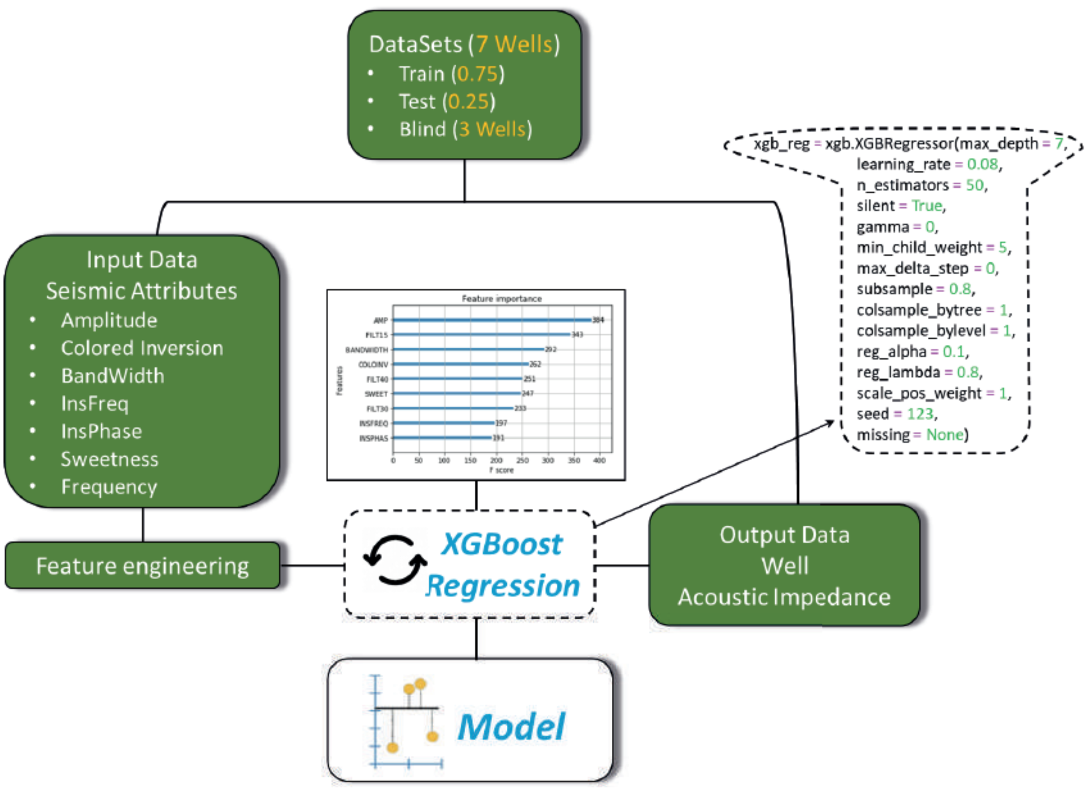


*Figure 2. The schematic model using XGboost regression algorithm in the study.*

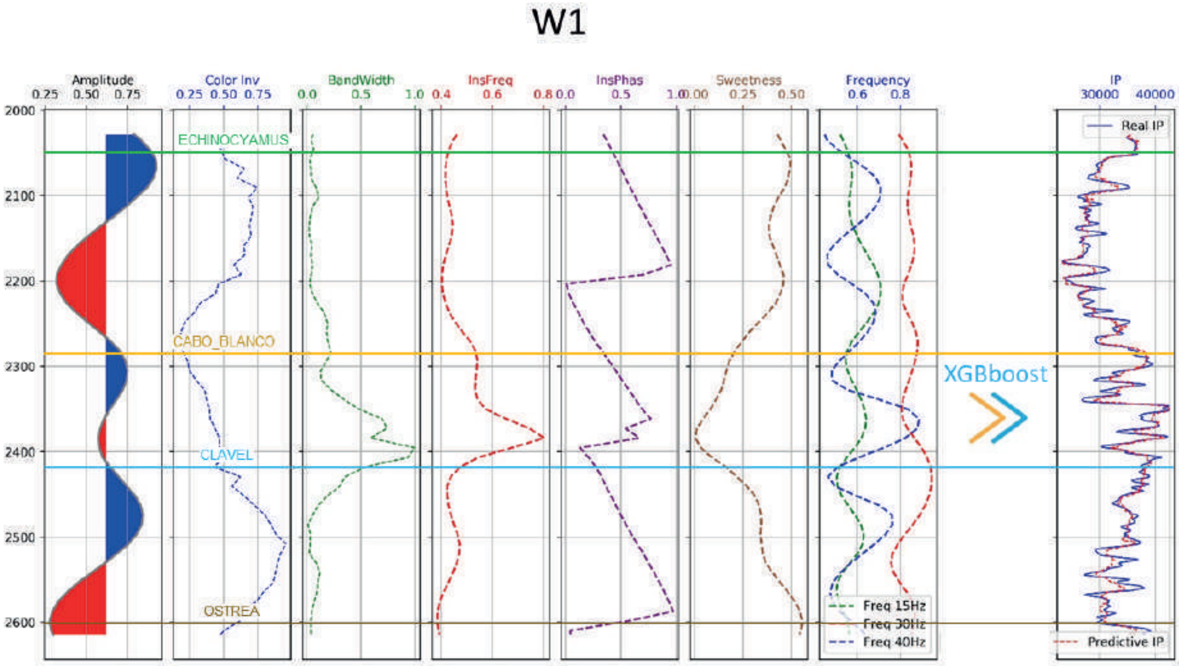


Figure 3. Shows the extracted amplitude of nine seismic attributes in the Well "W1", which were used in the machine learning using XG-Boost algorithm tool to obtain a relation between all of these attributes and the acoustic impedance, the red dotted line show accurately prediction of IP in the well "W1".

**Workflow of the study and discussion of results**

The workflow begins creating 1428 pseudo wells inside the block which are equally separated 25 meters, then the next step was to extract the seismic trace of the seismic cube and eight seismic attribute volumes which were normalize in order to use the XGBoost regression model to predict acoustic impedance. Once all wells has the predicted Ip as log a 3D model with higher seismic resolution were performed to populate the property inside the geocellular model including the train wells. As an alternative step the 3D geocellular model was converted to seismic volume catching the resolution of the geocellular model, coupled with a rock physics template where is possible to get a relation between low impedance are closely related to good porosity and oil saturated sand bodies. Figure 4.

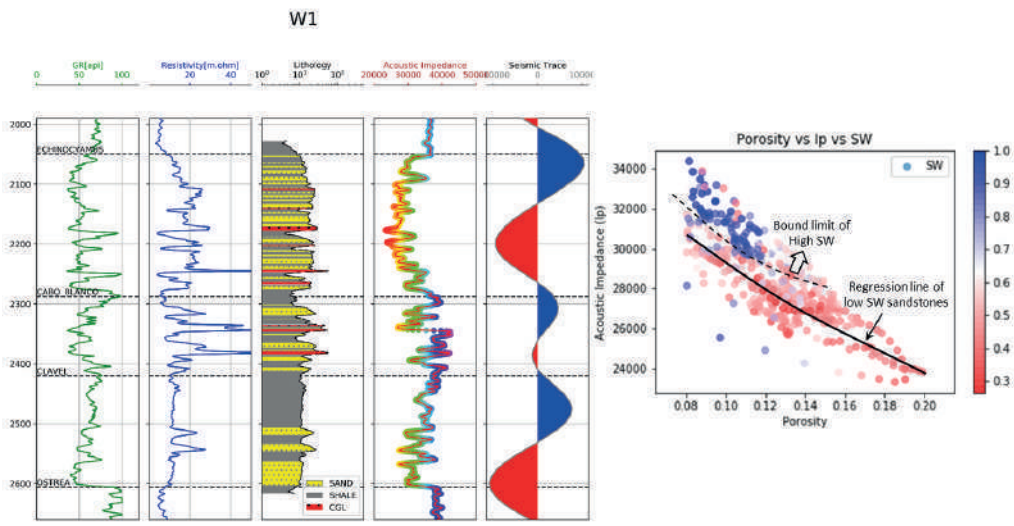


*Figure 4. The well "W1" is a representative well of the area of study, the main reservoirs are inside the Echinocyamus and Clavel tops which are sandstones from a Fluvial-Deltaic environment. According to the seismic well-tie the Echinocyamus top and Ostrea top correspond respectively to peak and trough. Moreover, it is possible to make a rock properties model where high values of Ip correlate with low values of porosity and also draw a dotted line which could separate sandstone of high water saturation (SW) from low Sw.*

Finally, the whole workflow is illustrated in the (Figure 5.) which allow to deploy an alternative seismic characterization where isolated sand bodies were found and the connectivity of others sand bodies was well defined. As a result, injector wells were activated to increase the oil recovery factor and two recently deviated wells confirm there is still a remaining oil saturated sand bodies.

There are zones where the model could not predict accurately and one reason could be the different date of logs (1980) and seismic acquisition (1998), many years after waterflooding and production life in the block could affect the porous media in sand bodies plus the anisotropy present in delta fluvial system.

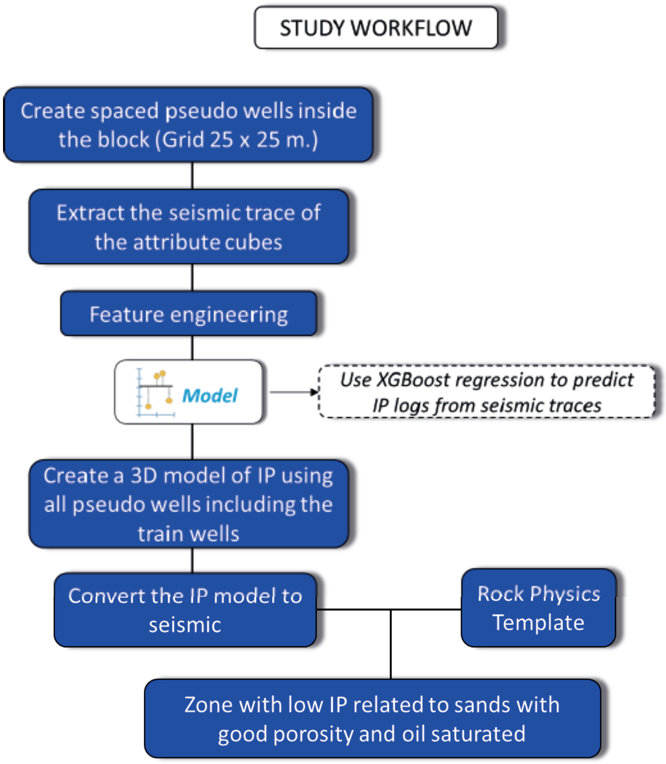


*Figure 5. Schematic process that was used in the study area using the XGBoost regression model.*

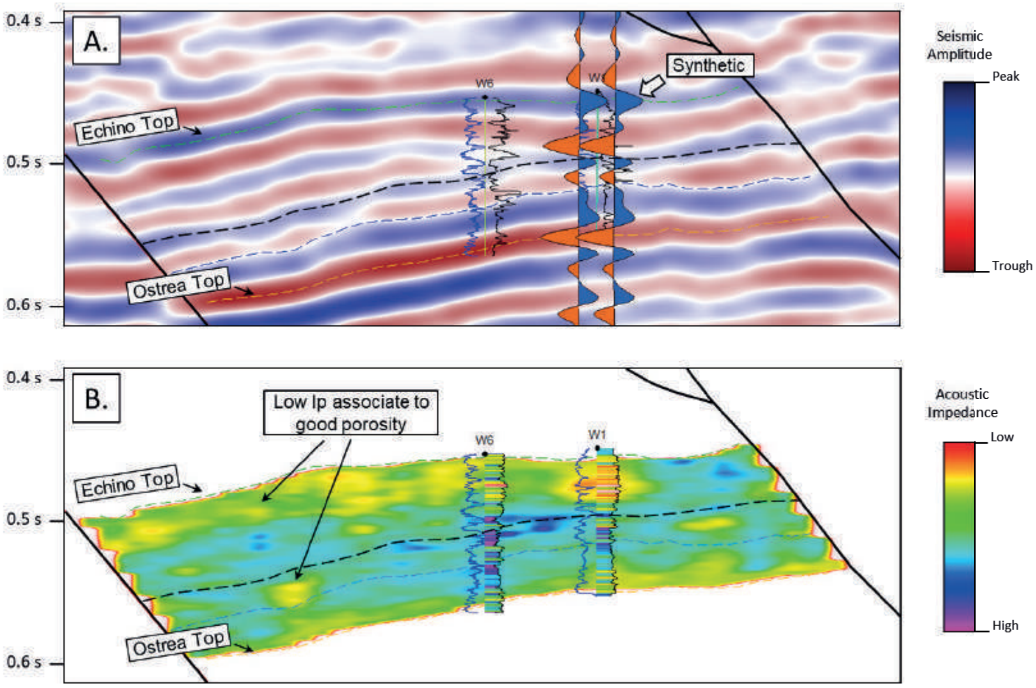


*Figure 6. Shows two pictures A is the seismic amplitude volume where Echino top (Peak) and Ostrea top (Trough) were used to set up a time window of the main reservoir sandstones. And B is the predicted acoustic impedance volume from the XGboost model where its resolution is noticeable greater than seismic amplitude volume, whereby it is feasible to correlate sandstones of good porosities with low values of Ip.*

## Conclusions

Get an additional tool to seismic characterization using Machine Learning with the algorithm XGBoost it is possible to get a regression model to relate seismic attributes with acoustic impedance in wells is a prominent alternative to grasp the anisotropy behavior of the reservoir that only with seismic reflection could not be feasible. Furthermore, using the alternative methodology plus geostatistical and rock physics template produce a better 3D geocellular model that allow us to find areas with low impedance associate to sands with good porosity that were still oil saturated and increase the oil recovery factor.

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