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A Federated Learning approach to use confidential hydrocarbon extraction data for investigating coastal subsidence

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Hydrocarbon reservoirs can be situated below low-lying coastal plains. Extraction from these reservoirs are known to cause substantial amounts of subsidence. Yet, the relative contribution of hydrocarbon extraction to total subsidence is often ignored in many coastal areas around the world. The primary reason for such negligence is because hydrocarbon extraction data are often confidential and therefore difficult to access for scientific research purposes. Incorporating the effects of hydrocarbon extraction in coastal subsidence research is however critical, as reservoirs can be depleted for decades in a row, causing decimeters of subsidence. Furthermore, gas is recently labeled by the European Union as a 'green energy,' motivating countries to increase production from low-lying coastal areas. Therefore, taking coastal subsidence by hydrocarbon extraction into account with datasets that are commonly private is essential for understanding regional subsidence processes, and eventually to design mitigation or adaptation strategies.

In this study, we present the outline of a workflow being developed to deploy hydrocarbon extraction data for subsidence modelling while acknowledging data privacy constraints. The targeted area is the urbanized coastal plain of Friesland (The Netherlands), which is subsiding by compaction of ca. 2-3 km deep gas reservoirs, as well as by surficial processes such as peat oxidation and clay shrinkage.

The core of the method is a Federated Learning framework for Neural Networks on vertically partitioned data including cryptographic techniques. Federated Learning implies that a central model can be trained on data which is only stored locally. Therefore, the data does not leave the premises of the data-owner (in this case the hydrocarbon operator), to protect confidential information. Such a model trains at each dataset and only model-updates are sent back and aggregated to the central server. The trained model and its output are shared between the parties involved.

Our workflow comprises a secure learning set-up for gas reservoir pressure depletion. The workflow uses the library FATE (FAir, Transparent and Explainable decision making), which combines secure inner sect (a Multi-Party Computation) techniques with a bottom and top split Neural Network, combining the outputs of the bottom models with an interactive layer. The technique of Neural Network was selected for flexibility in algorithms used, such as future intertwining of the workflow with physical models (e.g., transfer learning and physics informed neural networks). Current work focuses on extracting relevant information on feature importance causing subsidence from the Federate Learning framework without compromising confidentiality.

Preliminary results show that a Federated trained model does not significantly increase the prediction error compared to a centrally trained model, suggesting that the developed approach can be a critical step forward in convincing hydrocarbon operators to provide their data in a confidential way. In this way, subsidence by hydrocarbon extraction can be integrated into overall coastal subsidence studies.

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