CLAIMS

1. A method for modeling a subsurface region, comprising:

obtaining a trained machine learning network, the trained machine learning network being trained at a frequency of training data that is matched to an expected frequency of input data to which the machine learning network is applied;

obtaining an initial petrophysical parameter estimate;

applying the trained machine learning network to the initial petrophysical parameter estimate to predict a geologic prior model;

obtaining geophysical data for the subsurface region;

obtaining geophysical parameters for the subsurface region; and

performing a petrophysical inversion with the geologic prior model, the geophysical data, and the geophysical parameters to generate a rock type probability model and an updated petrophysical parameter estimate;

wherein each one of (i) applying the trained machine learning network and (ii) performing the petrophysical inversion is carried out using a geophysical data analysis system.

2. The method of claim 1, wherein the geophysical data comprise seismic data, and the geophysical parameters comprise elastic parameters.

3. The method of claim 2, wherein the elastic parameters are derived from the seismic data.

4. The method of any one of claims 1-3, wherein the petrophysical inversion comprises an optimization procedure.

5. The method of any one of claims 1-4, wherein the initial petrophysical parameter estimate and the updated petrophysical parameter estimate each comprise at least one of porosity and volume of clay.

6. The method of any one of claims 1-5, wherein obtaining the trained machine learning network comprises training the machine learning network with a training dataset to predict rock type probabilities from petrophysical parameters.

7. The method of claim 6, wherein the machine learning network is trained to predict rock type probabilities at sub-seismic scales for inputs comprising petrophysical parameters obtained from seismic-scale data.

8. The method of claim 6 or claim 7, wherein the training dataset comprises a plurality of datasets having different frequency content and different sampling scales.

9. The method of claim 8, wherein the different frequency content and different sampling scales of the datasets include both sub-seismic scale and seismic scale datasets, wherein the frequency of sub-seismic scale datasets is higher than the frequency of the seismic scale datasets.

10. The method of any one of claims 6-9, further comprising creating the training dataset by generating synthetic well logs using an existing forward model.

11. The method of any one of claims 6-10, wherein the training dataset comprises at least 1000 well logs.

12. The method of any one of claims 1-11, further comprising:

after performing the petrophysical inversion, checking for convergence of the updated petrophysical parameter estimate; and

if the check for convergence fails, iteratively:

applying the trained machine learning network to the updated petrophysical parameter estimate of a preceding iteration to predict an updated rock type probability model and another geologic prior model;

performing a petrophysical inversion with the another geologic prior model, geophysical data, and geophysical parameters to generate another rock type probability model and another updated petrophysical parameter estimate; and

checking for convergence of the another updated petrophysical parameter estimate.

13. The method of any one of claims 1-12, wherein the machine learning network comprises at least one of a deep neural network, a recurrent neural network, a convolutional neural network, and a generative adversarial network.

14. The method of any one of claims 1-13, further comprising managing hydrocarbons based at least in part upon the rock type probability model.

15. The method of any one of claims 1-14, wherein the geophysical data analysis system comprises:

a processor; and

a display configured to display graphical representations of a geophysical dataset, wherein the processor is configured to:

apply the trained machine learning network to the initial petrophysical parameter estimate to predict the geologic prior model; and

perform the petrophysical inversion with the geologic prior model, geophysical data for the subsurface region, and geophysical parameters for the subsurface region to generate the rock type probability model and the updated petrophysical parameter estimate.

16. A method of hydrocarbon management comprising:

obtaining a trained machine learning network, wherein obtaining the trained machine learning network comprises training the machine learning network with a training dataset to predict rock type probabilities at sub-seismic scales from input comprising petrophysical parameters obtained from seismic-scale data, the trained machine learning network being trained at a frequency of training data that is matched to an expected frequency of input data to which the machine learning network is applied;

obtaining an initial petrophysical parameter estimate;

applying the trained machine learning network to the initial petrophysical parameter estimate to predict a geologic prior model;

obtaining geophysical data for a subsurface region;

obtaining geophysical parameters for the subsurface region;

performing a petrophysical inversion with the geologic prior model, the geophysical data, and the geophysical parameters to generate a rock type probability model and an updated petrophysical parameter estimate;

interpreting the rock type probability model to identify geologic features of the subsurface region; and

managing hydrocarbons based at least in part upon the identified geologic features;

wherein each one of (i) applying the trained machine learning network and (ii) performing the petrophysical inversion is carried out using a geophysical data analysis system.

17. The method of claim 16, wherein:

the geophysical data comprise seismic data,

the geophysical parameters comprise elastic parameters, and

the elastic parameters are derived from the seismic data.

18. The method of claim 16 or claim 17, wherein the petrophysical inversion comprises an optimization procedure.

19. The method of any one of claims 16-18, wherein the initial petrophysical parameter estimate and the updated petrophysical parameter estimate each comprise at least one of porosity and volume of clay.

20. The method of claim 19, further comprising creating the training dataset by generating synthetic well logs using an existing forward model.

21. The method of claim 19 or claim 20, wherein the training dataset comprises at least 1000 well logs.

22. The method of any one of claims 19-21, wherein the training dataset comprises a plurality of datasets having different frequency content and different sampling scales.

23. The method of claim 22, wherein the plurality of datasets include one or more seismic scale datasets and one or more sub-seismic scale datasets of higher frequency than the frequency of the seismic scale datasets.

24. The method of any one of claims 16-23, further comprising, using the geophysical data analysis system:

after performing the petrophysical inversion, checking for convergence of the updated petrophysical parameter estimate; and

if the check for convergence fails, iteratively:

applying the trained machine learning network to the updated petrophysical parameter estimate of a preceding iteration to predict an updated rock type probability model and another geologic prior model;

performing a petrophysical inversion with the another geologic prior model, geophysical data, and geophysical parameters to generate another rock type probability model and another updated petrophysical parameter estimate; and

checking for convergence of the another updated petrophysical parameter estimate.

25. The method of any one of claims 16-24, wherein the machine learning network comprises at least one of a deep neural network, a recurrent neural network, a convolutional neural network, and a generative adversarial network.

26. The method of any one of claims 16-25, wherein the geophysical data analysis system comprises

a processor; and

a display configured to display graphical representations of a geophysical dataset, wherein the processor is configured to:

apply the trained machine learning network to the initial petrophysical parameter estimate to predict the geologic prior model; and

perform the petrophysical inversion with the geologic prior model, geophysical data for the subsurface region, and geophysical parameters for the subsurface region to generate the rock type probability model and the updated petrophysical parameter estimate.