Estimation of peat thickness in Indonesia from airborne time domain EM data through machine learning

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SUMMARY

We have developed a novel way of using machine learning with neural networks to directly estimate peat thickness from airborne electromagnetic (AEM) data. AEM data were acquired in Indonesia as part of a project to develop a new methodology to map peat thickness and help address the issue of peat degradation and illegal development. Ensembles of fully connected feedforward neural networks were trained using data measured by the AEM receiver in locations where the peat thickness was known. The AEM data were not inverted. The neural networks were then used to predict peat thickness for the rest of the data set. Hyper-parameters of the neural network ensemble were optimized using a one-at-a-time grid search. Over the 61 locations where peat cores were collected the median absolute deviation between estimated and measured peat thickness was 0.63 meters. A plot of predicted peat thickness versus measured peat thickness was also made and the linear fit of this plot had an R squared of 0.77.

The resulting map of estimated peat thickness agrees with both the map of peat thickness produced by traditional inversion methods and with the prior knowledge about the peat structure in the area. The peat thickness estimates from machine learning and traditional inversion diverge along the bank of a nearby river, where the estimates from machine learning appear to produce a more realistic result. The method developed here represents a new way of extracting the information of interest directly from the acquired AEM data, with the results produced by this method in agreement with those from a traditional inversion approach.

Key words: Machine learning, neural networks, peat, time-domain electromagnetics

INTRODUCTION

Alteration of peatlands across the globe contributed 5% of global greenhouse gas (GHG) emissions in 2006 (Hooijer et al. 2010). Seventy per cent of these GHG emissions are from the degradation and development of peatland in Indonesia (Hooijer et al. 2010). In 2016 the Indonesian government, with support from the Packard Foundation, announced a contest with the goal of developing a new methodology for mapping peatlands across the country. In support of a joint submission to this contest led by Rosemary Knight of Stanford University and Sonia Silvestri of Duke University, the airborne electromagnetic (AEM) system called SkyTEM was flown over a test site in West Kalimantan, Indonesia, in November 2017. Ground-based field work such as coring, ground penetrating radar, and electrical conductivity probing were also conducted concurrently in the study area. Figure 1 shows the SkyTEM flight lines and the locations where cores were collected.

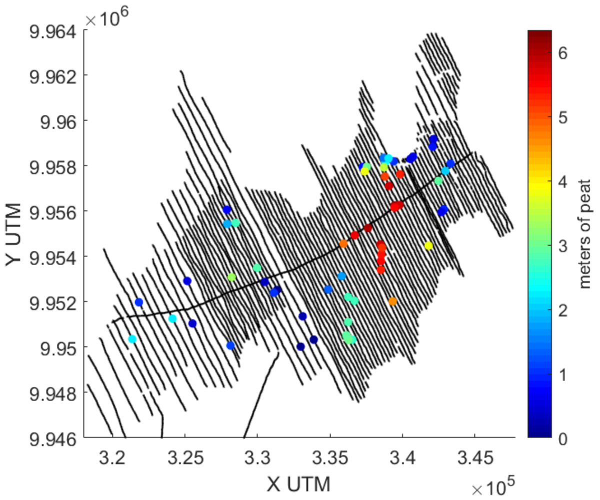

Figure 1. Map view of the SkyTEM flight lines and the locations where the peat was sampled. The color of each point reflects the thickness of peat measured at that core location.

The SkyTEM system is a time-domain electromagnetic (TEM) method that was developed in Denmark to map aquifer systems and study groundwater flow (Sørensen and Auken 2004). The system uses magnetic induction with transmitter and receiver loops to map the resistivity structure in the subsurface. Modelling completed for the first phase of the Indonesian peat contest showed that we should be able, with the SkyTEM system, to image a thin layer of resistive peat overlying a conductive mineral substrate. A literature review of studies conducted in Indonesia showed that a thin resistive layer of peat overlying a conductive mineral substrate is a common configuration of peatlands in Indonesia (Comas et al. 2015).

Traditional processing of TEM data involves inverting the measured response to obtain the resistivity structure in the subsurface. As the objective in this case was to extract a single variable—thickness of peat—from the AEM data, it was hypothesized that it would be possible to train machine learning (ML) models to directly estimate the peat thickness from the acquired SkyTEM data. Gunnick et al. (2012) used neural networks in a similar manner, to estimate the thickness of clay till from electromagnetic data, but they used the resistivity structure generated from the inverted data. The idea behind the work done here was to estimate the peat thickness directly from the data measured by the system, without inverting it for resistivity. Standard inversion techniques produce reliable results for the subsurface resistivity structure, but selecting the right constraints and model set up for a given problem can require extensive domain knowledge or large amounts of time spent fine-tuning parameters (Vignoli et al. 2015; Herckenrath et al. 2013). As a two-layer neural network (NN) can approximate any arbitrary function (Rumelhart et al. 1986; Ferrari et al. 2005), the NN should be able to learn the transfer function that produces peat thickness from the SkyTEM data, thus allowing us to estimate peat thickness directly from the measured data. After training on all of the locations where the peat thickness is known, the NN can then produce an estimate of peat thickness for all the other locations where SkyTEM data were acquired.

METHOD AND RESULTS

Summary of Approach

Several readily available ML models such as classical Naïve Bayes, support vector machines, classifier trees, and K-nearest neighbour were applied to the dataset but the results were poor. These simple ML algorithms were all from the classifier training toolbox in Matlab (MATLAB™ 2016b). We therefore developed an alternate approach. Ensembles of five fully connected feedforward NNs were constructed and trained using Matlab's neural network toolbox. The ensembles were trained using the synthetic data and the field data and validated using hold one out cross validation for all of the field examples (Kohavi 1995). The ensemble's hyper-parameters were optimized through a local grid search algorithm, where each hyper-parameter such as regularization factor or network layout were tuned one at a time to find the value that gave the best performance. This kind of one-at-a-time optimization will find the optimal result if the effect of the interactions between the hyper-parameters are small (Saltelli et al. 2000).

Training Data

The training dataset was the set of core locations, close to SkyTEM flight lines, where the peat thickness was measured in the field. The measured TEM data was split into time gates which describe how much current was measured in the receiver coil over some time interval after the transmitter loop was turned off. Measured signal amplitude from the first thirty time gates, along with other variables found to be important such as surface elevation and system height, were used as the predictor variables while peat thickness was the target variable. As there were only 61 core measurements of peat thickness that could be used for the training dataset, synthetic SkyTEM data were generated by creating a 5-layer earth model and forward modelling, resulting in a large enough dataset to train the NNs.

Synthetic Data

The synthetic data were generating by creating 10,000 5-layer earth models and forward modelling the SkyTEM response for each earth model. The SkyTEM system uses a dual moment pulse with a low moment designed for the near subsurface and a high moment for resolving deeper structures. Both moments were measured in the field in Indonesia so the synthetic data involved both moments. In the five-layer model used to generate the synthetic data, the first layer represented the peat, the next three layers represented a variable thickness transition zone, and the final layer was the underlying mineral substrate. The thickness of each of the layers was randomly sampled from uniform distributions with the peat thickness varying from 0.1 to 7 meters (the thickest peat observed in our study area), the three transition layers each varying from 0.1 to 1 meter in thickness, and the underlying mineral substrate extending to the bottom of the model. The resistivity of each of these layers was randomly sampled from uniform distributions with the same ranges as the electrical conductivity data measured on core samples in the field and laboratory. Figure 3 shows all of the synthetic SkyTEM data overlain by the acquired SkyTEM data. As the acquired data are contained within the synthetic data we assume that our synthetic data approximate the acquired data, so we can use them in the training of the neural networks.

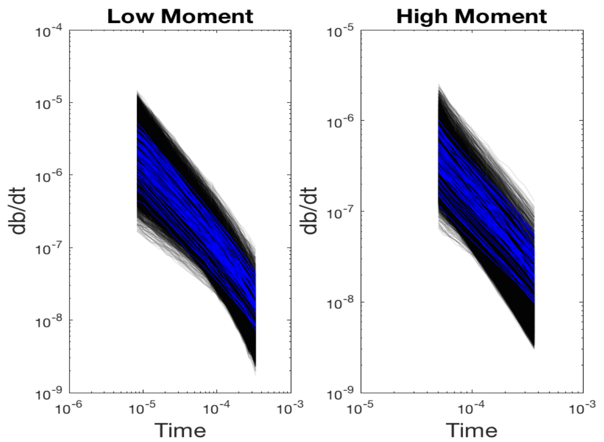

Figure 2. Comparison of the amplitudes of each time gate of the synthetic versus acquired SkyTEM data. Synthetic examples are in black and field examples are in blue.

Neural Networks

The neural nets used were all constructed and trained using the Neural Network Matlab toolbox (MATLAB™ 2016b). The performance of a specific neural network configuration was assessed by training the network on the synthetic data pairs, SkyTEM along with the peat thickness from the synthetic earth model, and then on all but one of the field data pairs – the acquired SkyTEM data and the closest measurement of peat thickness from coring. The trained network would then make a prediction of peat thickness for the held out field data pair. This would be repeated for all of the 61 field data pairs. The distribution of errors would be compared to previous results with particular care being paid to the precent of estimations within 0.5 meters and 1 meter of the true peat thickness.

The neural networks were trained and tested in ensembles of five with the average of the predictions of the individual networks taken as the prediction of the ensemble. Training and testing neural networks in ensembles helps reduce the chance that one poorly trained network will skew the results (Hansen and Salamon 1990).

The optimization of neural network hyper-parameters was performed by training and testing an ensemble of five neural networks with hold-one-out cross validation on the field data pairs while varying one hyper parameter at a time to find the value that gave the best performance. The hyper-parameters optimized in this manner were network layout, number of synthetic examples included, training function, neural network type, and regularization factor.

Fully connected pattern fitting, feedforward and cascade feedforward NNs were all tested before selecting fully connected feedforward NNs as the best performing type.

Figure 6, included at the end of the abstract, shows a schematic representing a fully connected feedforward NN. Figure 6 also shows what was found to be the optimal layout of a three layer net with 30 neurons in the first layer, 15 in the second, and 5 in the third. The optimization found that including all 10,000 of the synthetic data pairs in the training data gave better results than including none or some of the synthetic data pairs.

Bayesian regularization was found to be the best performing training function; however Levenberg-Marquardt backpropagation was used as it had similar performance and much faster training time (Foresee and Hagan 1997; Hagan and Menhaj 1994).

Results

The final ensemble of trained NNs, when trained on the synthetic data and the field data, and tested with hold one out cross validation produced estimates with a median absolute deviation of 0.63 meters over the 61 field examples. 50% of the predictions had an absolute deviation of 0.6 meters or less from the measured peat thickness, and 75% of the predictions had an absolute deviation of 1.2 meters or less. Figure 3 is a plot of the estimated peat thickness at each core location plotted against the measured peat thickness values. The linear fit was calculated and the R squared value is 0.77.

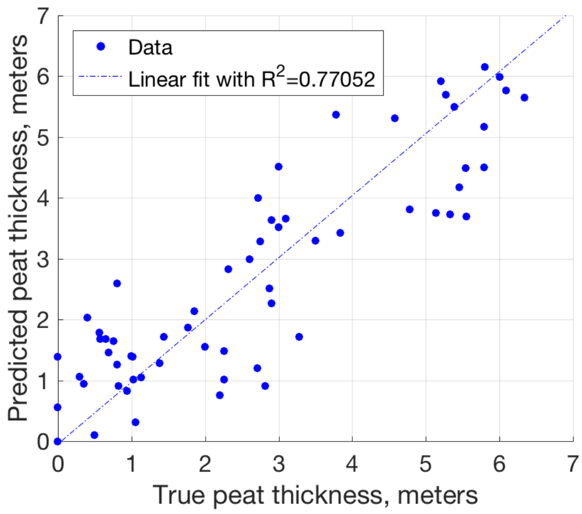

Figure 3. Predicted versus measured peat thickness with linear fit shown as dashed line.

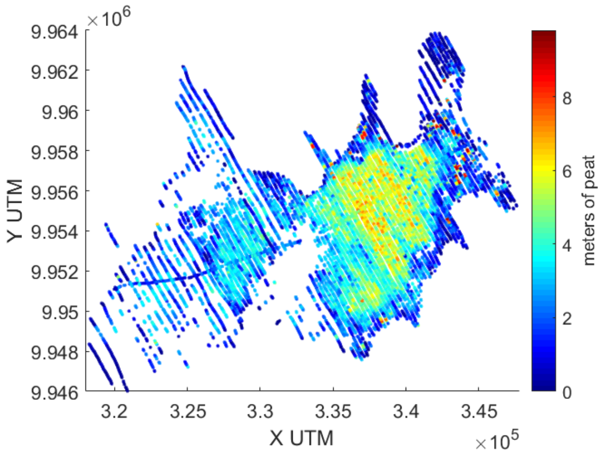

Figure 4. Final map of estimated peat thickness produced with machine learning. The color represent the thickness of peat at each location.

This ensemble was then used to predict a peat thickness for every location at which SkyTEM data were acquired. SkyTEM locations that had missing or bad data were not used, so the coverage in the estimated peat thickness maps is different from the planned coverage shown in Figure 1. The final peat thickness estimate is shown in Figure 4. The map of peat thickness estimated via the final ensemble of neural networks reproduced all of the main structures of interest known to be present in the peat. Figure 5 shows the difference between this estimate of peat thickness and the result produced by taking the 50 ohm-m interface in the inverted resistivity data as the peat boundary. The difference map shows that the two estimations generally agree over the main peat bodies but have some deviation on the side of the meandering boundary along the north of the study area which is a large river. As peat does not have the right environment to form along the bank of a large river (Supardi et al. 1993), the values in the difference map likely represent errors in the 50 ohm-m interface and not errors in the estimate of peat thickness from the neural networks.

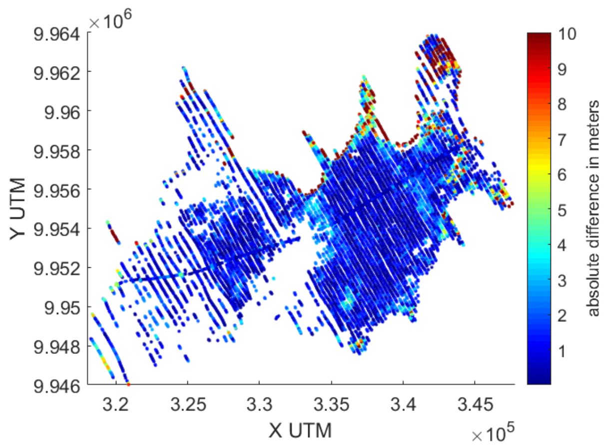

Figure 5. Map of the absolute difference between the peat thickness estimate produced with machine learning and the peat thickness estimate based on the 50 ohm-m interface. The color represents the absolute difference at each location.

CONCLUSIONS

Our results demonstrate an ability for machine learning models, specifically shallow fully connected neural networks, to "learn the physics" behind complex geophysical measurements and extract the information of interest – in this case peat thickness - directly from the measured data. The results compare favourably to those obtained by state-of-the-art inversion techniques. This method is also an improvement over peat estimation methods centred around elevation. Peat thickness can be estimated by taking any elevation changes above some flat datum to signify changes in peat thickness. We examined this relationship and found that, while there is a correlation between elevation and peat thickness, the relationship varies spatially and the estimation produced leans heavily on the assumption that the underlying substrate is flat. This assumption may hold for some low-lying areas of Indonesia, however, any changes in substrate topography, as are present in large portions of the country, will render estimation methods centred around elevation inaccurate.

Our method is the only way in which to map the top and the bottom of a thin layer of peat without making assumptions about the underlying topography. There are however, limitations to the method we have developed. The thickness of the resistive peat is a relatively simple parameter that has a direct influence on the acquired SkyTEM data. Estimating more complicated subsurface structure directly from the data should be possible, as any information used by inversion techniques is also available to the ML models, but this would require a more complicated model and training data setup.

Acknowledgements

We would like to thank the Packard Foundation for the funding from grant # 2017-65823 which provided the funding to fly the SkyTEM survey. Sonia Silvestri received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 747809 for the project CReScenDo. We would also like to thank Stanford University and the Duke Wetland Center for their support for the field survey.

REFERENCES

Comas, X., Terry, N., Slater, L., Warren, M., Kolka, R., Kristiyono, A., … Darusman, T. (2015). Imaging tropical peatlands in Indonesia using ground-penetrating radar (GPR) and electrical resistivity imaging (ERI): implications for carbon stock estimates and peat soil characterization. Biogeosciences, 12(10), 2995–3007.

Dan Foresee, F., & Hagan, M. T. (1997). Gauss-Newton approximation to bayesian learning. IEEE International Conference on Neural Networks - Conference Proceedings, 3,

Ferrari, S., & Stengel, R. F. (2005). Smooth function approximation using neural networks. IEEE Transactions on Neural Networks, 16(1), 24–38.

Gunnink, J. L., Bosch, J. H. A., Siemon, B., Roth, B., & Auken, E. (2012). Combining ground-based and airborne em through Artificial Neural Networks for modelling glacial till under saline groundwater conditions. Hydrology and Earth System Sciences, 16(8), 3061–3074.

Hagan, M. T., & Menhaj, M. B. (1994). Training Feedforward Networks with the Marquardt Algorithm. IEEE Transactions on Neural Networks, 5(6), 989–993.

Hansen, L. K., & Salamon, P. (1990). Neural Network Ensembles. IEEE Transactions on Pattern Analysis and Machine Intelligence, 12(10), 993–1001.

Herckenrath, D., Fiandaca, G., Auken, E., & Bauer-Gottwein, P. (2013). Sequential and joint hydrogeophysical inversion using a field-scale groundwater model with ERT and TDEM data. Hydrology and Earth System Sciences, 17(10), 4043–4060.

Hooijer, A., Page, S., Canadell, J. G., Silvius, M., Kwadijk, J., Wösten, H., & Jauhiainen, J. (2010). Current and future CO 2 emissions from drained peatlands in Southeast Asia. Biogeosciences, 7(5), 1505–1514.

MATLAB, Neural Network Toolbox Release 2016b, Classifier Training Toolbox Release 2016b, The MathWorks, Inc., Natick, Massachusetts, United States

Kohavi, R. (1995). A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection 2 Methods for Accuracy Estimation. Proc. of IJCAI'95, 1137–1145.

Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. Nature, 323(6088), 533–536.

Saltelli, A., Chan, K., & Scott, E. M. (Eds.). (2000). Sensitivity analysis (Vol. 1). New York: Wiley.

Supardi, Subekty, A. D., & Neuzil, S. G. (1993). General geology and peat resources of the Siak Kanan and Bengkalis Island peat deposits, Sumatra, Indonesia. Modern and Ancient Coal-Forming Environments, 45–62.

Sørensen, K. I., & Auken, E. (2004). SkyTEM–a new high-resolution transient electromagnetic system. Exploration Geophysics, 35(3), 191–199.

Vignoli, G., Fiandaca, G., Christiansen, A. V., Kirkegaard, C., & Auken, E. (2015). Sharp spatially constrained inversion with applications to transient electromagnetic data. Geophysical Prospecting, 63(1), 243–255.

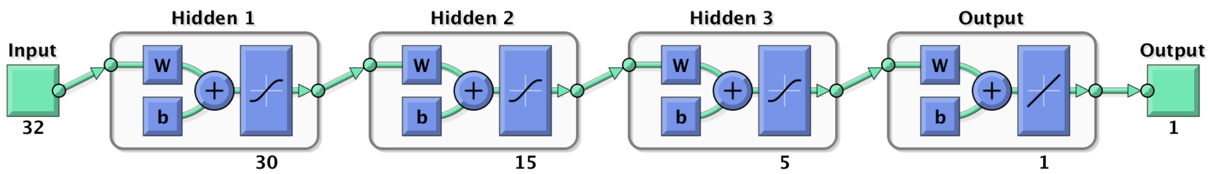

Figure 6. Example neural network architecture. The numbers below each section represent the number of inputs and outputs for the first and last layer respectively, and the number of neurons for the other three layers.