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# Assessing below-ground carbon and nitrogen accumulation of green infrastructure using machine learning methods, targeting sub-tropical bioretention basins

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**Abstract.** This study presents an assessment of below-ground carbon dynamics of green infrastructure using artificial intelligence, targeting sub-tropical bioretention basins in South East Queensland, Australia. This extended abstract describes the context for the study and the significance of the work, which was recognised and enabled through the international Microsoft Artificial Intelligence (AI) for Earth Grants (2018 Grant winner). Four different scenarios were tested with three different approaches for modelling of the regression values. The three different machine learning methods were applied to predict belowground carbon and nitrogen, based on soil physical characteristics data entry. The neural network model performed better in predicting both the carbon and nitrogen concentration in all the scenarios. The implication of this study provides a profound shift in the type of platform that can be used, wherein machine learning methods can assist decision-makers in finding low-cost proxies for measuring carbon and nitrogen capture in bioretention basins.

## 1. Introduction

Bioretention basins are one of the most frequently implemented green stormwater devices with a promising performance in heavy metal, nutrient and nitrogen removal [1]. However, many studies have reported the lack of maintenance and inspection as the reason for their failure [2, 3]. Therefore, monitoring of the stormwater assets is required to determine the long-term performance and effectiveness of the designed system and to predict the required maintenance activities [4]. However, there is little understanding of the long-term soil quality condition assessment of bioretention basins in relation to other physical characteristics of soil filter media. This current study aimed to develop an artificial neural network model that uses different soil physical characteristics to predict soil carbon and nitrogen.

## 2. Method

The published results of a study on bioretention soil filter media were used in this study [5]. Three main types of machine learning prediction models, namely random forests (RF), support vector machines (SVM) and neural network (NN) were used in this study on four different scenarios. The three sampling locations within a site were combined in the scenario I and II to present the soil properties in each different depth. Accordingly, the analysis was performed on 96 data points. On the other hand, each sample data was taken as a separate data point in the scenarios III and IV (291 data points). A 5-fold cross-validation method was used to test the performances of various machine learning models in the two scenarios. The accuracy metric to predict the regression activity called Pearson correlation coefficient  $R^2$  between the experimental and predicted toxicities was used.

## 3. Results and discussion



The models were trained to predict belowground carbon/nitrogen content. Table 1 shows the results of 5-fold cross-validation regression values of scenario I and II for both carbon/nitrogen across different applied methods. The NN performs better than the SVM and RF in all scenarios. The NN approach shows the ability to generate the soil carbon prediction models, in which 73% and 76% of the carbon values can be explained by this prediction in scenarios I and III. However, the ability of a linear regression model between the target parameters and each feature individually would not exceed 25%. This evidence demonstrates the substantial ability of the trained neural network model in predicting carbon/nitrogen values based on a set of physical features.

**Table 1.** The regression values for carbon and nitrogen in the scenarios I, II, III and IV using three different methods.

Scenarios	R <sup>2</sup> Value	Applied Method		
		SVM	RF	NN
Scenario I	Nitrogen	0.48	0.45	0.63
	Carbon	0.65	0.63	0.73
Scenario II	Nitrogen	0.66	0.69	0.75
	Carbon	0.61	0.65	0.83
Scenario III	Nitrogen	0.55	0.48	0.67
	Carbon	0.69	0.67	0.76
Scenario IV	Nitrogen	0.69	0.63	0.74
	Carbon	0.65	0.70	0.83

#### 4. Conclusion

In this study, artificial intelligence methods were used to predict belowground carbon and nitrogen, based on soil physical characteristics data entry in bioretention basins in the sub-tropical climate of South East Queensland, Australia. Four different scenarios were tested with three different machine learning methodologies for modelling of the regression values. The results show that the machine learning methodologies far outweigh the traditionally statistical analysis of correlation. Furthermore, the results show that the NN model performs better than the SVM, RF in predicting both the carbon and nitrogen concentration in all the scenarios. The study has shown that although the inclusion of the carbon and nitrogen isotopes as the features in the scenario II and IV slightly increase the accuracy of the predicting models, the simplicity of scenario I and III might be more appealing for practical asset assessment. The trained NN models show the R<sup>2</sup> values of 0.73 and 0.63 for the soil carbon and nitrogen prediction models respectively. However, the use of statistical and mathematical analysis to estimate the areal carbon density based on site' age show the R<sup>2</sup> values of only 0.44. The outcome of this study demonstrates the substantial ability of the trained neural network models in predicting carbon and nitrogen values based on a set of physical features. Also, the developed model in this study can be employed in constructed wetlands as a nitrogen management strategy to reduce the destructive effects of nitrogen discharge to the Great Barrier Reef in SEQ, Australia.

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