Slit-LIBS: A Novel Strategy to Improve the Efficiency of Soil Nutrient Measurement from a Stand-off Distance

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Abstract

In this paper, a Slit coupled Laser induced breakdown spectroscopy (s-LIBS) technique combined with machine learning algorithm is proposed to measure the soil nutrients (Macro nutrients: N, P, K, Ca, Mg, S and Micro nutrients: Fe, Zn, B, Cu, Mn) from a stand-off distance (0.6 m to 2 m). The laser induced plasma created on the soil surface starts to expand in all directions at supersonic velocities. A portion of the plasma optical radiation propagates towards the soil surface and get reflected. It is also evident that the surface reflection phenomenon isinfluenced by soil texture and incident plasma wavelengths.Thus, these reflected rays will create an uncertainty to the soil LIBS spectral intensities and further affects the estimation capability of machine learning algorithms. To mitigate the effect of reflected ray in the LIBS data, the spectral information is gathered by utilizing a slit (rectangular slit of 30 mm x 1 mm) placed on top of the soil sample. A total of 50 number of soil samples are collected from different geospatial locations of Tamilnadu, India. The experiments are carried out by varying the laser irradiances between 2 $\times 10^{10}$ W/cm^2 to 7 $\times 10^{10}$ W/cm^2. An investigation to identify an appropriate machine learning algorithms [Multiple Linear Regression (MLR), Support Vector Regression (SVR), Partial Least Square Regression (PLSR), Least Absolute Shrinkage and Selection Operator (LASSO) and Gaussian Process Regression (GPR)] in relation to the estimate of soil nutrients is carried out.

Experimental study shows that the relationship [Pearson correlation coefficient (r)] between the LIBS spectral peak intensities and its corresponding soil nutrient concentration (determined through standard lab) get enhanced, when the experimentation is carried out with slit arrangement. The r value of Potassium(K I- 766 nm line) is increased from 0.15 (without slit) to 0.65 (with slit).Also, the other evaluation metrics such as the Coefficient of Determination (R^2) and Root Mean Square Error (RMSE) get improved with slit arrangement, irrespective of considered machine learning algorithms. It is observed that the usage of Gaussian Process Regression method has resulted in achieving higher R^2 value (Potassium, 0.79 (without slit), 0.94 (with slit)) compared with other regression methods.The above specified trend is observed irrespective of the elemental nutrient content. On a similar note, the estimated RMSE value for Potassium is of 60.54 (without slit) and 43.60 (with slit). The improvement in estimation of nutrient content in soil is mainly attributed to the absorption of plasma radiation travelling towards the target surface by the black slit arrangement. The placement of slit (slit-LIBS) on top of soil surface helps in identifying the S II @ 545 nm emission line, otherwise it gets submerged in continuum radiation (without slit).

The Relative Standard Deviation (RSD) of the peak intensity (769 nm K I line) get decreased from 14.01% (0.6 m) to 3.22% (2 m), upon increasing the Stand-off collection distance. Theoretically, the decrease in RSD value should increase the R^2 valueof machine learning algorithm. But, the experimental analysis reveals that a higher R^2value (0.62 @ 0.6 m, 0.65 @ 1 m, 0.81 @ 1.5 m and 0.71 @ 2 m) is obtained at a Stand-off collection distance of 1.5 m. At a distance of above 1.5 m, the R^2 valuegets deteriorated due to the lack of optical emission being coupled to the collection optics. Thus, after extensive experimentation, the optimised parameters to estimate the soil nutrient content are Experimental setup: slit-LIBS, Stand-off collection distance=1.5 m, Laser irradiance= 7$\times 10^{10}$ W/cm^2 and machine learning model = Gaussian Process Regression (GPR).