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**Simultaneously estimating crop biomass and nutrient parameters  
using UAS remote sensing and multitask learning**

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**Abstract.**

*Rapid and accurate estimation of crop growth status and nutrient levels, such as aboveground biomass (AGB) and canopy concentrations of nitrogen (N), phosphorus (P), and potassium (K), is critical for precision agriculture and field-based high-throughput plant phenotyping. Recent developments in Uncrewed Aircraft Systems (UAS) and sensor technologies have enabled the collection of high spatial and spectral resolution remote sensing data over large areas at lower costs. Combining deep learning-based modeling with high-resolution UAS remote sensing has emerged as a crucial tool for crop monitoring and plant trait estimation. Typically, the estimation of multiple related plant traits is conducted using a single task learning (STL) approach, where separate models are developed for each individual plant trait or task. However, the STL approach can be time-consuming and may have lower accuracy. Alternatively, the multitask learning (MTL) approach can conduct multiple prediction tasks simultaneously with improved accuracy through a single deep learning model. The objective of this work is to explore the potential of multitask learning and UAS multispectral remote sensing for the simultaneous estimation of corn (*Zea mays* L.) AGB, and canopy N, P, and K concentrations. UAS imagery was collected from an experimental corn field throughout the 2022 growing season in South Dakota, USA. Various spectral and texture features were derived from the UAS imagery and used as input variables for the deep learning models. A one-dimensional Convolutional Neural Network (1D-CNN) deep learning model was employed as the base model for both the STL and MTL approaches. The results show that the MTL approach yielded superior results in estimating canopy N, P, and K concentrations and produced slightly poorer yet comparable results for AGB estimation compared to the STL approach. This study provides valuable insights into the applicability of deep learning-based multitask learning for the simultaneous estimation of different plant traits. The results of this study can also be beneficial for other stakeholders, such as plant breeders, precision agriculture specialists, and farm managers.*

**Keywords.**

*Multitask learning, deep learning, Uncrewed Aircraft Systems (UAS), crop biomass and nutrient.*

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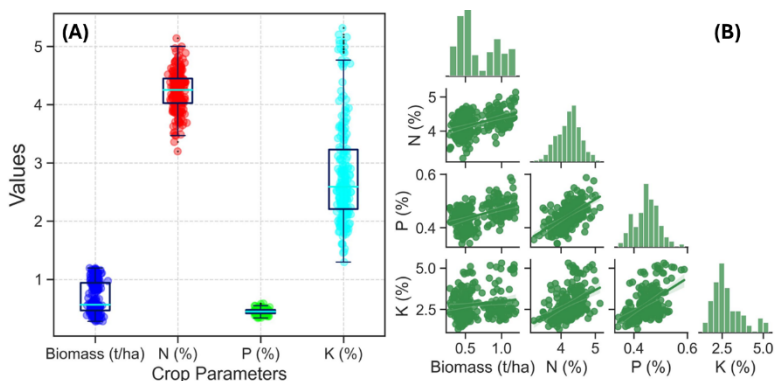
# 1. Introduction

Crop aboveground biomass (AGB) and canopy nitrogen (N), phosphorus (P), and potassium (K) concentrations are important crop traits and agronomic indicators that reflect crop growth and nutrient status. Accurate and rapid estimation of these parameters at low cost over large areas is critical for precision agriculture (Maimaitijiang et al. 2020) and in-season nutrient management. Traditional approaches, involving field sampling and lab analysis to measure plant traits such as AGB and canopy N, P, and K concentrations, are time-consuming, labor-intensive, and costly. In recent years, Uncrewed Aircraft Systems (UAS)-based remote sensing technologies combined with machine/deep learning-based modeling approaches have provided viable alternatives to traditional methods for crop monitoring and the estimation of various plant traits at a fine spatial scale (Dhakal et al. 2023). Deep learning methods have been broadly implemented to estimate plant traits such as AGB and crop canopy N concentrations using UAS-based high-resolution multispectral or hyperspectral imagery. However, the estimation of crop canopy P and K concentrations using remote sensing data has been less explored. Additionally, previous studies estimating multiple plant traits typically develop individual deep learning models for each specific plant trait, which is known as single task learning (STL) approaches. This STL-based modeling strategy requires developing multiple models. On the other hand, Multitask Learning (MTL) (Caruana 1997) is a deep learning approach that estimates multiple related tasks simultaneously through a single model, rather than learning each task independently and developing multiple models as the STL approach. MTL often achieves improved performance for each individual task by leveraging knowledge from other tasks and benefits from more generalized common features across various tasks. This approach can be more efficient and accurate (Zhang and Yang 2018). However, the MTL approach is less explored for the estimation of multiple plant traits using UAS remote sensing data. Therefore, the aims of this work are to 1) investigate the potential of UAS-based multispectral imagery in estimating different corn parameters such as AGB and canopy N, P, and K concentrations; and 2) examine the performance of MTL in estimating multiple related corn parameters compared to STL.

## 2. Materials and Methods

### 2.1 Test site and data

An experimental corn field was established in Brookings County, South Dakota, USA. The corn was planted between May 23 and June 6, 2022. Various crop management practices, including starter fertilizer placement, downforce application during planting, and the application of different N rates, were conducted. A total of 263 corn AGB samples were collected at the V2 and V6 growth stages, and lab-based analysis was conducted to measure canopy N, P, and K concentrations using the AGB samples. The data range and distribution patterns of the corn AGB, N, P, and K concentration values are displayed in Figure 1(A). Additionally, the histogram distribution and correlation relationships among the four corn parameters are shown in Figure 1(B).



**Figure 1. Data range and distribution patterns of the corn AGB, N, P and K concentrations (A); the histogram distribution of the abovementioned four corn parameters and their correlation relationship (B).**

UAS multispectral imagery was collected synchronically with biomass sampling at V2 and V6 of corn growth stages in 2022. A DJI Matrice 300 RTK UAS equipped with a Micasense Altum multispectral sensor was used to capture high-resolution multispectral imagery at an altitude of 50 meters and a flight speed of 5 m/s, with 80% side and frontal overlaps. Agisoft Metashape software was utilized for UAS imagery

orthomosaicking and radiometric calibration.

## 2.2 Methods

A series of spectral (i.e., vegetation indices) and texture features were extracted using the UAS imagery from each AGB sampling spot and used as input variables for deep learning-based regression models. A detailed list of the input features can be found in Dilmurat et al. (2022). Deep learning algorithm one dimensional Convolutional Neural Network (1D-CNN) was used as the base model for the STL and MTL. 80% of randomly selected corn AGB, N, P and K samples were used as training data, and the remaining 20% samples were used for model testing. The coefficients of determination ( $R^2$ ), root mean square error (RMSE) and relative RMSE (RMSE%), were used as model evaluation metrics to assess and compare the performance of STL and MTL deep learning models.

## 3. Results

Table 1 presents the model testing results for the estimation of corn AGB, N, P, and K concentrations using STL and MTL based on the 1D-CNN method. Overall, the MTL approach yielded superior performance in estimating corn N, P, and K concentrations compared to the STL approach. For corn AGB estimation, the MTL approach showed slightly poorer yet comparable performance to the STL approach. This indicates the superior efficiency and accuracy of the MTL approach in estimating multiple related crop parameters using UAS remote sensing data. Additionally, both STL and MTL approaches based on the 1D-CNN method successfully estimated corn canopy N, P, and K concentrations, with  $R^2$  values of 0.59, 0.62, and 0.60, respectively. In both the 1D-CNN-based STL and MTL approaches, corn AGB estimation resulted in  $R^2$  values of 0.86 and 0.88, respectively, which are higher compared to the  $R^2$  values for estimating other corn parameters.

Methods	Metrics	Biomass (t/ha)	N (%)	P (%)	K (%)
STL	R2	0.88	0.56	0.54	0.57
	RMSE	0.11	0.21	0.04	0.69
	RMSE%	15.45	4.97	7.88	24.18
MTL	R2	0.86	0.59	0.62	0.60
	RMSE	0.11	0.21	0.03	0.66
	RMSE%	16.65	4.81	7.13	23.24

## 4. Conclusion

Both the STL and MTL methods, based on 1D-CNN deep learning, successfully estimated corn AGB, and canopy N, P, and K concentrations using UAS multispectral imagery. The MTL approach outperformed the STL approach in estimating corn canopy N, P, and K concentrations, and yielded slightly poorer yet comparable results in estimating corn AGB. UAS-based multispectral imaging, combined with the deep learning approaches employed in this research, provides important insights for the efficient and accurate simultaneous estimation of multiple related crop parameters and traits.

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