YIELD ESTIMATION OF RICE USING MULTISPECTRAL IMAGERY FROM UAV

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Keywords: Multispectral, UAV, Vegetation Indices, NDVI, Digital Surface Model, Digital Elevation Model, Regression, Correlation, Yield estimation

SUMMARY

Agriculture is vital in sustaining human life and providing food security for the increasing population. Sustainable development goals (SDGs) especially SDG 2: Zero Hunger and SDG 12: Responsible Consumption and Production have stressed optimizing crop yield to meet the increasing demand for food security. The practice of accurate yield estimation plays a crucial role in achieving these goals since it is a key to helping farmers and communities to plan better, use resources wisely and make decisions to ensure that agricultural productivity meets the growing demand sustainably. The article aims to estimate rice yield using regression models based on plant characteristics, including plant height, plant age, and farm management data such as the amount of DAP, zinc, Urea and Potash used and vegetation indices derived from unmanned aerial vehicle (UAV) data. The specific objectives are to analyze the correlation between indices, develop relationships between yield and plant characteristics, and develop regression models based on the type of rice plant. The study was conducted in six different sites in Dhanusha District of Madhesh province during the month of June, August and September. A total of 19 vegetation indices were calculated from multispectral and RGB imageries. Statistical measures such as mean, standard deviation, minimum, maximum, and sum were obtained from zonal statistics in GIS software. The developed regression models showed good accuracy in estimating rice yield, with R-squared values of approximately 74% with a predicted R-squared value of approximately 69%. The study contributes to the field of precision agriculture by demonstrating the feasibility of using farmer's data collected in the field to ensure food security and economic resilience in the face of climate change.

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1 INTRODUCTION

Before the actual harvest of rice crop, remote estimation of rice yield is crucial to global food security as rice serves as a staple meal for a substantial section of the world's population. Approximately 66% of the Nepalese population is estimated to rely on agriculture for their livelihood (Nepal Economic Forum,2022). It makes a major contribution to the national economy and accounts for one-third of the country's GDP (MN Poudel, 2016). Despite recent technological advances, the increasing population and climate change still raise important challenges for improved agricultural systems in terms of productivity, security and sustainability, especially in developing countries like Nepal(Fernandez-Beltran et al., 2021). Traditional techniques of on –ground spot measurement that depends on manual labor and visual examination across the field is problematic to estimate agriculture production due to time consumption, delayed crop management and inefficient input application giving restriction to scalability, sustainability, reliability and precision.

Many works in the literature exemplify the facts that UAVs, also referred to as drones, are widely being used in agriculture because of their capacity to gather real-time, high-resolution data over huge agricultural regions (Liu,2020). These data are vital for optimizing crop management practices, including the early detection of pests, diseases, nutrient deficiencies, and other stress factors that can impact yield and quality directly and indirectly equipping farmer with information regarding irrigation, fertilizer dose estimation, and controlling pests, to increase yields of crops reducing labor expenses with the optimal allocation of resources. The primary objective of this research is to open up possibilities to more productive, sustainable, and climate-resilient agricultural methods by precisely estimating rice yield using multispectral imagery collected by unmanned aerial vehicles (UAVs) and advanced analysis tools. The report focuses to connect the capabilities of multispectral imagery obtained through UAVs to accurately estimate rice yield. By using effective analysis techniques and models, this project aims to develop a solid methodology capable of anticipating and estimating rice yield with a higher degree of accuracy. Numerous vegetation indices along with farm management data can be utilized to assess crop health productivity and yield assessment in a comprehensive manner (Smith, J. D., & Johnson, A. (2018)).The given study utilizes multi-linear regression models based on the varieties of rice plant for accurate yield estimation of rice that allows farmers to optimize resource allocation, improve crop management practices, and mitigate risks associated with varying environmental factors.

2 STUDY AREA

The sites were located in Dhanusha District in the Madhaesh Province: five from Laxminiya Municipality (Wards 01, 03, 04, 05, and 06) and one from Janakpur sub-metropolitan (Ward 14). All study sites were similar in size containing of around 5-15 parcel plots. These locations were chosen to reflect a range of agricultural methods, local environmental circumstances, and rice-growing approaches.

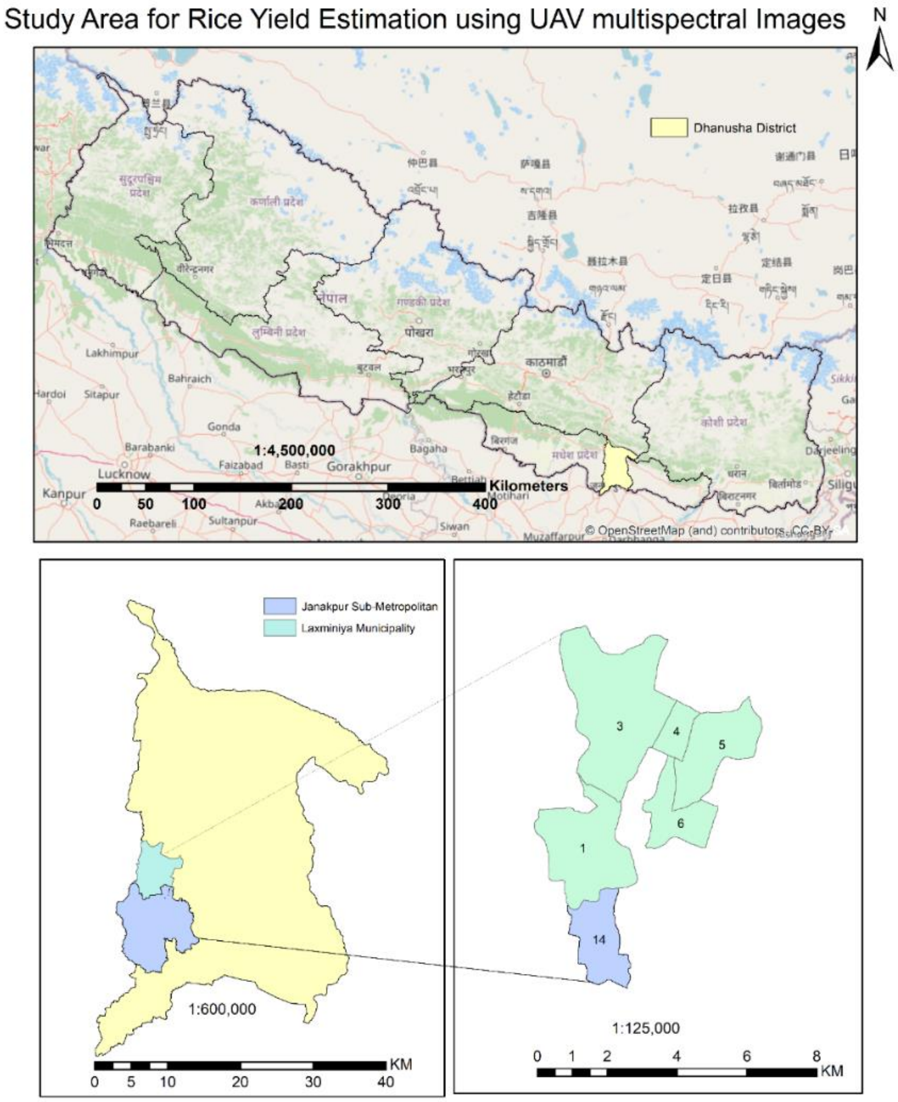


Figure 1Study Area for Yield Estimation

Every site had some kind of irrigation infrastructure like bore wells or tiny running canals, except Wards 01 and 14 (no irrigation system and delayed monsoon) and 05 (located in a rice research center with a well-established irrigation system with careful fertilizer placement and strict monitoring). These locations were all located on level ground with uniform elevations, and they all had standard conditions.

3 METHODOLOGY

3.1 SECONDARY DATA COLLECTION

The flowchart of the working procedure is shown below.

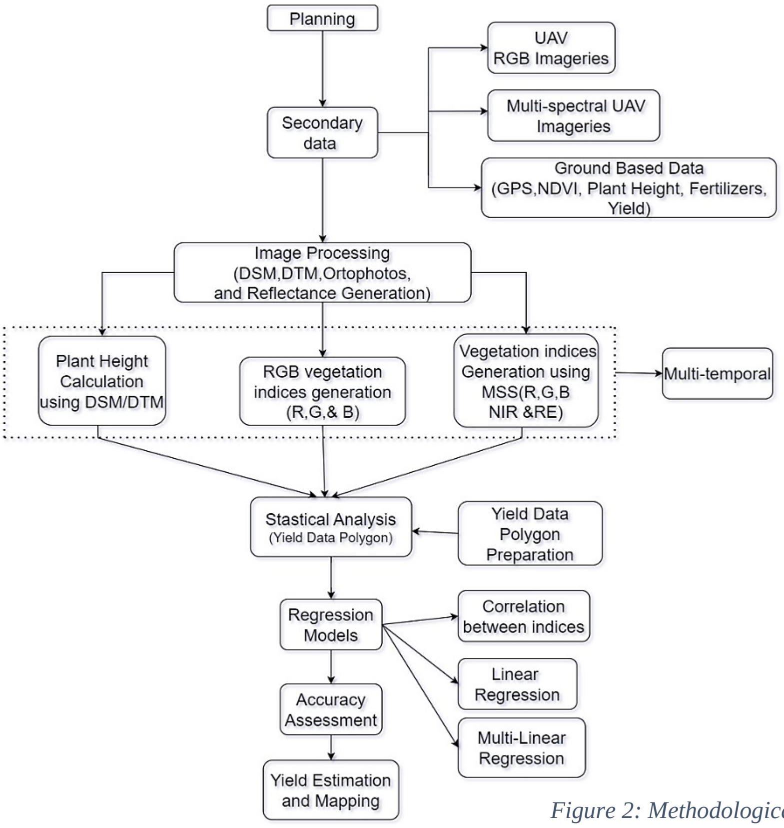


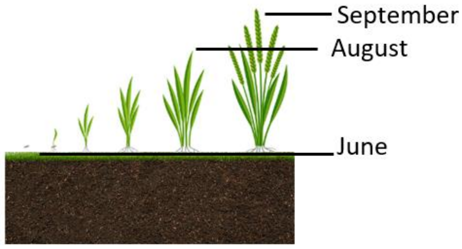
Figure 2: Methodological Chart

Table 1Secondary Data Collection

S.N.	Contents	Remarks
1	RGB UAV	R, G,B images of 6 sites (Multi-temporal) June, August and September
2	Multispectral UAV	R, G,B,NIR and Red Edge band images of 6 sites (Multi-temporal) August and September
4	NDVI Measurement Device	Measure NDVI values of sample areas.
5	Plant Height	Measure plant height of sample areas
6	Farm Management	Amount of various fertilizers (DAP, Urea, Potash, Zinc, Zyme, Aluminum Sulphate), date of transplant
7	HandGPS	Location of sample areas
8	Yield Volume	Yield data of all sample areas

3.2 PLANT HEIGHT ESTIMATION

The Plant height is a key parameter for rice yield estimation (Bareth, 2014). In this study, the plant height was estimated using multispectral & RGB drone data with the help of Digital Surface Model (DSM) and Digital Terrain Model (DTM). The height difference between DSM and DTM provides an approximation of vertical aspect of vegetation. The plant height has been computed by subtracting June DTM from September DSM and August DSM respectively. Thus, it was possible to estimate the plant height at two different growth stages of rice crop. This estimation is done for all sites. The estimated plant heights are compared with ground truth measurements obtained through manual field based measurements. The estimated values (after removal of false values i.e., trees and other artificial created objects) shows strong relationship with ground truth measurements which indicates the accuracy and reliability of this technique.



Iyakalinin. (n.d.). Rice Plant Growth Stages. vectorstock

Figure 3: Typical Plant Height at different months

3.3 VEGETATION INDICES GENERATION

The reflectance data generated by PIX4D Enterprise from the multispectral drone enabled the creation of 19 distinct vegetation indices for six sites in both August and September time-periods respectively. Raster calculator was used to perform this operation in GIS environment. Since multi-temporal images were used, flight conditions and flying height were different each time. Hence, all generated vegetation indices underwent resampling to a uniform 5cm Ground Sample Distance (GSD) to maintain consistency.

Table 2 Vegetation Indices with their formula

S.N.	Name	VI	Formula	References
1	Red-edge Chlorophyll Index	Clrededge	$\frac{NIR}{REDEDGE} - 1$	(Broge & Mortensen, 2002)
2	Difference Vegetation Index	DVI	$2.4 * NIR - RED$	(Richardson & Wiegand, 1977)
3	Enhanced Vegetation Index	EVI	$2.5 * \frac{NIR - RED}{NIR + 6 * RED - 7.5 * BLUE -}$	(A. Huete et al., 2002)
4	Excess Green Index	ExG	$\frac{2 * GREEN - RED - BLUE}{RED + GREEN + BLUE}$	(Woebbecke et al., 1995)
5	Excess Green minus Excess Red	ExGR	$ExG - ExR$	(Users, n.d.)
6	Excess Red	ExR	$\frac{1.4 * RED - GREEN}{RED + GREEN + BLUE}$	(Meyer & Neto, 2008)

7	Green Normalized Difference Vegetation Index	GNDVI	$\frac{NIR-GREEN}{NIR+GREEN}$	(Gitelson & Merzlyak, 1998)
8	Green Red Vegetation Index	GRVI	$\frac{GREEN-RED}{GREEN+RED}$	(Tucker, 1979)
9	Modified Chlorophyll Absorption in Reflectance Index 1	MCARI1	$[1.2*(2.5*(NIR-RED)-1.3*(NIR-GREEN))$	(Daughtry et al., 2000)
10	Modified Green Red Vegetation Index	MGRVI	$\frac{GREEN^2-RED^2}{GREEN^2+RED^2}$	(Bendig et al., 2014)
11	Normalized Difference Red-edge	NDRE	$\frac{NIR-REDEDGE}{NIR+REDEDGE}$	(Barnes et al., 2000)
12	Normalized Difference Vegetation Index	NDVI	$\frac{NIR-RED}{NIR+RED}$	(Ustuner et al., 2014)
13	Optimized Soil Adjusted Vegetation Index	OSAVI	$\frac{NIR-RED}{NIR+RED+0.16}$	(Rondeaux et al., 1996)
14	Red-edge Difference Vegetation Index	REDVI	$NIR-RE$	(Cao et al., 2013)
15	Red Green Blue Vegetation Index	RGBVI	$\frac{GREEN^2-BLUE*RED}{GREEN^2+BLUE*RED}$	(Bendig et al., 2014)
16	Soil Adjusted Vegetation Index	SAVI	$\frac{1.5*(NIR-RED)}{NIR+RED+0.5}$	(A. R. Huete, 1988)
17	Simple Ratio	SR	$\frac{NIR}{RED}$	(Birth & McVey, 1968)
18	Visible Atmospherically Resistant Index	VARI	$\frac{GREEN-RED}{GREEN+RED-BLUE}$	(Gitelson et al., 2002)
19	Wide Dynamic Range Vegetation Index	WDRVI	$\frac{a*NIR-REDEDGE}{a*NIR+REDEDGE}$ a=[0.1,0.2], generally a=0.2	(Gitelson, 2004)

3.4 FARM MANAGEMENT DATA PREPARATION:

In-situ measurements were carried out in collaboration with the farmers to obtain important details such as types of rice plant, quantities of fertilizers used, frequency of fertilizer application, date of transplantation, and additional relevant data. The transplantation dates for all parcels within the site were precisely recorded. The date of the drone flight over that specific site was obtained from the drone imagery. By subtracting the recorded date of transplantation from the date of the drone flight, the plant age data in terms of days was obtained. For each parcel across all six sites, thorough records were maintained detailing the types of fertilizers applied, their respective quantities, and the frequency of applications. This comprehensive dataset encompassed all relevant information associated with each fertilizer use. The main used fertilizers were DAP (Ammonium Phosphate), Urea, Potash, Zinc, Zyme and Aluminum Sulphate.

3.5 STATISTICAL ANALYSIS

The analysis involves computing key statistical measures (mean, median, minimum, maximum, range and standard deviation) relating to the values observed within the sample space of vegetation indices. In each site's parcel, specific areas demarcated as sample spaces were selected for measuring rice yield. These spaces were then represented using yield polygons created in AutoCAD, preserving the orientation of the sample space. A 2m * 2m hollow masking polygon was used to extract the values from the vegetation indices to compare them with the yield of that particular area.

3.6 REGRESSION ANALYSIS

Single linear regression is a fundamental statistical technique that involves examining the relationship between two variables: one independent variable (vegetation index) and one dependent variable (rice yield). It seeks to establish a linear equation that best represents the association between these variables. Hence, linear regression with all 19 vegetation indices and farm data (DAP, potash, urea, zinc, zyme, aluminum sulphate), plant height and plant age was calculated and analyzed.

Multi-linear regression involves using multiple independent variables to predict a dependent variable. It analyses the relationship of each independent variables with the dependent variable and hence assigns weight to each of them creating an overall unique equation. When performing multi-linear regression, data from all wards were merged incorporating various vegetation indices alongside critical agricultural variables like DAP, potash, urea, zinc, aluminum sulphate, zyme, plant age, and plant height.

4 RESULTS

4.1 Single Linear Regression

The linear regression analysis performed on both August and September data showed that the correlations for August were overall weaker than those for September which might be due to the heterogeneous nature of plant height and growth stages during the August data collection. Images captured varying conditions, ranging from green, fit plants to recently planted areas with minimal growth. Accordingly, the drone imagery for August portrayed a landscape with sparse vegetation alongside soil and water remnants, potentially impacting the correlation strength.

Table 3 R squared values of Linear Regressions of August and September

AUGUST			**SEPTEMBER**	
S.N.	**Index**	**R-squared values**	**Index**	**R-squared values**
1	DAP	0.02	CLRE	0.00001
2	PLANT HEIGHT	0.05	NDRE	0.02
3	POTASH	0.07	DAP	0.02
4	ZINC	0.10	REDVI	0.04
5	WDRVI	0.17	PLANT HEIGHT	0.06
6	UREA	0.27	POTASH	0.07
7	CLRE	0.28	ZINC	0.10
8	NDRE	0.29	EVI	0.24

9	RGBVI	0.30	UREA	0.25
10	EXG	0.30	WDRVI	0.27
11	REDVI	0.30	RGBVI	0.35
12	SR	0.31	EXG	0.38
13	EXGR	0.32	SAVI	0.40
14	DVI	0.32	DVI	0.40
15	GNDVI	0.33	OSAVI	0.40
16	EXR	0.33	EXGR	0.47
17	EVI	0.33	MCARI1	0.50
18	SAVI	0.34	MGRVI	0.51
19	OSAVI	0.34	SR	0.51
20	NDVI	0.34	GNDVI	0.52
21	GRVI	0.34	EXR	0.52
22	MGRVI	0.34	VARI	0.52
23	MCARI1	0.34	GRVI	0.53
24	VARI	0.40	NDVI	0.55

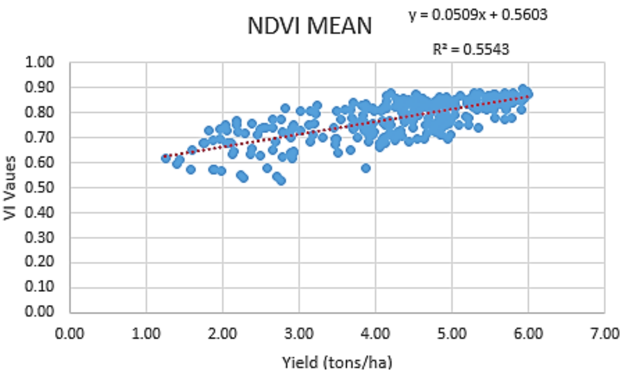


Figure 4Linear Regression of NDVI with Yield (September)

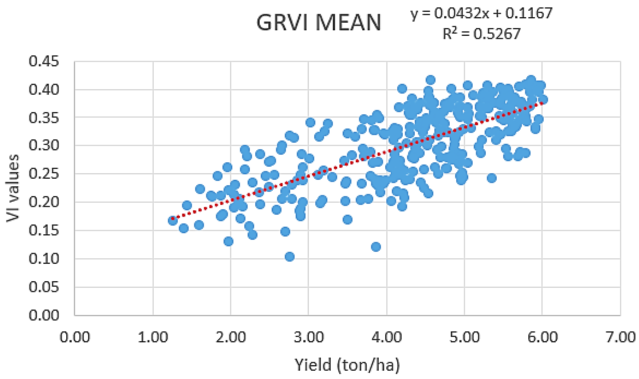


Figure 5 Linear Regression of GRVI with Yield (September)

X=independent variable (VI), y=dependent variable (yield)

4.2 Multi-linear Regression

In conducting a comprehensive analysis, data of all wards were merged to perform a multilinear regression incorporating various vegetation indices alongside critical agricultural variables like DAP, potash, urea, zinc, aluminum sulphate, zyme, plant age, and plant height. This multivariate model, with rice-plant type as the categorical predictor, yielded a robust R-squared value of 74.26%, adjusted R-squared values of 72.46% with the predicted R-squared value is 69.72% showcasing the model's robustness and substantial explanatory power. The analysis utilized a total of 306 samples, with detailed information on the vegetation indices, farm management data, and parameters used provided in the table below.

Table 4 Parameter table for Multi-linear Regression

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	47.5	12.9	3.70	0.000	
EXR	-300.0	76.6	-3.92	0.000	19469.76
GNDVI	34.8	16.5	2.11	0.036	1244.64
MCARI1	115.2	85.8	1.34	0.180	25.78
MGRVI	-7.54	3.73	-2.02	0.045	138.41
NDVI	-38.7	18.2	-2.12	0.035	1721.23
SR	-0.174	0.148	-1.17	0.243	207.94
VARI	80.5	20.2	3.99	0.000	3820.00
GRVI	-391	104	-3.78	0.000	42156.99
EXGR	13.96	5.42	2.57	0.011	445.01
OSAVI	12340	3030	4.07	0.000	149501.81
DVI	819	248	3.30	0.001	181.41
SAVI	-25402	6056	-4.19	0.000	146562.01
Plant Height	0.0669	0.0631	1.06	0.290	1.72
PlantAge	0.02784	0.00449	6.20	0.000	2.35
UREA_	-0.0024	0.0365	-0.07	0.947	3.52
PaddyVariety					
OV	-0.433	0.141	-3.07	0.002	1.77
Sambha	-0.510	0.251	-2.03	0.043	8.08
Sona	-0.596	0.138	-4.31	0.000	3.88
Katarni	-0.387	0.183	-2.12	0.035	10.44

Table 5 Equations with plant type as the Categorical Predictor

PaddyVariety
▪ Katarni Correct yield equation = 47.5 - 300.0 EXR + 34.8 GNDVI + 115.2 MCARI1 - 7.54 MGRVI - 38.7 NDVI - 0.174 SR + 80.5 VARI - 391 GRVI + 13.96 EXGR + 12340 OSAVI + 819 DVI - 25402 SAVI + 0.0669 Plant height + 0.02784 PlantAge - 0.0024 UREA - 0.387 POTASH + 0.0231 DAP
▪ Sambha Correct yield equation = 47.0 - 300.0 EXR + 34.8 GNDVI + 115.2 MCARI1 - 7.54 MGRVI - 38.7 NDVI - 0.174 SR + 80.5 VARI - 391 GRVI + 13.96 EXGR + 12340 OSAVI + 819 DVI - 25402 SAVI + 0.0669 Plant height+ 0.02784 PlantAge - 0.0024 UREA - 0.387 POTASH + 0.0231 DAP
▪ Sona Correct yield equation = 46.9 - 300.0 EXR + 34.8 GNDVI + 115.2 MCARI1 - 7.54 MGRVI - 38.7 NDVI - 0.174 SR + 80.5 VARI - 391 GRVI + 13.96 EXGR + 12340 OSAVI + 819 DVI - 25402 SAVI + 0.0669 plant height+ 0.02784 PlantAge - 0.0024 UREA - 0.387 POTASH + 0.0231 DAP

- OV

Correct yield equation = 47.1 - 300.0 EXR + 34.8 GNDVI + 115.2 MCARI1 - 7.54 MGRVI - 38.7 NDVI - 0.174 SR + 80.5 VARI - 391 GRVI + 13.96 EXGR + 12340 OSAVI + 819 DVI - 25402 SAVI + 0.0669 plant height_+ 0.02784 PlantAge - 0.0024 UREA_ - 0.387 POTASH + 0.0231 DAP

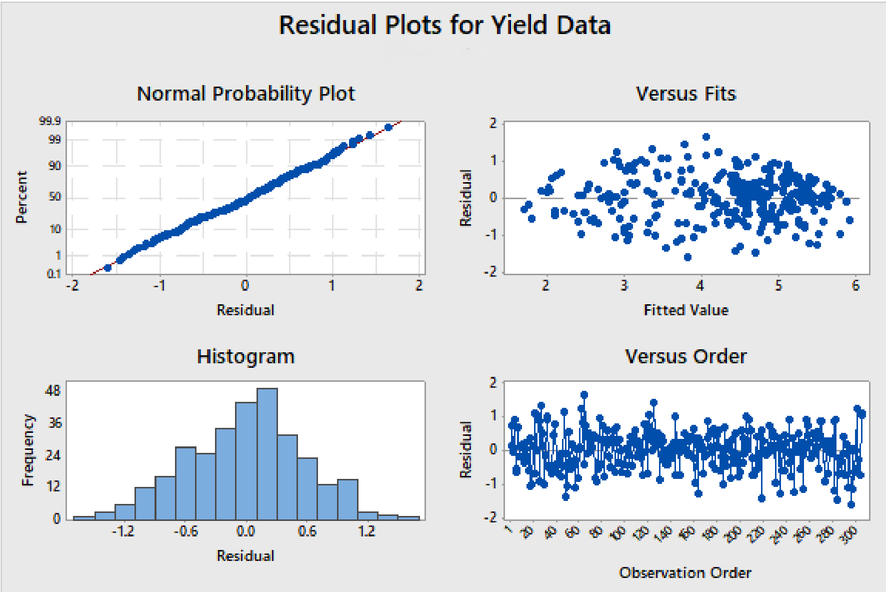
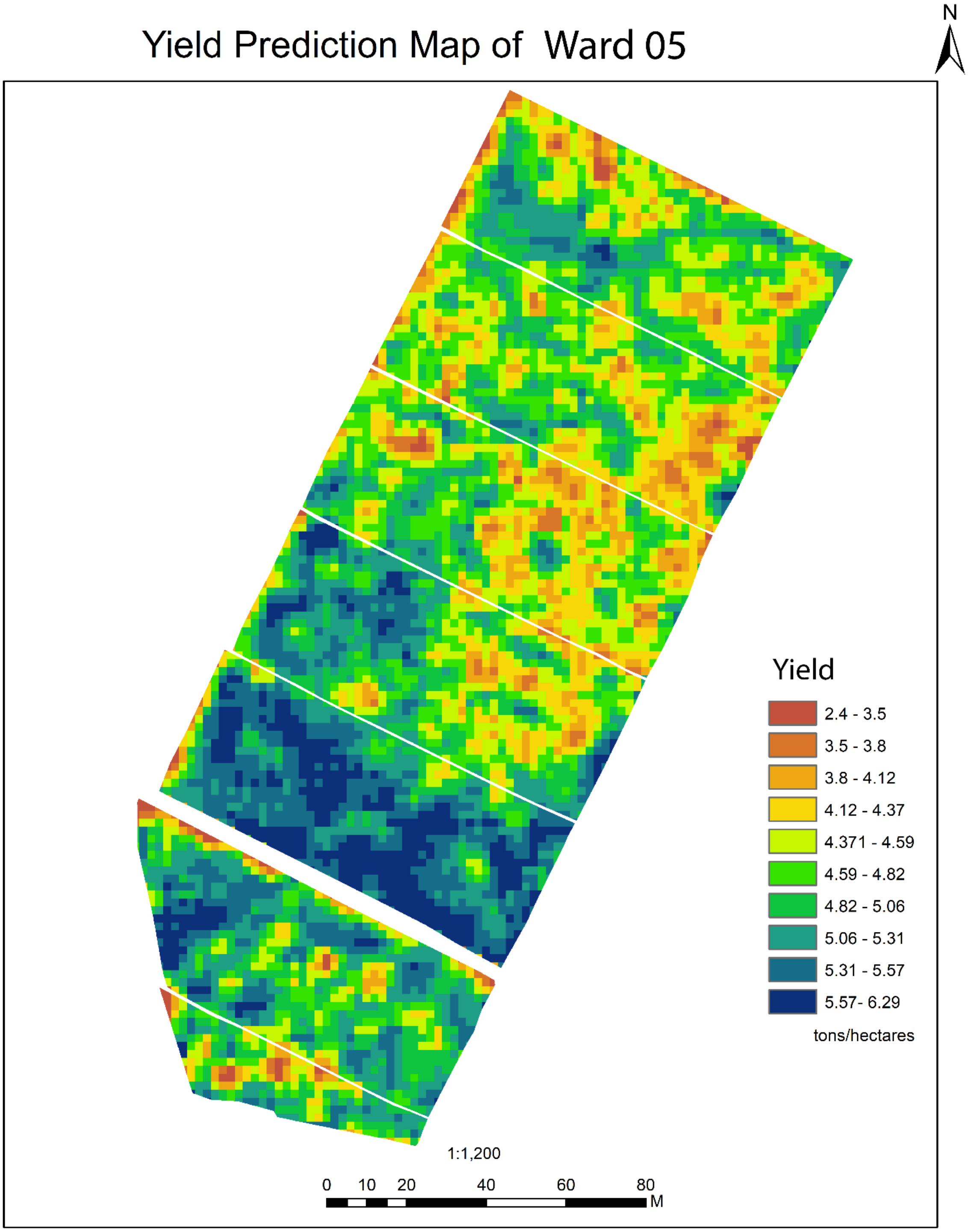


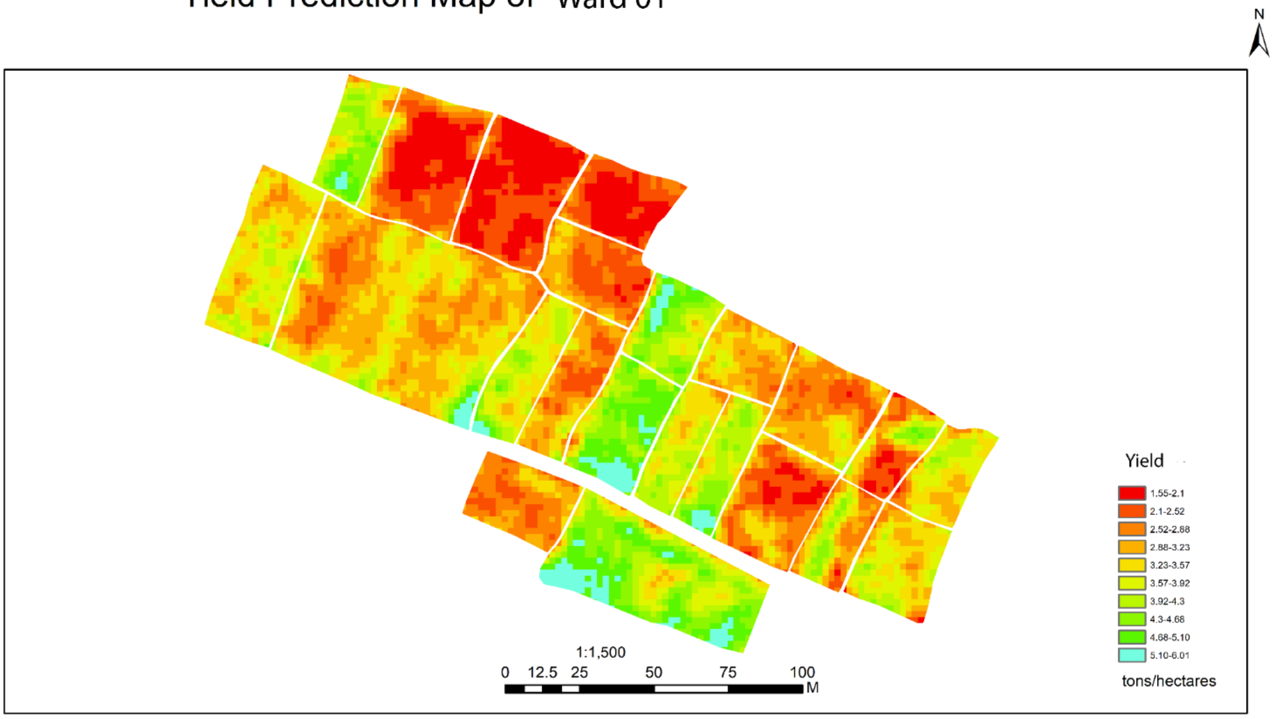
Figure 6 Residual Plots for Yield Data

4.3 Yield Prediction Mapping

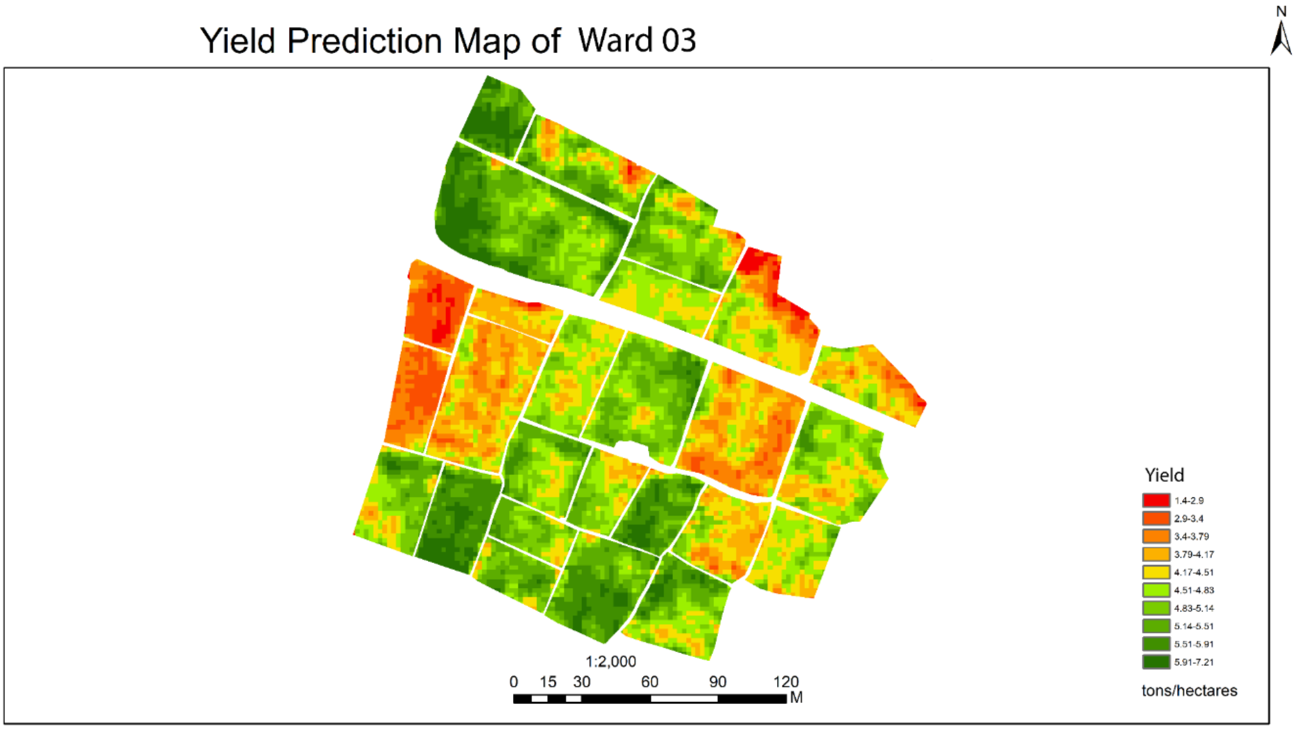
Different regression equations can be used in separate places having considered the dominant plant type. This approach allows for the utilization of specific equations that better predict and show suitable correlation. Consequently, it facilitates a more refined and precise predictive framework, optimizing the accuracy and applicability of the regression model across different study areas. Farm management data, encompassing fertilizer application, plant height, and plant age, were organized and transformed into raster layers. These layers were utilized for conversions and resampling processes to ensure compatibility with other regression variables. Then, the application of each unique regression formula was used within the raster calculator, generating the yield outputs. The results of these predictive computations for each study area, sum up the yield forecasts derived from the customized regression equations based on the dominant plant types prevalent within those specific regions. Maps presented below demonstrates the yield maps showcasing diverse yield levels represented by distinct color gradients, measured in tons per hectare. These maps are overlaid with RGB orthomosiacs captured in September, providing clear visuals of yield data and the field attributes of rice plants. This visualization clearly illustrates a convincing description: the correlation between yield variations and the vegetation's strength. Notably, regions boasting lush, vigorous plantations exhibit markedly higher yields, highlighting the direct link between crop vitality and production output. Conversely, areas with sparse or less healthy crops depict notably minimal yield levels. This integration of quantitative data and visual context not only depicts yield distribution but also perceptibly delineates the intricate interrelationship between crop health and resultant productivity within the study area. The yield output is represented in 10 classes for accurate and visually pleasing outputs.

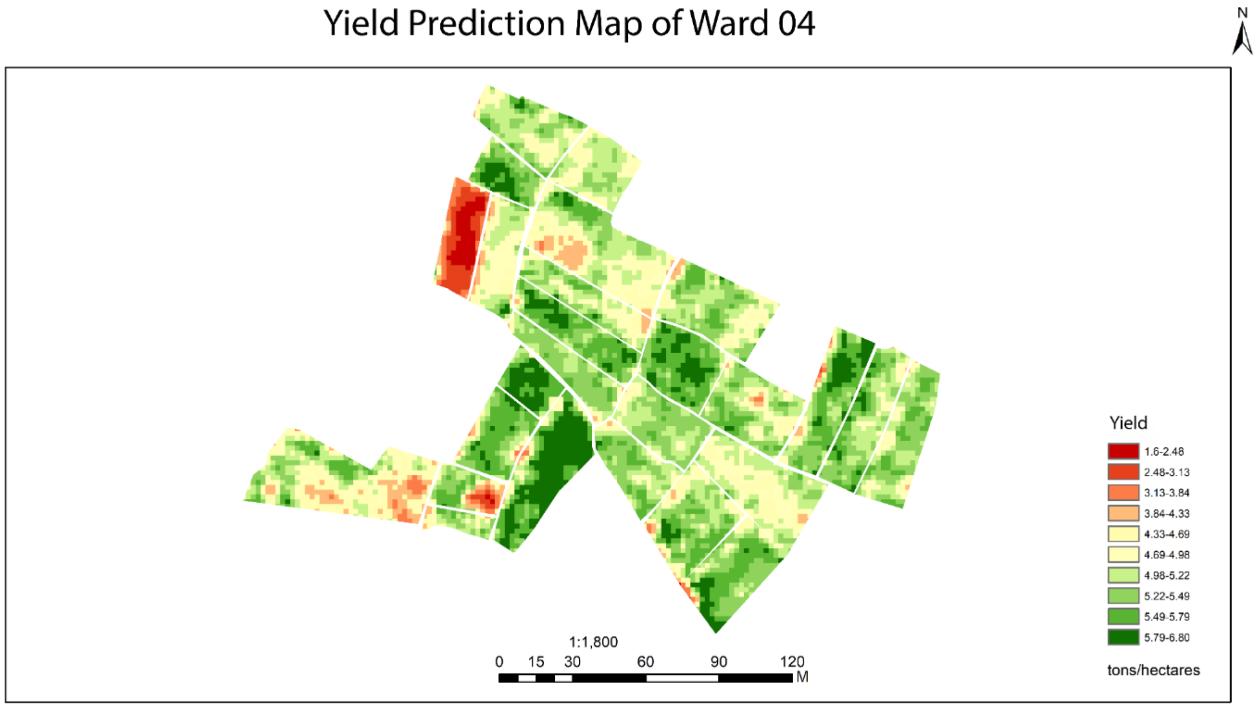


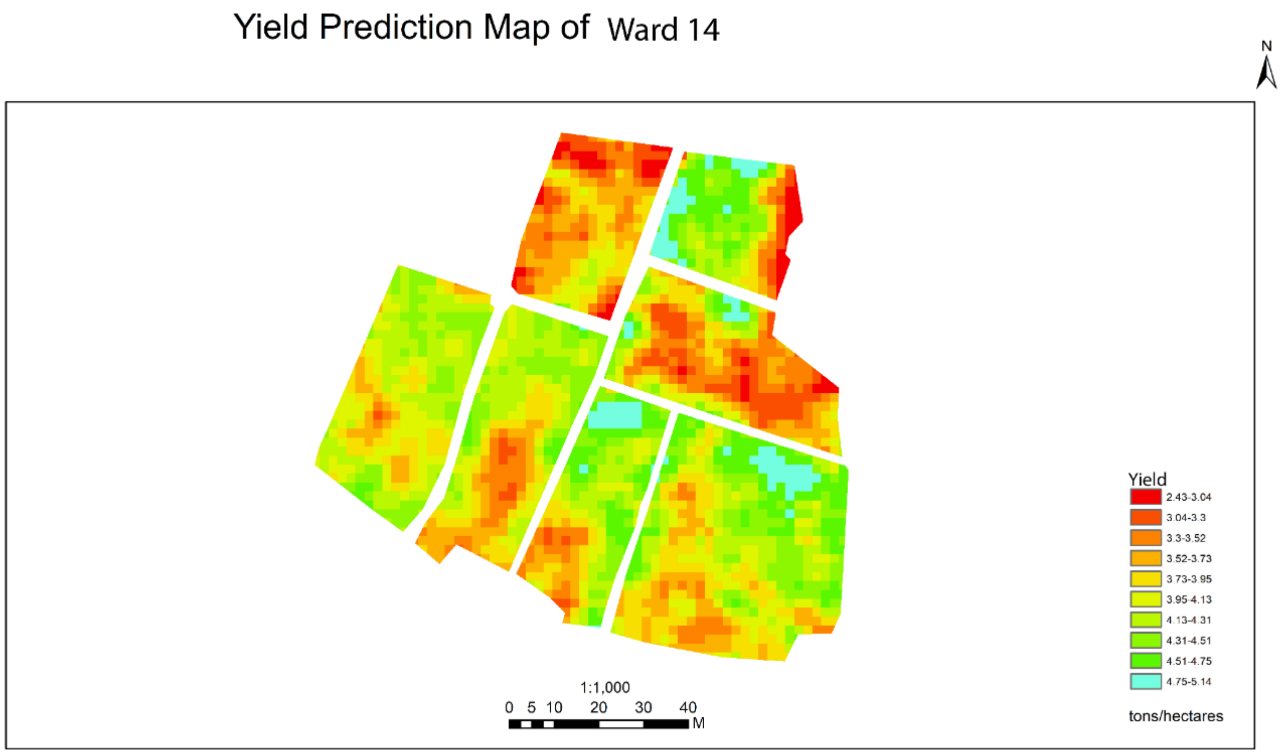
Yield Prediction Map of Ward 01

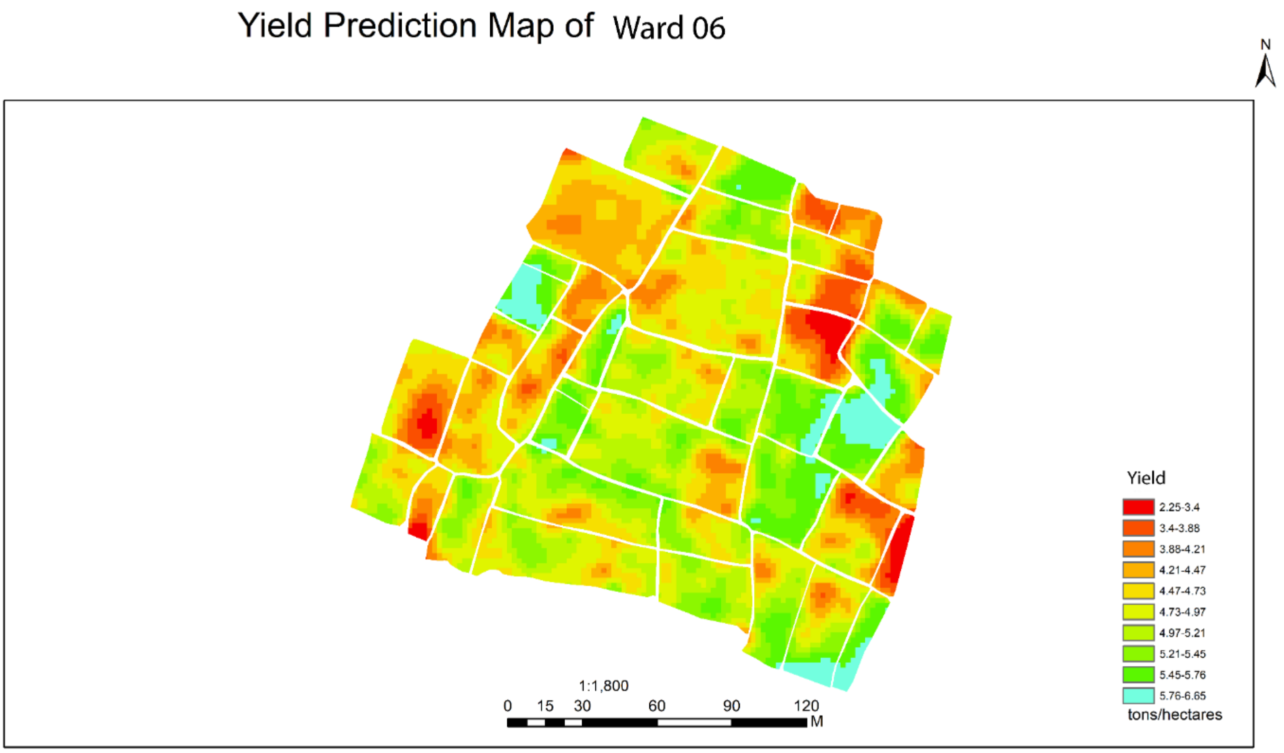


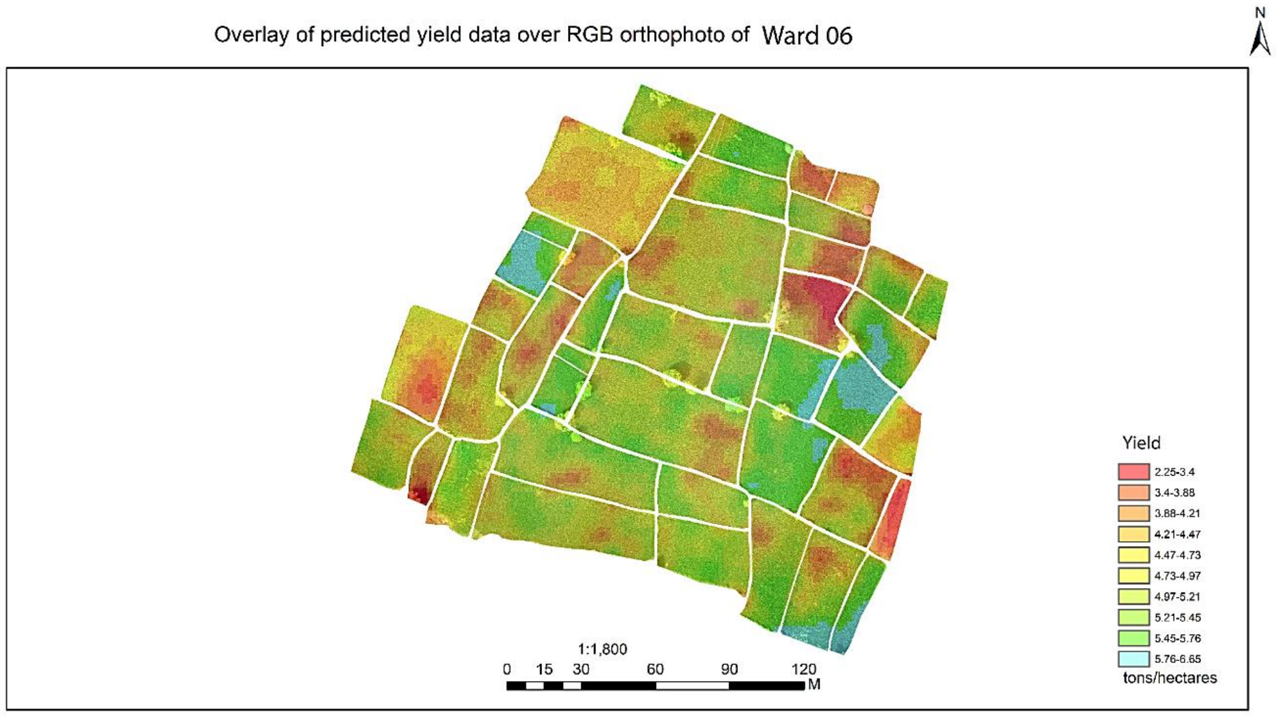
Yield Prediction Map of Ward 03




Yield Prediction Map of Ward 04
N
Yield
1.6-2.48
2.48-3.13
3.13-3.84
3.84-4.33
4.33-4.69
4.69-4.98
4.98-5.22
5.22-5.49
5.49-5.79
5.79-6.80
tons/hectares
1:1,800
0 15 30 60 90 120
M


Yield Prediction Map of Ward 14
N
Yield
2.43-3.04
3.04-3.3
3.3-3.52
3.52-3.73
3.73-3.95
3.95-4.13
4.13-4.31
4.31-4.51
4.51-4.75
4.75-5.14
tons/hectares
1:1,000
0 5 10 20 30 40
M


Yield Prediction Map of Ward 06
N
Yield
2.25-3.4
3.4-3.88
3.88-4.21
4.21-4.47
4.47-4.73
4.73-4.97
4.97-5.21
5.21-5.45
5.45-5.76
5.76-6.65
tons/hectares
1:1,800
0 15 30 60 90 120
M


Overlay of predicted yield data over RGB orthophoto of Ward 06
N
Yield
2.25-3.4
3.4-3.88
3.88-4.21
4.21-4.47
4.47-4.73
4.73-4.97
4.97-5.21
5.21-5.45
5.45-5.76
5.76-6.65
tons/hectares
1:1,800
0 15 30 60 90 120
M

SUMMARY:

An important milestone toward revolutionizing rice yield estimation in a nation like Nepal that is encountering the dual challenges of sustainability and productivity, is the integration of UAV-based multispectral imagery and data analysis tools. With an R-squared value of 74.26% and a predicted R-squared value of 69.72%, the generated regression models in this study that utilized 19 different vegetation indices and farm management data to estimate rice yield showed predictable accuracy. The crop yield and vegetation indices obtained from RGB imagery showed a strong correlation, suggesting that RGB cameras could potentially be employed for estimating yield in the absence of multispectral sensors. Strong correlations between crop yield and vegetation indices such as NDVI, GRVI, VARI, EXR, GNDVI, SR, MGRVI, and MCARI1, were detected. For different rice plant types, a different regression equation was obtained that highlights the importance of considering crop-specific characteristics in yield estimation. The comparison of the strength of correlation between vegetation indices derived from MSS vs RGB sensor and the relationship (linear and multi-linear) between yield, vegetation indices, plant characteristics (plant height, seedling age, plant age), and farm management data (amount and types of fertilizers) can unlock extensive opportunity for agriculture application including accurate rice estimation. Machine learning algorithms and integration of climate-smart practices (CSA) such as weather, precipitation, temperature, and soil properties can further enhance yield estimation of rice using multispectral-UAV technology.

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6 BIOGRAPHICAL NOTES

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