PRECISION AGRICULTURE IN NEPAL: MULTIPHASE STUDY OF WHEAT GENOTYPES USING MULTISPECTRAL UAV IMAGERIES

Binod Prasad BHATTA, Gorakh Nath PANDEY, Mamta KADEL, Sadikshya ADHIKARI, Manoj Kumar BHAT, Sujan SAPKOTA, Shreejan POKHAREL and Shangharsha THAPA
Nepal

Keywords: climate change, multispectral imagery, wheat monitoring, crop surface model

SUMMARY

Nepal's agricultural sector, employing two-thirds of the population and contributing 26% to the national GDP, faces significant challenges from limited land resources, rapid population growth, and climate change impacts. Traditional farming practices and environmental stressors hinder wheat production, a vital crop that contributes 4.63% to the GDP. This study aimed to identify the best-performing wheat genotypes among ten varieties using multispectral UAV imagery, chlorophyll content measurements, grain yield data and plant height. The study area, approximately 900 square meters near the National Biotechnology Research Center, provided optimal conditions for monitoring plant growth and health. By monitoring wheat across various phenological stages, growth patterns were visualized, and correlation analyses were performed between vegetation indices (VIs) and in-situ measurements. Our findings show that VIs like NDVI effectively monitor wheat health and growth. Genotypes WK 2891 and WK 2430 consistently showed higher VI values, indicating better health and biomass production. These genotypes also exhibited the highest NDVI values at peak growth (0.805 and 0.803) and the highest grain yields (0.745 and 0.695 kg/m^2). Conversely, genotypes WK 1204 and Himganga had the lowest NDVI values (0.614 and 0.705) and the lowest yields (0.598 and 0.507 kg/m^2). NDVI and CIRedEdge were particularly effective for assessing health over time, with NDVI showing the highest correlation with SPAD readings (R^2=0.7451) and yield predictions (R^2=0.634). Including corrections for camera properties and sun irradiance improved the accuracy of the VI values, with the corrected datasets consistently showing higher VI values. Plant height measurements from the crop surface model (CSM) also correlated strongly with in-situ measurements (R^2=0.78), validating the use of UAV-derived data for monitoring crop growth. Time series analysis of VIs provided insights into the crop's growth stages, with peak values indicating robust growth in early April. The strong correlations between spectral indices and grain yield confirm their usefulness in precision agriculture, helping to optimize agricultural management and improve productivity. By identifying the best-performing wheat genotypes and the most effective vegetation indices, this study contributes to enhanced crop monitoring practices, addressing the challenges posed by climate change and environmental stressors in Nepal's agricultural sector.

PRECISION AGRICULTURE IN NEPAL: MULTIPHASE EVALUATION OF WHEAT GENOTYPES USING MULTISPECTRAL UAV IMAGERIES

Binod Prasad BHATTA, Gorakh Nath PANDEY, Mamta KADEL, Sadikshya ADHIKARI, Manoj Kumar BHAT, Sujan SAPKOTA, Shreejan POKHAREL, Shangharsha THAPA

1. Introduction

Nepal, like many of the South Asian countries, has been undergoing rapid population growth during the last few decades (UNFPA, 2017). Due to the influence of factors including population growth, geography, and land resource constraints, food self-sufficiency at the country level is inhibited (Liu et al., 2023; Carole & Jolly, and Barbara, 1993), increasing challenges associated with limited land resources and productivity. In addition low production, distribution, poor access to food in remote areas, low income, and the ongoing climate change crisis have been the key factors for increasing food deficiency in Nepal (Chemjong & KC, 2020; Shrestha & Khanal, 2020).

Environmental factors like heat stress, drought, and flooding are key contributors to declining crop production. By the end of the twenty-first century, sea levels could rise by 59 centimeters, and global temperatures may increase by 2.0 to 6.4 °C, leading to more frequent extreme weather events (Alotaibi, 2023). These changes disrupt agriculture by increasing runoff, reducing groundwater recharge, and shifting rainfall patterns. In Nepal, for example, mid-July rainfalls have moved to mid-August, negatively impacting crop yields (Malla, 2009). Such conditions stunt plant growth, damage tissues, and cause nutrient deficiencies, further reducing yields (Qadir et al., 2019).

Traditional crop management often lacks precision and real-time data, leading to inefficient resource use and yield loss. Visual monitoring of plant diseases by scouts is also prone to inaccuracy and bias (Neupane & Baysal-Gurel, 2021). Modern technology, like Remote Sensing, offers a cost-effective way to analyze vegetation, estimate crop yields, and monitor biomass over large areas by utilizing the electromagnetic spectrum to assess plant health from a distance (Nowatzki, 2017)

The main applications for remote sensing of vegetation are based on the following light spectra: Ultraviolet region (UV), which goes from 10 to 380 nm; visible spectra, which are composed of the blue (450–495 nm), green (495−570 nm), and red (620–750 nm) wavelength regions; and near and mid infrared band (850–1700 nm) (Nowatzki, 2017). However, satellite data often face limitations for high-resolution precision agricultural applications due to the trade-off between their temporal and spatial resolutions, as well as frequent cloud cover (Yang et al., 2019).

The time has come to increase agricultural yields by adopting systematic and efficient production systems using modern information technology and agricultural science (Shrestha & Khanal, 2020). A feasible approach is site-specific precision agriculture using low-cost Unmanned Aerial Vehicles (UAVs). UAVs can provide high spatial, temporal, and spectral resolution imageries at low cost offering great possibilities for precision agriculture (Gracia-Romero et al., 2017). Multispectral UAVs record information beyond the visible spectrum, aiding in crop health monitoring by detecting diseases, pests, nutritional deficits, and other stressors (Deng et al., 2018; Tsouros et al., 2019).

Different Vegetation Indices (VIs) can be used to analyze crop health using the visible bands, near infrared, and red edge bands. It is a single value calculated by transforming the observations from multiple light spectral bands, there are numbers of VIs among which one of the most used and implemented indices calculated from multispectral information as normalized ratio between the red and near infrared bands is the Normalized Difference Vegetation Index (NDVI) whose direct use is to characterize canopy growth or vigor (Xue & Su, 2017).

Many studies has been done on Multispectral Imageries-based agricultural applications, such as leaf chlorophyll content estimation (Narmilan et al., 2022), yield prediction (Shahi et al., 2023), leaf area index (LAI) estimation (Zu et al., 2024), plant height and biomass estimation (Zhang et al., 2023), plant growth monitoring (M. Li et al., 2022), plant diseases monitoring (De Silva & Brown, 2023), etc.

In Nepal, the leading agency for agricultural enhancement has yet to implement UAV technology for crop health monitoring. Therefore, in collaboration with the National Biotechnology Research Centre (NBRC), this research aims to study different wheat genotypes. The primary objective is to identify the best-performing genotypes among ten distinct wheat varieties using UAV-derived vegetation indices, chlorophyll content measurements, plant height and grain yield data. Additionally, the study seeks to identify effective vegetation indices and explore the relationship between vegetation indices, chlorophyll content, grain yield, and plant height. This comprehensive approach will enable the NBRC to provide farmers with high-performing, disease-resistant wheat genotypes, ultimately enhancing wheat production.

2. Materials and Methodology

2.1 Study Area

The study was conducted at Lalitpur, Nepal (south-central part of the Kathmandu Valley) near the National Biotechnology Research Centre (NBRC). It lies at an elevation of 1350 meters from mean sea level. The study site comprises wheat fields covering an approximate area of 900 square meters. This field is divided into 25 other small plots (5m*4m) with 10 different wheat genotypes and their replication. The figure of the plot with the plot number is shown in the figure along with the name of the genotypes. These wheat fields are chosen as the focal point of the study due to their proximity to the NBRC and suitability for monitoring and comparison purposes.

The sowing date was around the end of December 2023 and harvest took place on May 2024. The weather data was collected from the site "WEATHER UNDERGROUND" (*Kathmandu, Nepal Weather History | Weather Underground*, 2024). The average minimum temperature of the study site was 11.67 °C and the average maximum temperature was 25 °C during the study time period.

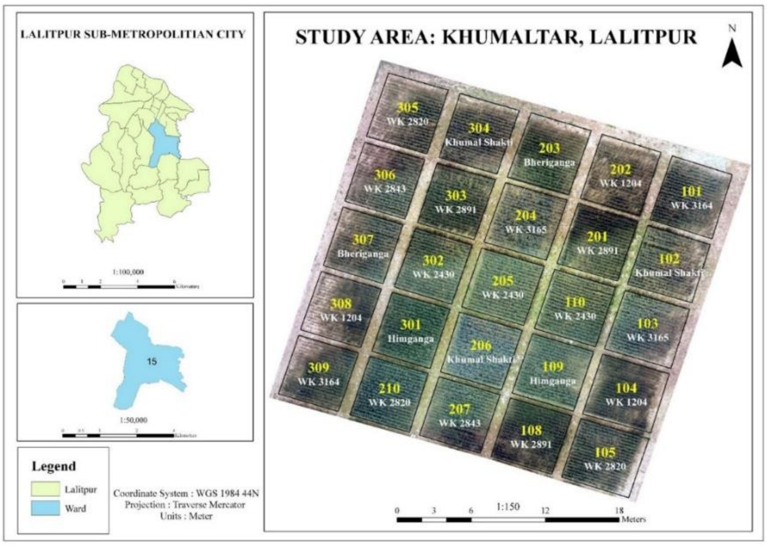


Figure 1: Wheat Field Study Area in Ward 15, Lalitpur: A 900 m² site at the National Biotechnology Research Centre, featuring 25 plots with 10 wheat genotypes for detailed monitoring and comparative analysis.

2.2 Ground Measurement and Data Collection

In-situ measurements were collected during various growth stages of the wheat crop to complement UAV imagery and provide a detailed crop health assessment. Chlorophyll content, plant height, and grain yield were recorded across ten genotypes. SPAD measurements and plant heights were taken within a 0.2 m x 0.2 m area, while grain yield was measured at harvest within 1 m x 1 m sub-plots. Multispectral UAV images were captured during key growth stages; tillering, jointing, booting, heading, and maturity through multiple flights, ensuring comprehensive coverage for analysis.

2.3 Image Processing and outcomes

Ground control points (GCPs) were used for UAV image processing to correct image distortions and ensure proper alignment. Radiometric corrections were applied to enhance data quality. A 3D textured model was then generated using automatic tie points, and orthomosaics and vegetation index maps were created by correcting perspective distortions and mapping true reflectance values.

The study produced high-precision, geo-referenced orthomosaics to monitor wheat crop health across growth stages. A Digital Terrain Model (DTM) was developed to represent the bare ground surface, while a Digital Surface Model (DSM) included all surface features to assess plant height and growth variations. Crop Surface Models (CSMs) and Vegetation Indices (VIs) were generated to monitor plant health by comparing DSMs from different growth stages with the bare-earth elevation and calculating VIs from reflectance data. The results were validated against SPAD data, grain yield, and ground-measured plant heights, ensuring effective tracking of crop growth and vegetation health.

Table 1: Vegetation Indices used in this study

Name	Abbreviation	Equation	References
Normalized Difference Vegetation Index	NDVI	$NDVI = \frac{NIR - RED}{NIR + RED}$	(Rouse J.~W. et al., 1974)
Red Edge Chlorophyll Index	CIRE	$CIRedEdge = \frac{NIR}{Red\ Edge} - 1$	(A. A. Gitelson et al., 2006)
Green Chlorophyll Index	CIGreen	$CIGreen = \frac{NIR}{GREEN} - 1$	(A. A. Gitelson et al., 2006)
Normalized Difference Red Edge Index	NDRE	$NDRE = \frac{NIR - RedEdge}{NIR + RedEdge}$	(A. Gitelson & Merzlyak, 1994)

3. Results

3.1 Time Series Analysis

3.1.1 Vegetation Indices Map

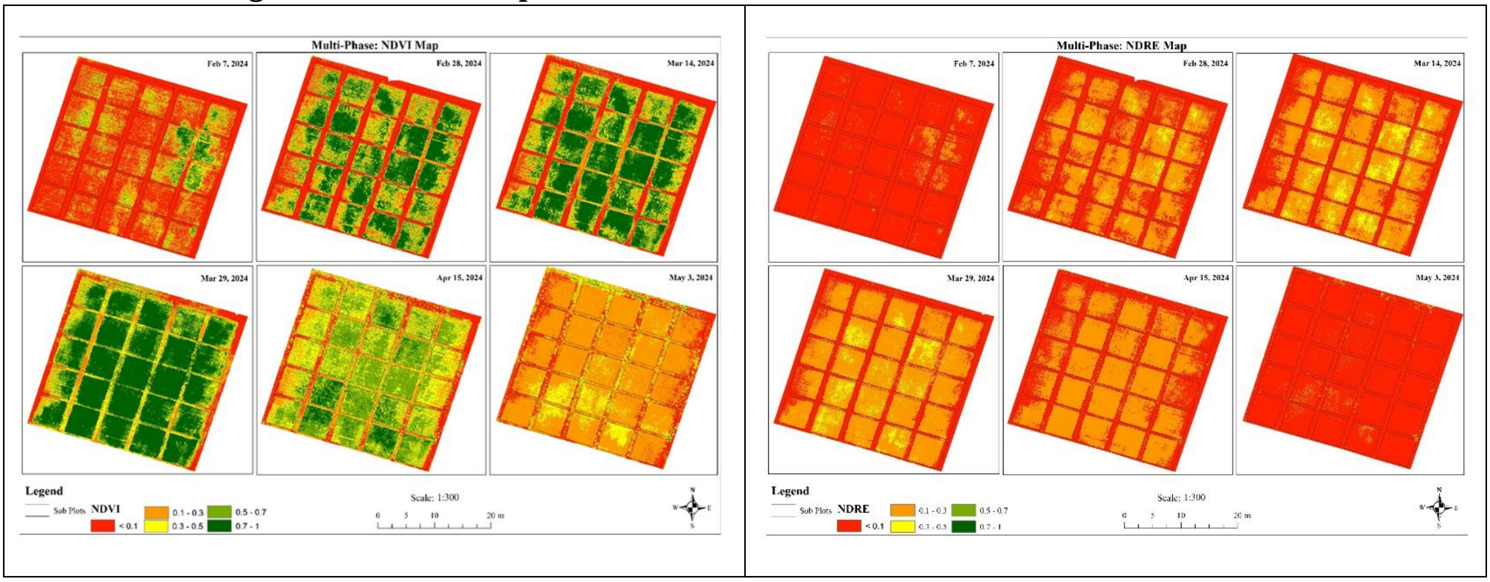


Figure 2: Multi-Phase Vegetation Indices Map (NDVI, NDRE) that shows the indices values during the different phenological stages of ten different wheat genotypes.

The figure presents a series of maps tracking NDVI, NDRE with data collected on specific dates from February to May. These indices are used to analyze the health and density of vegetation in the area, revealing changes over time. For instance, NDVI maps indicate changes in greenness and vegetation density, NDRE maps highlight chlorophyll content and plant health.

3.1.2 Time Series Analysis of Vis throughout the lifecycle of the crop

By analyzing time series data of vegetation indices, it is possible to track phenological stages, assess vegetation health, and identify critical trends in crop development. In this study, various vegetation indices throughout the growth of the wheat crop provide insights into trends and patterns in crop growth. The time series data for NDVI, CIRedEdge, and NDRE values across various wheat genotypes from February 7 to May 3, 2024, highlighting key growth stages are shown below.

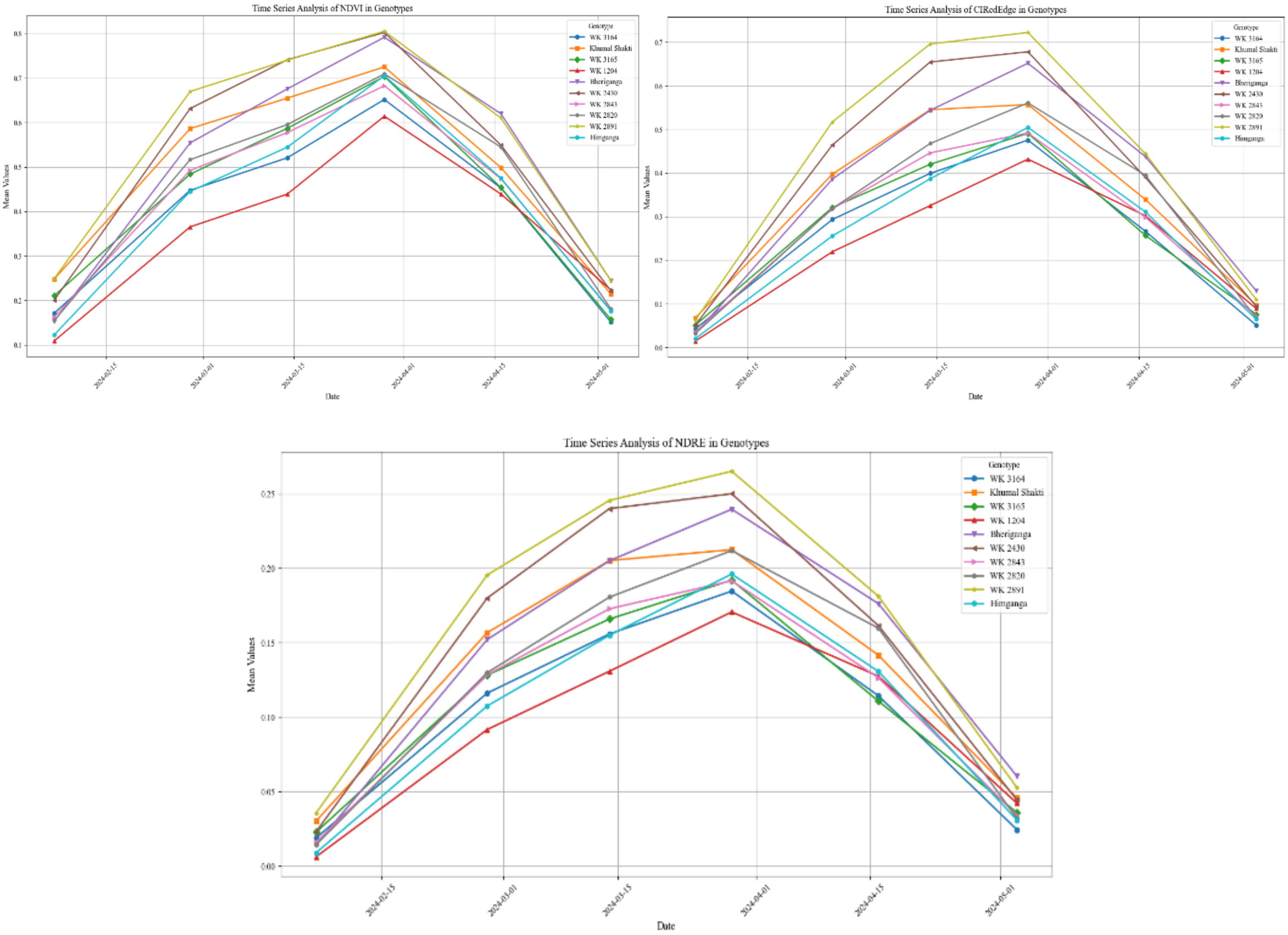


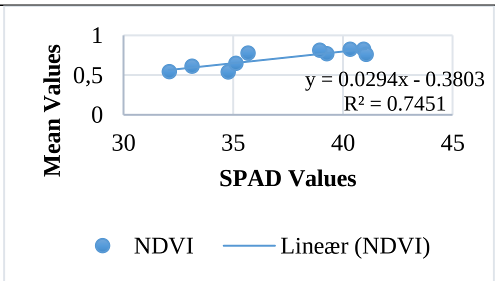
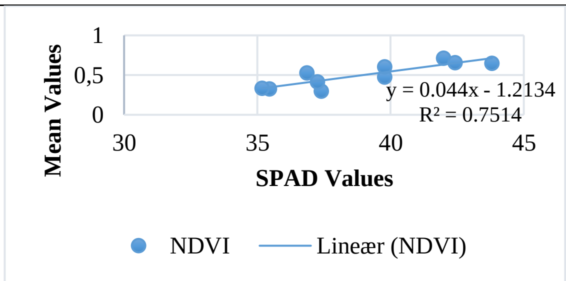
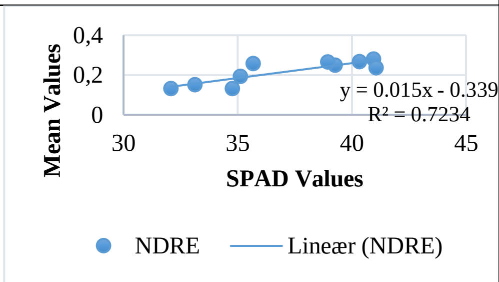
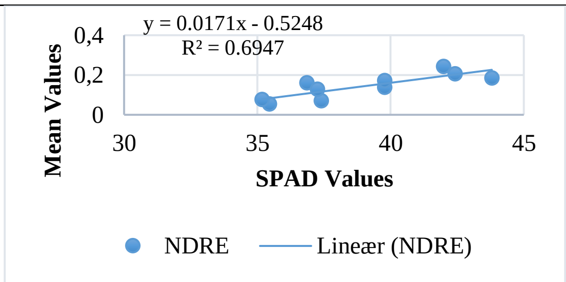
Figure 3: Time series of NDVI, CIRedEdge, and NDRE values for various wheat genotypes from February 7 to May 3, 2024, illustrating changes in vegetation health and growth stages throughout the crop cycle.

During early growth, NDVI values were low (0.2-0.3), reflecting limited biomass and chlorophyll content, but increased during the vegetative phase, peaking in early April (0.7-0.8). Genotypes WK 2891 and WK 2430 exhibited the highest NDVI values (0.805 and 0.803), indicating superior growth, while WK 3164 and Himganga showed lower peaks (0.614 and 0.705).

CIRedEdge values were initially low (0.02-0.03) and peaked in early April (0.4-0.7), with WK 2891 and WK 2430 showing the highest values (0.722 and 0.678). A decline followed as the plants aged. NDRE values also started low (0.01-0.02) and peaked in early April (0.2-0.25), with WK 2890 and WK 2430 reaching the highest values (0.275 and 0.257), while Himganga and WK 1204 had lower peaks (0.178 and 0.187). NDRE values decreased as plants entered the reproductive stage.

3.2 Relationship between Vegetation Indices and SPAD data

The relationship between vegetation indices and SPAD readings has been studied. SPAD measurements provide chlorophyll content. This measurement was collected during two critical growth stages: the flag leaf stage and the flowering stage. The analysis revealed strong positive correlations between SPAD readings and several vegetation indices, including NDVI, NDRE, CIRedEdge, and CIgreen.

VIs	March 29, 2024	April 15, 2024
NDVI		
NDRE		

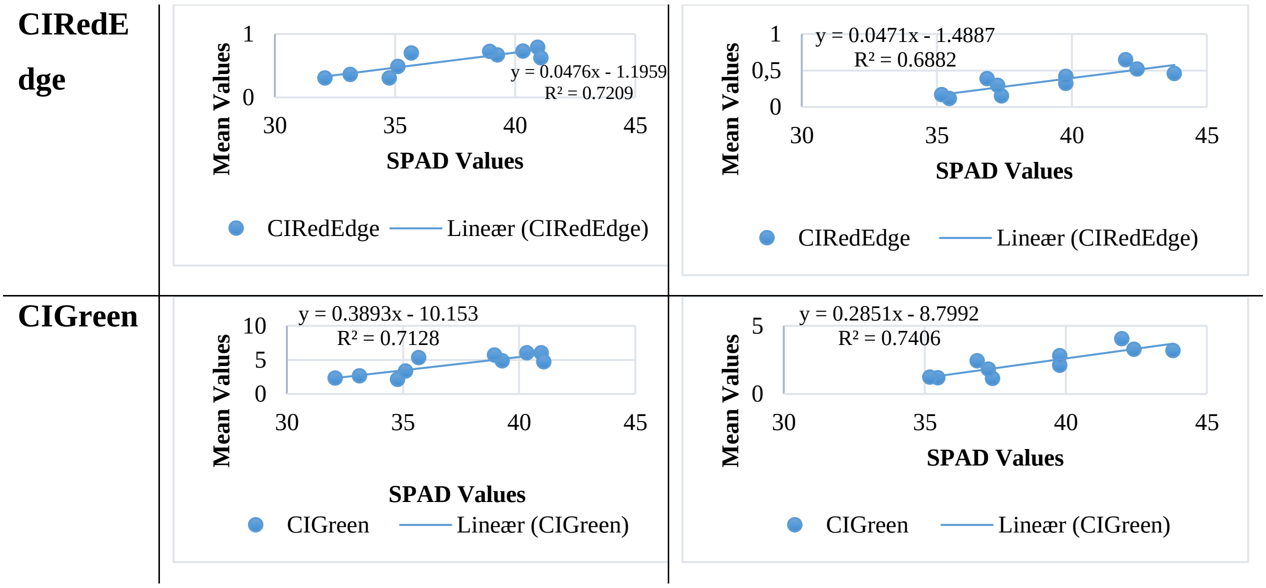


Figure 4: The scatter plots of the vegetation indices versus SPAD values are shown for two different phenological stages.

The study found a positive linear correlation between NDVI and SPAD readings, with NDVI showing a strong correlation during both the flag leaf period and the flowering stage, with R^2 values of 0.75 in both stages. Similarly, NDRE also exhibited a positive linear correlation with SPAD readings, with R^2 values of 0.72 and 0.70 in the flag leaf and flowering stages, respectively. NDRE values below 0.6 during mid-to-late season growth may indicate potential crop damage, making NDRE a valuable tool for assessing disease resistance. CIRedEdge also showed a strong positive correlation with SPAD readings, with R^2 values of 0.72 and 0.69, indicating that higher CIRedEdge values correspond to higher chlorophyll content and healthier vegetation. CIgreen exhibited a positive linear correlation with SPAD readings, with R^2 values of 0.71 and 0.74. Higher CIgreen values, indicative of greater chlorophyll content.

3.3 Relationship of indices with the grain yield

.

March 29, 2024

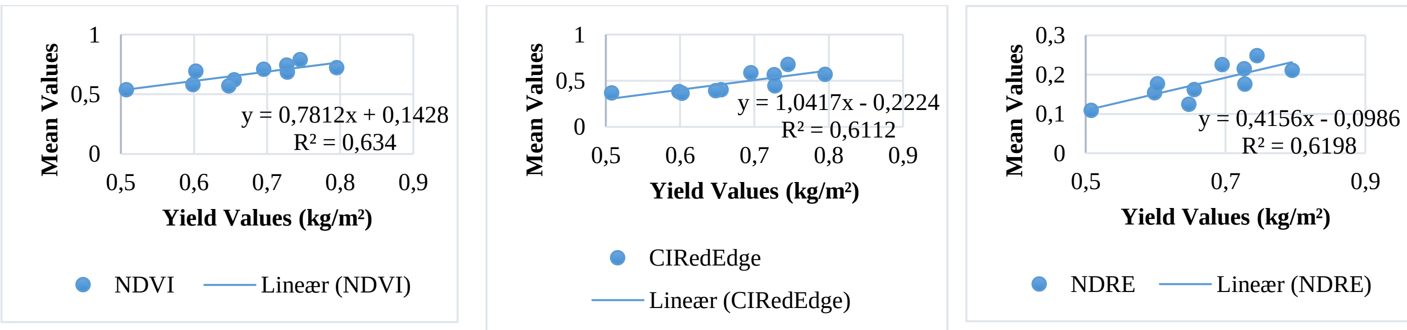


Figure 5: Relationship between indices and grain yield.

Different indices viz. NDVI, CIRedEdge, and NDRE were calculated with the data set of March 29, 2024 which was the sixth phase data collection to identify which of the indices better predicts the grain yield.

The NDVI has a strong correlation with yield (R^2=0.634), making it a reliable tool for assessing vegetation health and predicting yields. CIRedEdge also shows a strong correlation (R^2=0.6112), indicating its usefulness in early detection of crop stress due to its sensitivity to chlorophyll content. Additionally, NDRE demonstrates a significant correlation (R^2=0.6198), highlighting its role in assessing biomass and nitrogen content. These findings confirm the importance of these spectral indices for effective crop health monitoring and accurate yield prediction.

3.4 Growth Monitoring through Crop Surface Model

Plant height was assessed by comparing the initial bare earth model (Feb 7) with models from Feb 28, Mar 14, Mar 29, and Apr 15. The CSM map (Figure 14) tracks growth, starting with 0.0-0.2 meters on Feb 28, increasing to 0.2-0.4 meters by Mar 14, and reaching 0.3-0.5 meters on Mar 29. By Apr 15, peak vegetative height is observed at 0.4-0.7 meters, crucial for yield prediction and harvest planning. The CSM-derived heights closely match in-situ measurements, confirming the accuracy of UAV-based multispectral imagery for monitoring crop growth.

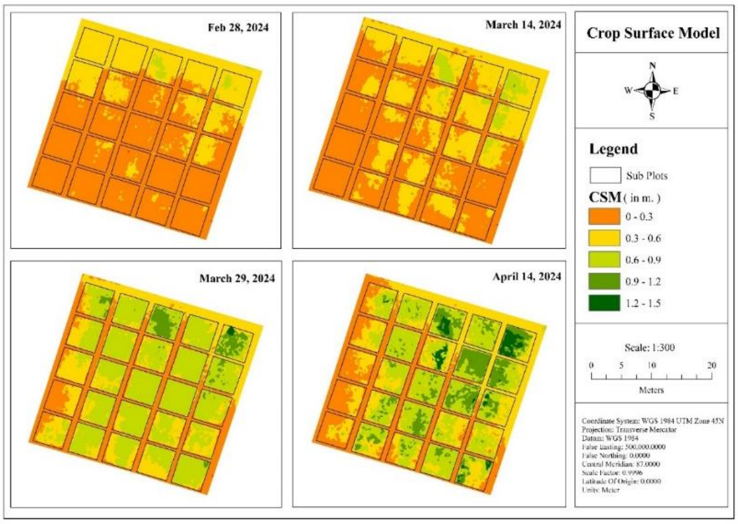


Figure 6: Crop Surface model in four different phases.

The crop surface model heights showed a strong positive correlation with in-situ measurements (R^2 = 0.78), confirming a strong positive correlation.

The chart below illustrates this relationship:

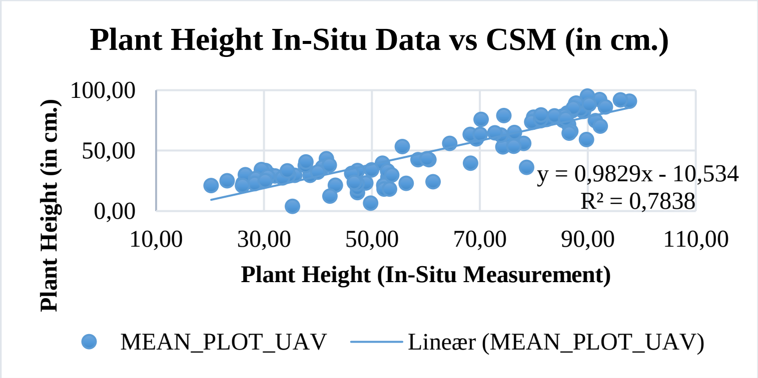


Figure 7: The plant height relationship between In-Situ Data and CSM

4. Discussion

The NDVI, CIRedEdge, and NDRE indices provide valuable insights into the growth patterns of different wheat genotypes. Higher index values during peak growth stages indicate greater biomass and healthier vegetation (Tucker, 1979). Genotypes WK 2891 and WK 2430 consistently outperformed others, suggesting superior growth and productivity. In contrast, genotypes like Himganga and WK 1204 showed slower growth and less dense canopies. The decline in these indices post-peak corresponds with the natural aging process as plants transition into reproductive and grain-filling stages. These findings highlight the importance of vegetation indices in monitoring crop health and guiding agricultural practices.

The study confirmed that NDVI has a strong correlation with yield (R^2=0.634), reinforcing its role as a reliable indicator of vegetation health and yield prediction, as established by(Tucker, 1979). CIRedEdge's strong correlation (R^2=0.6112) supports (A. A. Gitelson et al., 2003), emphasizing its effectiveness in early crop stress detection due to its sensitivity to chlorophyll. NDRE's significant correlation (R^2=0.6198) aligns with (Barnes et al., 2000), showing its value in assessing biomass and nitrogen content, particularly in dense vegetation where NDVI may saturate. These results affirm the importance of spectral indices in precision agriculture for crop monitoring and yield prediction.

Grain yield is the effective indicator for studying the best-performing wheat genotypes (Pandey et al., 2017; Tanin et al., 2022). In this study, the vegetation indices NDVI, CIRedEdge, and NDRE were correlated with grain yield to identify which vegetation indices show the highest correlation. Among these, NDVI shows the highest correlation (R^2=0.634) with the grain yield. This finding is consistent with the work of (Tucker, 1979), who demonstrated that NDVI is a crucial index for estimating plant biomass and health due to its sensitivity to chlorophyll and canopy structure. CIRedEdge also exhibited a strong correlation (R^2=0.6112), this supports the research of (A. A. Gitelson et al., 2003), who emphasized the index's sensitivity to chlorophyll content and its ability to detect subtle changes in plant health before visible symptoms appear. NDRE also showed a significant correlation (R^2=0.6198). This finding is consistent with studies by (Barnes et al., 2000), who found NDRE to be particularly useful in dense vegetation areas where traditional indices like NDVI might saturate.

Plant height is a critical indicator of crop growth, closely associated with plant architecture, lodging resistance, and overall yield performance (Gao et al., 2020; R. Li et al., 2019; Wang et al., 2017). The study led by (Cen et al., 2019) found a correlation of R^2=0.97 between plant height obtained from in-situ measurements and the crop surface model. Similarly, Ji et al., (2022) reported a correlation of R^2=0.99. In this study, (R^2=0.78), which is close to the values obtained in these studies but relatively lower. Potential causes for this discrepancy could include less accurate height measurements of the ground control points (GCPs), wind disturbances during the flight affecting plant height, and measurement errors in the scale used for determining plant height. In this study, WK 2891 exhibited the maximum height, while WK 1204 showed the minimum at maturity, highlighting genetic variability in wheat growth. WK 2891's taller height suggests greater biomass and potential grain yield, while WK 1204's shorter stature may indicate adaptation to resource-limited conditions. Spatial analysis revealed significant height variations, with better growth in the middle and eastern areas, likely due to differences in irrigation and soil properties.

5. Conclusion

This study identified the best-performing wheat genotypes among ten varieties by analyzing vegetation indices (VIs) from UAV imagery, chlorophyll content, grain yield, and plant height. Key findings include the effectiveness of NDVI, CIRedEdge, and NDRE in monitoring wheat health and growth dynamics, with NDVI and CIRedEdge being particularly effective. NDVI showed the highest correlation with SPAD readings (R^2=0.7451) and crop yield prediction (R^2=0.634). Among the genotypes, WK 2891 and WK 2430 exhibited the highest NDVI values at peak growth (0.805 and 0.803, respectively) and the highest grain yields (0.745 and 0.695 kg/m², respectively), while WK 1204 and Himganga had lower NDVI values (0.614 and 0.705, respectively) and lower yields (0.598 and 0.507 kg/m², respectively). Radiometric corrections for camera and sun irradiance significantly improved the accuracy and reliability of VI values, underscoring their importance for accurate UAV data. Strong positive correlations were observed between VIs and SPAD readings, validating their ability to reflect chlorophyll content. Plant height measurements from the crop surface model (CSM) also correlated strongly with in-situ measurements (R^2=0.78), supporting the use of UAV data for crop monitoring. Time series analysis of VIs throughout the growth cycle provided insights into the phenological stages, with peak VI values in early April corresponding to robust growth and high chlorophyll content. The strong correlations between spectral indices and grain yield values confirmed their effectiveness in precision agriculture, with NDVI, CIRedEdge, and NDRE being particularly valuable in predicting yields and optimizing nitrogen management. Overall, this study demonstrates the potential of UAV-based vegetation indices in precision agriculture, contributing to improved crop monitoring. The findings highlight the value of these indices in non-destructively assessing crop health and optimizing agricultural practices. Future research should focus on refining these techniques and exploring their applicability across different crops and environmental conditions to further enhance agricultural monitoring.

Funding: This research study received a grant from Nepal Remote Sensing and Photogrammetry Society (NRSPS).

References

Alotaibi, M. (2023). Climate change, its impact on crop production, challenges, and possible solutions. *Notulae Botanicae Horti Agrobotanici Cluj-Napoca*, *51*(1), 1–39. https://doi.org/10.15835/nbha51113020

Barnes, E. M., Clarke, T., Richards, S. E., Colaizzi, P. D., Haberland, J., Kostrzewski, M., Waller, P. M., Choi, C. Y., Riley, E., Thompson, T. L., Lascano, R. J., Li, H., Moran, M. S., Robert, P. C., Rust, R. H., & Larson, W. E. (2000). *Coincident detection of crop water stress, nitrogen status and canopy density using ground-based multispectral data.*

Carole, L., & Jolly and Barbara, B. T. (1993). Population and Land Use in Developing Countries. In *Population and Land Use in Developing Countries*. https://doi.org/10.17226/2211

Cen, H., Wan, L., Zhu, J., Li, Y., Li, X., Zhu, Y., Weng, H., Wu, W., Yin, W., Xu, C., Bao, Y., Feng, L., Shou, J., & He, Y. (2019). Dynamic monitoring of biomass of rice under different nitrogen treatments using a lightweight UAV with dual image-frame snapshot cameras. *Plant Methods*, *15*(1), 32. https://doi.org/10.1186/s13007-019-0418-8

Chemjong, B., & KC, Y. (2020). Food Security in Nepal: A Review. *Rupantaran: A Multidisciplinary Journal*, *4*(1), 31–43. https://doi.org/10.3126/rupantaran.v4i1.34015

De Silva, M., & Brown, D. (2023). Multispectral Plant Disease Detection with Vision Transformer-Convolutional Neural Network Hybrid Approaches. *Sensors (Basel, Switzerland)*, *23*(20). https://doi.org/10.3390/s23208531

Deng, L., Mao, Z., Li, X., Hu, Z., Duan, F., & Yan, Y. (2018). UAV-based multispectral remote sensing for precision agriculture: A comparison between different cameras. *ISPRS Journal of Photogrammetry and Remote Sensing*, *146*, 124–136. https://doi.org/https://doi.org/10.1016/j.isprsjprs.2018.09.008

Gao, Z., Wang, Y., Tian, G., Zhao, Y., Li, C., Cao, Q., Han, R., Shi, Z., & He, M. (2020). Plant height and its relationship with yield in wheat under different irrigation regime. *Irrigation Science*, *38*(4), 365–371.

Gitelson, A. A., Gritz †, Y., & Merzlyak, M. N. (2003). Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. *Journal of Plant Physiology*, *160*(3), 271–282. https://doi.org/https://doi.org/10.1078/0176-1617-00887

Gitelson, A. A., Keydan, G. P., & Merzlyak, M. N. (2006). Three-band model for noninvasive estimation of chlorophyll, carotenoids, and anthocyanin contents in higher plant leaves. *Geophysical Research Letters*, *33*(11). https://doi.org/10.1029/2006GL026457

Gitelson, A., & Merzlyak, M. N. (1994). Spectral Reflectance Changes Associated with Autumn Senescence of Aesculus hippocastanum L. and Acer platanoides L. Leaves.

Spectral Features and Relation to Chlorophyll Estimation. *Journal of Plant Physiology*, *143*(3), 286–292. https://doi.org/https://doi.org/10.1016/S0176-1617(11)81633-0

Gracia-Romero, A., Kefauver, S. C., Vergara-Díaz, O., Zaman-Allah, M. A., Prasanna, B. M., Cairns, J. E., & Araus, J. L. (2017). Comparative Performance of Ground vs. Aerially Assessed RGB and Multispectral Indices for Early-Growth Evaluation of Maize Performance under Phosphorus Fertilization. *Frontiers in Plant Science*, *8*. https://doi.org/10.3389/fpls.2017.02004

Ji, Y., Chen, Z., Cheng, Q., Liu, R., Li, M., Yan, X., Li, G., Wang, D., Fu, L., Ma, Y., Jin, X., Zong, X., & Yang, T. (2022). Estimation of plant height and yield based on UAV imagery in faba bean (Vicia faba L.). *Plant Methods*, *18*(1), 26. https://doi.org/10.1186/s13007-022-00861-7

Kathmandu, Nepal Weather History | Weather Underground. (2024). https://www.wunderground.com/history/daily/np/kathmandu

Li, M., Shamshiri, R. R., Weltzien, C., & Schirrmann, M. (2022). Crop Monitoring Using Sentinel-2 and UAV Multispectral Imagery: A Comparison Case Study in Northeastern Germany. *Remote Sensing*, *14*(17). https://doi.org/10.3390/rs14174426

Li, R., Li, M., Ashraf, U., Liu, S., & Zhang, J. (2019). Exploring the relationships between yield and yield-related traits for rice varieties released in China from 1978 to 2017. *Frontiers in Plant Science*, *10*, 543.

Liu, Y., Yang, Y., Zhang, C., Xiao, C., & Song, X. (2023). Does Nepal Have the Agriculture to Feed Its Population with a Sustainable Diet? Evidence from the Perspective of Human-Land Relationship. *Foods (Basel, Switzerland)*, *12*(5). https://doi.org/10.3390/foods12051076

Malla, G. (2009). Climate Change and Its Impact on Nepalese Agriculture. *Journal of Agriculture and Environment*, *9*, 62–71. https://doi.org/10.3126/aej.v9i0.2119

Narmilan, A., Gonzalez, F., Salgadoe, A. S. A., Kumarasiri, U. W. L. M., Weerasinghe, H. A. S., & Kulasekara, B. R. (2022). Predicting Canopy Chlorophyll Content in Sugarcane Crops Using Machine Learning Algorithms and Spectral Vegetation Indices Derived from UAV Multispectral Imagery. *Remote Sensing*, *14*(5). https://doi.org/10.3390/rs14051140

Neupane, K., & Baysal-Gurel, F. (2021). Automatic Identification and Monitoring of Plant Diseases Using Unmanned Aerial Vehicles: A Review. *Remote Sensing*, *13*(19). https://doi.org/10.3390/rs13193841

Nowatzki, J. (2017). *Agricultural Remote Sensing Basics AE1266*. *June*, 1–4. www.ag.ndsu.nodak.edu

Pandey, G., Yadav, L., Tiwari, A., Khatri, H. B., Basnet, S., Bhattarai, K., Gyawali, B., Rawal, N., & Khatri, N. (2017). Analysis of Yield Attributing Characters of Different Genotypes of Wheat in Rupandehi, Nepal. *International Journal of Environment, Agriculture and Biotechnology*, *2*(5), 2374–2379. https://doi.org/10.22161/ijeab/2.5.13

Qadir, T., Akhtar, K., Ahmad, A., Shakoor, A., Saqib, M., Hussain, S., & Rafiq, M. (2019). Wheat Production Under Changing Climate: Consequences of Environmental Vulnerabilities on Different Abiotic and Biotic Stresses. *Journal of Global Innovations in Agricultural and Social Sciences*, *October*, 7–17. https://doi.org/10.22194/jgiass/7.842

Rouse J.~W., J., Haas, R. ~H., Schell, J. ~A., & Deering, D. ~W. (1974). Monitoring Vegetation Systems in the Great Plains with Erts. In *NASA Special Publication* (Vol. 351, p. 309).

Shahi, T. B., Xu, C. Y., Neupane, A., Fleischfresser, D. B., O'Connor, D. J., Wright, G. C., & Guo, W. (2023). Peanut yield prediction with UAV multispectral imagery using a cooperative machine learning approach. *Electronic Research Archive*, *31*(6), 3343–3361. https://doi.org/10.3934/ERA.2023169

Shrestha, M., & Khanal, S. (2020). Future prospects of precision agriculture in Nepal. *Archives of Agriculture and Environmental Science*, *5*(3), 397–405. https://doi.org/10.26832/24566632.2020.0503023

Tanin, M. J., Sharma, A., Saini, D. K., Singh, S., Kashyap, L., Srivastava, P., Mavi, G. S., Kaur, S., Kumar, V., Kumar, V., Grover, G., Chhuneja, P., & Sohu, V. S. (2022). Ascertaining yield and grain protein content stability in wheat genotypes having the Gpc-B1 gene using univariate, multivariate, and correlation analysis. *Frontiers in Genetics*, *13*, 1001904. https://doi.org/10.3389/fgene.2022.1001904

Tsouros, D. C., Bibi, S., & Sarigiannidis, P. G. (2019). A Review on UAV-Based Applications for Precision Agriculture. *Information*, *10*(11). https://doi.org/10.3390/info10110349

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, *8*(2), 127–150. https://doi.org/https://doi.org/10.1016/0034-4257(79)90013-0

UNFPA. (2017). Population Situation Analysis of Nepal. *UNFPA, Nepal*, 1-3,6. https://nepal.unfpa.org/sites/default/files/pub-pdf/Nepal Population Situation Analysis.pdf%0Ahttp://nepal.unfpa.org/sites/default/files/pub-pdf/Nepal Population Situation Analysis.pdf

Wang, Y., Zhao, J., Lu, W., & Deng, D. (2017). Gibberellin in plant height control: old player, new story. *Plant Cell Reports*, *36*, 391–398.

Xue, J., & Su, B. (2017). Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. *Journal of Sensors*, *2017*, 1353691. https://doi.org/10.1155/2017/1353691

Yang, Q., Shi, L., Han, J., Zha, Y., & Zhu, P. (2019). Deep convolutional neural networks for rice grain yield estimation at the ripening stage using UAV-based remotely sensed images. *Field Crops Research*, *235*, 142–153. https://doi.org/https://doi.org/10.1016/j.fcr.2019.02.022

Zhang, J., Zhao, Y., Hu, Z., & Xiao, W. (2023). Unmanned Aerial System-Based Wheat

Biomass Estimation Using Multispectral, Structural and Meteorological Data. *Agriculture*, *13*(8). https://doi.org/10.3390/agriculture13081621

Zu, J., Yang, H., Wang, J., Cai, W., & Yang, Y. (2024). Inversion of winter wheat leaf area index from UAV multispectral images: classical vs. deep learning approaches. *Frontiers in Plant Science*, *15*. https://doi.org/10.3389/fpls.2024.1367828

BIOGRAPHICAL NOTES

Binod Prasad Bhatta, Gorakh Nath Pandey, Mamta Kadel, Sadikshya Adhikari, Manoj Kumar Bhat are the recently graduated students from Department of Geomatics Engineering, Kathmandu University. Mr. Sujan Sapkota is a lecturer at Kathmandu Univeristy. Mr. Shreejan Pokharel is scientist at the National Biotechnology Research Centre (NBRC). Mr. Shangharsha Thapa is PhD candidate at Lund University at Sweden.

CONTACTS

Mr. Binod Prasad Bhatta
Department of Geomatics Engineering,
Kathmandu University
Email: Prasad.binodbhatta11@gmail.com

Mr. Gorakh Nath Pandey
Department of Geomatics Engineering,
Kathmandu University
Email: aarogya.pandey5@gmail.com

Ms. Mamta Kadel
Department of Geomatics Engineering,
Kathmandu University
Email: mamtakadel88@gmail.com

Ms. Sadikshya Adhikari
Department of Geomatics Engineering,
Kathmandu University
Email: adhikarisadikshya661@gmail.com

Mr. Manoj Kumar Bhat
Department of Geomatics Engineering,
Kathmandu University
Email: manojbhat2050@gmail.com

Mr. Sujan Sapkota
Department of Geomatics Engineering,
Kathmandu University
Email: sujansapkota27@gmail.com

Mr. Shreejan Pokharel
National Biotechnology Research Center,
Lalitpur
Email: pshreejan2009@gmail.com

Mr. Shangharsha Thapa
Lund Univeristy, Sweden
Email: shangharsha.thapa@nateko.lu.se