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When to Fly a Drone for Accurate Corn Yield Potential Prediction

Authored by Aarati Khulal, Graduate Research Assistant, School of Plant and Environmental Sciences, Virginia Tech; and Olga S. Walsh, Associate Professor - Grain Crops, Extension Specialist, School of Plant and Environmental Sciences, Virginia Tech

Introduction

Yield prediction is estimating or forecasting the achievable future output of a crop per unit of land. Accurate yield potential prediction helps to understand crop responses to different environmental factors and supports informed decisions for farmers. Knowing anticipated yield levels enables growers to optimize resource allocation, improve management practices, and plan harvest (Van Klompenburg et al., 2020). It helps to guide crop insurance and marketing activities, and aids in securing better financial opportunities (Lobell et al., 2015; Rembold et al., 2019).

1. Yield Goal vs Yield Potential

Traditionally, yield goal prediction has relied on historical yield records and prior experience, rules of thumb, sometimes supplemented by field sampling (Dyke and Avis, 1953; Wisiol, 1987). However, these approaches have limited scope and accuracy. Dahnke et al. (1988) defined yield goal as the 'yield per acre you hope to grow'. This concept entails establishing a pre-season yield goal and managing the crop for that expected yield. Previous research showed that the yield goal concept fails to accurately predict current-year yield due to the inherent unpredictability of the growing environment. In fact, both yield level and crop response to inputs (such as fertilizers) are independent, and both drive crop demand for nutrients (Raun et al., 2010; Arnall et al., 2013).

In contrast, in-season prediction of yield potential using remote sensing is a practical alternative for improved crop management. This approach accounts for temporal and spatial variability and is particularly beneficial for developing fertilizer recommendations (Raun et al., 2017).

2. Drones – the Unmanned Aerial Vehicles (UAVs)

With modern approaches to crop management that use in-field remote sensing data, it has become possible to better understand growing conditions, biomass production, photosynthetic activity, canopy height, and other key factors (Poudyal et al., 2023; Biswal et al., 2025) that are important for accurate yield potential prediction. Drones (Unmanned Aerial Vehicles, UAVs) equipped with spectral sensors have become popular tools for data collection in agricultural systems. These data include information on plant greenness, nutrient uptake, and canopy characteristics, which serve as valuable markers for predicting yield potential. Research has shown that sensor-based data are effective for estimating the yield potential of a variety of crops, including corn (Zea Mays L.) (Walsh et al., 2023; Killeen et al., 2024; Yuan et al. 2024). Employing drones makes collecting detailed data in a timely manner feasible, even for larger fields.

3. Vegetation Index

Vegetation Indices (VIs) are mathematical formulas that combine reflectance values from different spectral bands, which can be captured by sensors mounted on drones. VIs such as Normalized Difference Vegetative Index (NDVI), Green NDVI (GNDVI), and Red-Edge NDVI (NDRE) have been found to be excellent indicators of plant health, crop stand density and vigor, and crop response to inputs (Table 1). These VIs are influenced by soil

reflectance and canopy structure, which vary with crop growth stage and can affect yield potential prediction (Torino et al., 2014; Dyson et al., 2019).

Table 1. Common VI used in image-based remote sensing.

VI	What the VI measures	Remarks
NDVI	Vigor, vegetation density, greenness	Saturates in dense vegetation
GNDVI	Nitrogen status, Chlorophyll levels	Early sign of stress detection
NDRE	Vegetation health & Chlorophyll levels	Less sensitive to dense canopies

4. Drone Flights and Timing

Drone flights should be avoided on cloudy days or during early morning and late afternoon, as shadows and changing sun angles can affect the image quality. Flights are best conducted on clear days between 10 am and 2 pm. It is advised to avoid flying when wind speeds exceed 10 mph, since high winds can cause image blur and poor mosaicking of the whole-field image. Additionally, flights should be avoided after rain, as wet leaves can lead to unpredictable reflectance values and reduce data accuracy.

5. Optimal Growth Stage for flight

In corn production systems, soil reflectance is more pronounced during the early growth stages because the exposed soil between the crop rows tends to interfere with plant reflectance (Xue and Su, 2017; Almeida-Ñauñay et al., 2022). Drone imagery is most effective when the canopy is sufficiently developed (full canopy closure) to cover maximum soil surface and when differences in plant vigor among management zones or treatments are clearly expressed in canopy density, photosynthetic activity, and leaf color. Image-based observations are also most informative once the crop has absorbed most basal and in-season nutrients, resulting in substantial biomass accumulation. Figure 1 illustrates how canopy structure and reflectance of corn plants change from the early vegetative stage to the reproductive stage.

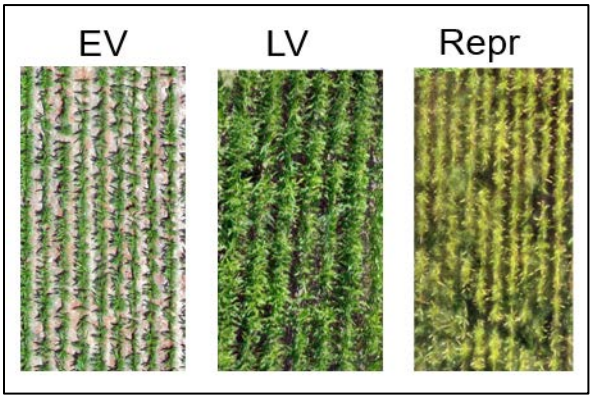

Figure 1. Drone images of corn at early vegetative (EV), late vegetative (LV), and reproductive (Repr) stages, showing increasing canopy closure and changes in reflectance that affect yield-prediction accuracy.

Recent field trials conducted across Virginia indicated that corn yield potential was most accurately predicted at the late vegetative growth stage prior to tassel visibility (Figure 2). At this stage, the established plant stand and well-developed crop canopy facilitate accurate remote sensing measurements. As leaves senesce, plants may start lodging. Reproductive structures, such as tassels and cobs, may also become visible. These factors can affect overall reflectance.

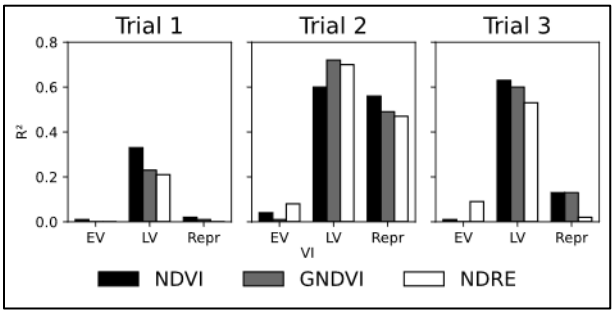

Figure 2. Effect of Corn Growth Stage on Drone-Based Yield Potential Prediction Accuracy (EV, LV, and R represent Early Vegetative, Late Vegetative, and Reproductive Stages)

The late vegetative stage in corn begins after the plant reaches approximately V11-V12. At this point, 11-12 fully collared leaves are present, and the plant begins rapid vertical growth as it progresses toward tasseling. The “V” designation refers to the number of leaves on the plant that have fully visible collars,

with each collared leaf representing one vegetative growth stage (e.g., V1, V2, V3,... Vn). This concept is illustrated in Figure 3.

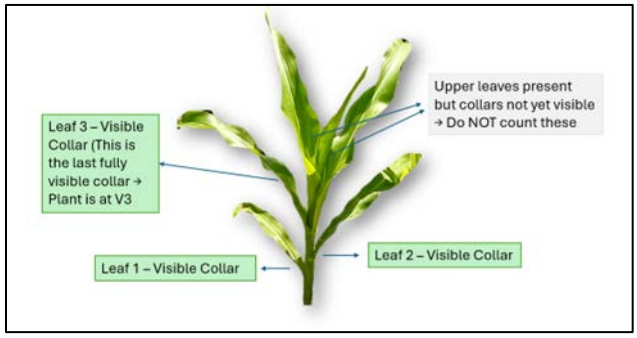

Figure 3. Identifying vegetative growth stages (V-stages) in corn.

6. Choosing the Right VI

Even though VI all relate to plant canopy characteristics, different VI are useful for different canopy types, growth stages, and crop attributes. NDVI is very effective in closed canopies and is commonly used to assess plant vigor; however, it tends to saturate in dense vegetation and with very high nutrient uptake values (Mutunga & Skidmore, 2004). In such cases, NDRE is advantageous because its spectral bands can penetrate deeper into the canopy and are less prone to saturation by comparison (Li et al., 2014). GNDVI is also useful for evaluating nitrogen uptake and chlorophyll variation (Gitelson et al., 1996, 2005) and is effective for detecting plant stress. Therefore, selecting the appropriate VI improves prediction reliability and accuracy.

Conclusion

Drone imagery is a valuable tool for estimating corn yield potential, with flight timing having a major impact on accuracy. Flights conducted during the late vegetative stage consistently have shown the strongest relationship between VIs and yield across multiple years and locations. By flying on clear, calm days and maintaining consistent flight settings, producers can obtain more reliable drone imagery and make better-informed management decisions. Choosing the appropriate growth stage and flight conditions ensures that these data contribute effectively to crop monitoring and yield prediction.

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References

Arnall, D.B., A.P. Mallarino, M.D. Ruark, G.E. Varvel, J.B. Solie, and M.L. Stone et al. 2013. “Relationship between Grain Crop Yield Potential and Nitrogen Response.” Agronomy Journal, 105: 1335–1344. doi: https://doi.org/10.2134/agronj2013.0034

Biswal, P., A. Faisal, D. K. Swain, G. D. Bhowmick, and G. Mohan. 2025. “NDVI Measured Is the Best Parameter for Yield Prediction at the Peak Vegetative Stage of Potato (Solanum tuberosum L.).” Climate Smart Agriculture, 2 (2): 100053.

Dahnke, W.C., L.J. Swenson, R.J. Goos, and A.G. Leholm. 1988. “Choosing a crop yield goal.” SF-822. North Dakota State Extension Service, Fargo.

Dyke, G. V., and P. R. D. Avis. 1953. “A Survey of Maincrop Potatoes I: Estimates of Yield, 1948–50.” The Journal of Agricultural Science, 43 (4): 450–5

Dyson, J., A. Mancini, E. Frontoni, and P. Zingaretti. 2019. “Deep Learning for Soil and Crop Segmentation from Remotely Sensed Data.” Remote Sensing, 11 (16): 1859.

Gitelson, A. A., A. Vina, V. Ciganda, D. C. Rundquist, and T. J. Arkebauer. 2005. “Remote Estimation of Canopy Chlorophyll Content in Crops.” Geophysical Research Letters, 32: L08403.

Gitelson, A. A., Y. J. Kaufman, and M. N. Merzlyak.1996. “Use of a Green Channel in Remote Sensing of Global Vegetation from EOS-MODIS.” Remote Sensing of Environment, 58 (3): 289–98.

Killeen, P., I. Kiringa, T. Yeap, and P. Branco. 2024. “Corn Grain Yield Prediction Using UAV-Based High Spatiotemporal Resolution Imagery,

Machine Learning, and Spatial Cross-Validation." Remote Sensing, 16 (4): 683.

Li, F., Y. Miao, G. Feng, F. Yuan, S. Yue, X. Gao, and X. Chen. 2014. "Improving Estimation of Summer Maize Nitrogen Status with Red Edge–Based Spectral Vegetation Indices." Field Crops Research, 157: 111–23.

Lobell, D. B., D. Thau, C. Seifert, E. Engle, and B. Little. 2015. "A Scalable Satellite-Based Crop Yield Mapper." Remote Sensing of Environment, 164: 324–33.

Mutanga, O., and A. K. Skidmore. 2004. "Narrow Band Vegetation Indices Overcome the Saturation Problem in Biomass Estimation." International Journal of Remote Sensing, 25 (19): 3999–4014.

Poudyal, C., H. Sandhu, Y. Ampatzidis, D. C. Odero, O. C. Arbelo, R. H. Cherry, and L. F. Costa. 2023. "Prediction of Morpho-Physiological Traits in Sugarcane Using Aerial Imagery and Machine Learning." Smart Agricultural Technology, 3: 100104.

Raun, W. R., Figueiredo, B., Dhillon, J., Fornah, A., Bushong, J., Zhang, H., & Taylor, R. 2017. "Can Yield Goals be Predicted?" Agronomy Journal, 109(5), 2389–2395. https://doi.org/10.2134/agronj2017.05.0279

Raun, W.R., J.B. Solie, and M.L. Stone. 2010. "Independence of Yield Potential and Crop Nitrogen Response." Precision Agriculture, 12: 508–518. doi: https://doi.org/10.1007/s11119-010-9196-z

Rembold, F., M. Meroni, F. Urbano, G. Csak, H. Kerdiles, A. Perez-Hoyos, and T. Negre. 2019. "ASAP: A New Global Early Warning System to Detect Anomaly Hot Spots of Agricultural Production for Food Security Analysis." Agricultural Systems, 168: 247–57.

Torino, M. S., B. V. Ortiz, J. P. Fulton, K. S. Balkcom, and C. W. Wood. 2014. "Evaluation of Vegetation Indices for Early Assessment of Corn Status and Yield Potential in the Southeastern United States." Agronomy Journal, 106 (4): 1389–1401.

Van Klompenburg, T., A. Kassahun, and C. Catal. 2020. "Crop Yield Prediction Using Machine Learning: A Systematic Literature Review." Computers and Electronics in Agriculture, 177: 105709.

Walsh, O. S., E. Nambi, S. Shafian, D. M. Jayawardena, E. O. Ansah, R. Lamichhane, and J. R. McClintick-Chess. 2023. "UAV-Based NDVI Estimation of Sugarbeet Yield and Quality Under Varied Nitrogen and Water Rates." Agrosystems, Geosciences & Environment, 6 (1): e20337.

Wisiol, K. 1987. "Choosing a Basis for Yield Forecasts and Estimates." In Plant Growth Modeling for Resource Management, Volume 1: Current Models and Methods, 75–103.

Yuan, J., Y. Zhang, Z. Zheng, W. Yao, W. Wang, and L. Guo. 2024. "Grain Crop Yield Prediction Using Machine Learning Based on UAV Remote Sensing: A Systematic Literature Review." Drones, 8 (10): 559.

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